ALIGNING EDUCATION AND LABOR MARKETS: UNDERSTANDING LABOR MARKET MISMATCHES AND TECHNOLOGY USE IN TÜRKİYE

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF SOCIAL SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

DENİZ PLEVNELİ DÜZÇAY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF DOCTOR OF PHILOSOPHY
IN
THE DEPARTMENT OF ECONOMICS

AUGUST 2024

Approval of the thesis:

ALIGNING EDUCATION AND LABOR MARKETS: UNDERSTANDING LABOR MARKET MISMATCHES AND TECHNOLOGY USE IN TÜRKİYE

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ABSTRACT

ALIGNING EDUCATION AND LABOR MARKETS: UNDERSTANDING LABOR MARKET MISMATCHES AND TECHNOLOGY USE IN TÜRKİYE

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August 2024, 329 pages

This thesis examines the misalignments between educational outputs and labor market demands in Türkiye. It comprises three main chapters. The first main chapter analyzes the incidence, correlates, and outcomes of education and skill mismatches, revealing a high prevalence of education and skill mismatch among full-time workers, which results in wage penalties and affects job satisfaction. The second main chapter extends the analysis to field-of-study mismatch, showing that a substantial portion of tertiary-educated workers are employed in fields unrelated to their studies, causing wage penalties. The third main chapter shifts focus to the demand side, analyzing how technology use and the nature of job tasks influence wage outcomes. It shows the wage benefits for workers using complex information and communication technologies (ICT) with higher education and those engaged in non-routine tasks, supporting theories of skill-biased technological change and task-based approaches. The findings collectively underscore the need for policy interventions that enhance the alignment of education outputs with labor market needs, emphasizing the role of technology in shaping labor market outcomes.

Keywords: education mismatch, skill mismatch, field of study mismatch, technology use, job tasks.

ÖZ

EĞİTİM VE İŞGÜCÜ PİYASALARININ UYUMU: TÜRKİYE'DE İŞGÜCÜ PİYASASI UYUMSUZLUKLARI VE TEKNOLOJİ KULLANIMINI ANLAMAK

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Bu tez, Türkiye'de eğitim çıktıları ile işgücü piyasası talepleri arasındaki uyumsuzlukları incelemektedir. Üç ana bölümden oluşmaktadır. İlk ana bölüm, eğitim ve beceri uyumsuzluklarının görülme sıklığını, ilişkili değişkenlerini ve sonuçlarını analiz ederek, tam zamanlı çalışanlar arasında eğitim ve beceri uyumsuzluğunun yaygın olduğunu, bunun da ücret kayıplarına yol açtığını ve iş tatminini etkilediğini ortaya koymaktadır. İkinci ana bölüm, analizi eğitim alanı uyumsuzluğuna genişleterek, yükseköğrenim gören çalışanların önemli bir kısmının alanlarıyla ilgili olmayan işlerde çalıştığını ve bunun da ücret kayıplarına neden olduğunu göstermektedir. Üçüncü ana bölüm, teknoloji kullanımının ve iş görevlerinin ücretleri nasıl etkilediğini analiz ederek odağı talep tarafına kaydırmaktadır. Kompleks bilgi ve iletişim teknolojilerini (BİT) kullanan ve yükseköğrenim gören çalışanlar ile rutin olmayan işlerde çalışanlar için ücret avantajlarını göstererek, beceri yanlısı teknolojik değişim ve iş görevleri tabanlı yaklaşım teorilerini desteklemektedir. Bulgular, eğitim çıktılarının işgücü piyasası ihtiyaçlarıyla uyumunu artıran politika müdahalelerine olan ihtiyacın altını çizerek, işgücü piyasası sonuçlarını şekillendirmede teknolojinin rolünü vurgulamaktadır.

Anahtar Kelimeler: eğitim uyumsuzluğu, beceri uyumsuzluğu, alan uyumsuzluğu, teknoloji kullanımı, iş görevleri.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to everyone who supported and guided me throughout my doctoral journey. First and foremost, I am profoundly grateful to my advisor, Prof. Meltem Dayıoğlu, for her invaluable guidance, encouragement, and patience. Her mentorship has been a constant source of inspiration, and her belief in my abilities has given me the confidence to complete this work. I have been incredibly fortunate to work under her supervision, and I deeply appreciate the time and effort she has invested in my development.

I also wish to extend my sincere thanks to the members of my dissertation committee, Prof. Şirin Saraçoğlu, Assoc. Prof. Hakan Ercan, Prof. Erol Taymaz, Prof. İsmet Koç and Prof. Seyit Mümin Cilasun. Their constructive feedback have significantly improved the quality of my research. I am thankful for the time they took to help me refine my work.

To my beloved spouse, Güney Düzçay, thank you for your unwavering support, understanding, and love. Your belief in me kept me going even in the most challenging times. I am incredibly fortunate to have you by my side, and this achievement is as much yours as it is mine. Your encouragement and understanding throughout this journey have meant the world to me.

My deepest gratitude goes to my parents, İnci and Fahrettin Plevneli. From the very beginning, your guidance and encouragement have shaped who I am today. Your endless support has been the foundation of my success, and I cannot express how much it means to me. Without your love and encouragement, this achievement would not have been possible.

Finally, I would like to acknowledge all those who have supported me in various ways throughout this process, whether through friendship, or simply offering a listening ear. Your kindness and generosity have been deeply appreciated. This dissertation would

not have been possible without the contributions of all these remarkable individuals, and I am deeply thankful for each and every one of you.

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CHAPTER 1

INTRODUCTION

From a developmental perspective, increasing the education level of a population is fundamental to enhancing economic growth and development. Education drives economic growth through several ways. First, it increases the human capital of the labor force, enhancing labor productivity and contributing to growth (Becker, 1964;1975). Secondly, education enhances the innovative capacity of an economy by fostering the development of new knowledge and technologies (Lucas, 1988; Romer, 1990). Thirdly, education facilitates the diffusion of knowledge by improving the ability of individuals to absorb and apply new information. By doing so, it helps the labor to effectively use advanced technologies, further promoting economic growth (Nelson and Phelps, 1966).

In this context, investment in education aims to produce a workforce that is not only larger but also more skilled and capable of driving technological advancement. Expanding higher education contributes to the development of a more educated workforce, which ideally leads to higher labor productivity and better economic outcomes. However, increasing educational attainment does not automatically translate into economic growth; rather, it represents the cultivation of a workforce with higher educational qualifications. A bigger challenge lies in ensuring that the education system aligns with the needs of the labor market by effectively preparing the workforce for these needs. This implies that the value of education lies not only in its quantity but also in its quality and relevance.

The relationship between education and economic growth has been extensively studied, with a significant focus on both the quality and quantity of schooling (Barro, 2013). Research over the past decades show the role of education quality in economic development. The focus has shifted from quantifying education through years of

schooling to evaluating the skills acquired. Hanushek and Kimko (2000) analyze the relationship between the quality of schooling and economic growth across countries. They find that the quality of education, as measured by student achievement scores [1], is a more significant determinant of economic growth than the quantity of education, such as years of schooling. Several studies have since found very similar results, including Lee and Barro (2001) and Bosworth and Collins (2003), to name a few.

More recently, by comparing OECD countries to non-OECD countries, Hanushek and Woessmann (2010) find that the effect of educational quality is more pronounced in non-OECD countries compared to OECD countries. Furthermore, they find that when countries are classified based on their GDP per capita in 1960, the impact of educational quality is significantly larger in low-income countries compared to high-income countries (Hanushek and Woessmann, 2009). Their conclusion for the developing countries is that "once there is a high-quality school system, it pays to keep children in school longer – but it does not pay if the school system does not produce skills" (Hanushek and Woessmann, 2010; p.248).

Expanding higher education means more people get education for longer periods, increasing the overall educational attainment of the population. This expansion can lead to a more skilled workforce, which is essential for economic development. However, as highlighted by Hanushek and Woessmann (2010), the benefits of this expansion are contingent on the quality of the education provided. Furthermore, while improving the quality is important, it is also essential to address how well the skills acquired through education align with labor market demands. A very important issue that arises in this context is *labor market mismatch*, which occurs when there is a misalignment between the skills possessed by workers and the skills demanded by the labor market.

This alignment between educational outcomes and labor market is very important in determining the overall effectiveness of educational investments. A successful entry

[1] They use six international student achievement test data to construct a measure of educational quality. The measure of education quality used includes mathematics and science scores from international tests spanning from the 1960s up to 1991.

into the labor market is not only defined by obtaining employment. An equally important measure of effective educational investments is the extent to which employment matches workers' levels of education, skills, field-of-studies. When individuals find jobs that fully utilize their qualifications, it not only improves job satisfaction and wages but also enhances their contributions to economic productivity. However, mismatches between educational outcomes and labor market demands can significantly undermine these benefits.

Labor market mismatches occur, in general, for two reasons. **First**, mismatches can be attributed to issues with the *quality* and *relevance* of education. The heterogeneity in educational quality means that even if two graduates come from the same field, their skills and ability can vary greatly. Variations in the quality of education between different institutions can lead to differences between graduates entering the job market. If the education provided does not meet the requirements of the labor market, some of these graduates may find themselves unable to secure employment that matches their level of education (McGowan and Andrews, 2015; 2017).

Moreover, the assessment of the alignment of an individual's education extends beyond skills to include the relevance of their field-of-study to their job. Field-of-study mismatch is the phenomenon where there is a misalignment between the field in which individuals are educated and the sector in which they are employed. From an economic perspective, field-of-study mismatches can lead to inefficiencies in the labor market. When individuals invest in training in certain fields, and these individuals end up working in unrelated sectors, returns on educational investments might diminish. To understand these aspects, it is necessary to look not only at education mismatch but also at other types of mismatches, which are skill mismatch and field-of-study mismatch (Robst, 2007; Montt, 2015).

A **second** and equally important factor contributing to labor market mismatch is the oversupply of graduates, especially in certain fields. This typically happens when higher education institutions produce more graduates than the job market can absorb, which creates an oversupply of highly educated individuals that the labor market does not require. This might result from a rapid expansion of higher education, where the volume of highly educated workers exceeds the labor market's capacity to absorb them

in matching jobs. An increase in educational attainment only translates to economic benefits if there is a corresponding demand for such skills in the labor market. If not, a significant portion of the labor force is misaligned with job market demands, and the potential productivity gains from education are not fully realized. This requires a careful and effective education planning, which involves ensuring quantitative and qualitative alignment between education, labor market, and production (Tekeli, 2012, p58).

Furthermore, rapid technological advancements can influence the relevance of certain skills and educational backgrounds in the labor market. We live in times where rapid advancements in information and communication technologies (ICT) continuously transform the workplace and production processes. Industries that go through digital transformation may suddenly require new technical skills that current workers or recent graduates do not possess, leading to a digital skills gap. For example, the shift from manual drafting to computer-aided design (CAD) in architecture field dramatically changed the skill sets required in these professions. Workers who fail to update their skills may find themselves mismatched in a job market that demands proficiency with new technologies.

Moreover, technological advancements often enhance the productivity of highly skilled workers more than that of less skilled workers. This can be explained by the concept of Skill-Biased Technological Change (SBTC), which posits that technological advancements tend to increase the demand for skilled labor, especially for those who are proficient in complex technical tasks that complement new technologies (Card and DiNardo, 2002). On the other hand, basic ICT skills are often associated with routine tasks that can be subject to automation. As a result, jobs requiring only basic skills are at a higher risk of wage stagnation or decline due to the pressures of automation and the oversupply of workers who possess these basic skills.

The overarching theme of this thesis addresses the complexities of a misalignment between education and labor market. Transformations in the education system require strategic planning; otherwise, this can lead to different forms of mismatches (i.e. education mismatch, skill mismatch and field-of-study mismatch) that affect economic outcomes. Furthermore, this thesis considers the mediating role of technology as both

a potential exacerbator of mismatches (when technological advancement outpaces educational adaptation) and as a solution (through enhanced digital literacy and technology-integrated education).

This thesis investigates these issues through **three main chapters**:

1. **The second chapter** examines the incidence, correlates and outcomes of educational and skill mismatches among full-time wage earners in Türkiye, and assesses how these mismatches affect wages and job satisfaction.
2. **The third chapter** focuses on field-of-study mismatch, analyzing whether tertiary educated full-time wage earners in Türkiye are employed in jobs that align with their academic fields. It examines the effects of field-of-study mismatch, together with education and skill mismatches, on wages and job satisfaction.
3. **The fourth chapter** addresses the role of technological advancements and changing skill demands in the labor market. It examines how different levels of ICT use and job task characteristics, together with educational attainment, influence wage outcomes in Türkiye.

Given this outline, **the contributions of this thesis are threefold:**

- It addresses all types of skill mismatches, including skill mismatch, which has not been previously researched for Türkiye, by leveraging data from the Programme for the International Assessment of Adult Competencies (PIAAC). This study not only analyzes skill mismatch but also contextualizes it with other types of labor market mismatch, offering a comprehensive view of their combined effect on the labor market outcomes.

The phenomenon of labor market mismatch has been extensively studied in literature, with a larger emphasis placed on education mismatch, which investigates the discrepancies between the educational qualifications that employees possess and the requirements of their jobs. Studies consistently show that overeducated workers, despite possessing higher qualifications, often earn less than their adequately educated counterparts in matched jobs. However, education mismatch analyses presume that the

educational requirements of a job accurately reflect the skills necessary for performing it and that a worker's formal educational qualifications are a complete representation of their human capital (McGuinness and Wooden, 2009).

Skill mismatch analysis provides a complement to education mismatch by offering a more comprehensive evaluation of labor market alignment. However, assessing the alignment between education and labor market needs brings forth another challenge: measuring skill mismatch. Measuring skill mismatch is difficult due to the lack of direct information about workers' skills and job requirements. Traditional methods involve survey questions asking workers for their self-assessment (Allen and van der Velden, 2001; Green and McIntosh, 2007). These approaches often suffer from measurement issues, such as overconfidence among respondents (Pellizzari and Fichen, 2014). Alternatively, some studies compare indicators of skill proficiency and skill use at work to determine overskilling (CEDEFOP, 2010; Desjardins and Rubenson, 2011). However, this method also faces challenges, including the assumption that self-reported skill use accurately reflects job requirements and the theoretical differences between skill use and skill itself.

Due to these issues, while education mismatch and field-of-study mismatch have received recent attention in Türkiye, there are no studies on the incidence and consequences of skill mismatch in the Turkish context. This thesis fills this gap in the literature by using detailed data from the PIAAC to explore skill mismatches in Türkiye, along with other forms of mismatch. The individual-level measure of skill mismatch, derived from PIAAC data, offers an accurate and comprehensive understanding of how well workers' skills align with job demands (Pellizzari and Fichen, 2014).

- Secondly, this thesis contributes to the literature by providing partial empirical support for SBTC and capital-skill complementarity, as well as the Routine Biased Technical Change hypotheses, within the context of Türkiye by examining how education, technology use, and the nature of job tasks influence earnings.

In the fourth chapter of the thesis, the focus shifts to the demand side of the labor market by examining how technology use, in conjunction with educational attainment,

influences labor market outcomes. This section discusses capital-skill complementarity and how different levels of technology use in a job can influence wages, emphasizing the role of technology in mediating the relationship between education and labor market outcomes. It shows how ICT use interacts with education and how these interactions affect wage outcomes. This approach goes beyond the binary variable for computer use, providing a more detailed understanding of the relationship between different levels of ICT skills and wages. Additionally, this chapter examines the impact of job tasks on wages by integrating job task characteristics into the models. This analysis shows how the nature of job tasks, alongside education, technology use, and cognitive abilities, influences earnings.

- Thirdly, this thesis also contributes to the existing literature on labor market mismatch in Türkiye by controlling for unobserved abilities, thereby minimizing omitted variable bias when examining the effects on wages.

The unobserved ability issue is very important when examining wage effects of labor market mismatch and technology use. It has long been recognized that workers who attended school longer may possess other characteristics, such as innate ability, which can lead them to earn higher wages irrespective of their level of education (Krueger and Lindahl, 2001). If these unobserved characteristics are not accounted for, comparisons of earnings across individuals with different levels of schooling would overstate the return to education. Similarly, this inclusion offers explanations for the factors that influence wage differences that may affect the productive use of technology in the workplace. In this thesis, by using data from OECD PIAAC, which includes direct measures of skills like literacy and numeracy, we aim to control for these unobserved abilities. This approach provides a more accurate assessment of the true effect of labor market mismatches and technology use on labor market outcomes in Türkiye.

Finally, conducting this study for Türkiye is significant due to the country's higher education expansion over recent decades and the economic transformations that continue to reshape its labor market. While this analysis is constrained by cross-sectional data, which limits the ability to directly measure the effects of higher education expansion over time, it enables the examination of the current incidence of

labor market mismatch and its consequences. Given this, the hypothesis posited is that in Türkiye, substantial misalignments exist between the educational system and labor market, leading to negative outcomes such as reduced wages and lower job satisfaction. This study aims to substantiate this hypothesis by quantifying the incidence and outcomes of all three types of labor market mismatches (i.e. education mismatch, skill mismatch, and field-of-study mismatch) and assessing the impact of technology use and job tasks on wages. The findings are expected to provide empirical support that shows the need for policy interventions in Türkiye to enhance the alignment between education and labor market demands.

CHAPTER 2

THE INCIDENCE, CORRELATES AND OUTCOMES OF LABOR MARKET MISMATCH IN TÜRKİYE

2.1. Introduction

Expanding higher education is widely regarded as a positive development, contributing to economic growth, social mobility, and individual well-being. Türkiye has witnessed a significant educational expansion over the past few decades, characterized by an increase in the number of higher education institutions and a broadening of access to tertiary education. Starting in the late 1990s and early 2000s, governments undertook several initiatives to increase access to higher education. This included the establishment of many new state and private universities to accommodate growing demand. As of the 2023-2024 academic year, Türkiye has a total of 208 higher education institutions (including public universities, private universities, and foundation vocational schools), up from 71 in 2000-2001 academic year.

In Türkiye, this massification of higher education has been driven by a recognition of its benefits, and the goal was to democratize education and provide greater opportunities for tertiary education to a larger segment of the population. Investments from both the government and individuals have supported this expansion. The Turkish government has made substantial investments in higher education, which includes funding for public universities, building new campuses, and providing budgets to support educational activities. In fact, in 2023, Türkiye dedicated 14.6% of its central budget to education [2], amounting to 651.377 billion Turkish Liras ($27.43 billion[3]).

[2] This includes expenditures for the Ministry of National Education, the Higher Education Council, the Higher Education Quality Council, and universities.

[3] Calculated using the average USD/TRY exchange rate of 23.74 for 2023 and 31.69 for 2024 until June. Data sourced from the Central Bank of the Republic of Türkiye (CBRT).

For 2024, the allocation increased by approximately 150% to 1 trillion 615.2 billion liras ($51.13 billion). This positioned education as the largest budgetary item in the budget (From the presentation by the Minister of National Education to the TBMM (the Grand National Assembly of Türkiye) Plan and Budget Commission in 2024).

These investments reflect a belief in the potential for higher education to provide better opportunities and economic prosperity. Individuals also contribute significantly to higher education by providing financial support to their children or through tuition fees at private universities. Many students invest in supplementary education, such as private tutoring and preparatory courses for university entrance exams, aiming to increase their chances of being placed in higher education institutions. In addition, students and their families bear the costs of living, textbooks, and other expenses associated with going to university. Additionally, the government offers various scholarship programs and financial aid packages to support students from low-income families, aiming to increase access to higher education and ensure that financial barriers do not prevent capable students from pursuing tertiary education.

However, all these investments in higher education by both the government and individuals can be seen as inefficient if there is no corresponding demand for the increased educational qualifications in the labor market. In Türkiye, there are growing concerns about the alignment of educational outcomes with labor market needs (Şenses, 2007; Çelik and Gür, 2013; Gür, 2016). Public discussions and many studies point that while educational attainment has increased, it has not always been accompanied by a corresponding increase in job opportunities, leading to mismatches in the labor market (Filiztekin, 2011; Ege and Erdil, 2023). Furthermore, these mismatches may lead to a wage penalty for affected individuals and causes productivity loss, as individuals are not using this education in their jobs. This productivity loss, combined with the wage penalty, is detrimental not only to individuals but also to the economy as a whole. Therefore, given the significant investments made by both the government and individuals, it is essential to address the issue of labor market mismatches.

The first chapter of the thesis is centered on understanding the implications of educational expansion on labor market mismatches in Türkiye. To this end, it analyzes

the incidence, determinants, and outcomes of education and skill mismatch in Türkiye. We aim to show that labor market mismatches lead to significant negative outcomes for workers in Türkiye. Although there is a comprehensive body of research on labor market mismatches internationally, studies addressing this issue within the Turkish context are limited. Furthermore, to the best of our knowledge, there are no studies that specifically analyze the effects of skill mismatches in Türkiye, due to previous limitations in data availability. This research aims to bridge this gap by examining different types of mismatches together between the qualifications of the workforce and the demands of Türkiye's labor market. Moreover, we extend the analysis to job satisfaction, an area less explored in the literature.

Much of the existing research on Türkiye has focused on education mismatch rather than skill mismatch due to the difficulties associated with obtaining data on skill levels and requirements. This thesis utilizes data from the Programme for the International Assessment of Adult Competencies (PIAAC) conducted by the OECD. PIAAC aims to address some of these data challenges. It is a comprehensive international survey designed to assess the skills and competencies of adults, which offers *objective, individual-level measures of skill levels* via standardized assessments and allows for a detailed analysis of the incidence and consequences of skill mismatch.

By combining individual self-assessments with objective measures of education and skill requirements, this thesis answers the following questions:

- What is the incidence of education mismatch among full-time employed workers in Türkiye, and how do subjective and objective assessments compare?
- What factors contribute to the likelihood of an individual being overeducated or undereducated in the labor market?
- How do individuals' perceptions of education mismatch compare with objective measures of mismatch?
- How does education mismatch, as assessed by both subjective and objective methods, affect the wages and job satisfaction of workers in Türkiye?
- What is the incidence of skill mismatch among full-time employed workers

in Türkiye?

- How do education and skill mismatches intersect, and what does this intersection reveal about labor market?
- What are the characteristics that significantly affect the probability of an individual being overskilled or underskilled?
- How do skill mismatches affect the wages and job satisfaction of workers?

Our findings indicate that there is a high incidence of education and skill mismatch among full-time workers in Türkiye. According to subjective assessments, 29% of workers perceive a mismatch between their education and their job requirements, with 16% experiencing overeducation and 13% undereducation. The objective approach further reveals that 42% of workers are mismatched in terms of their educational qualifications relative to their job requirements, with 31% being overeducated and 11% undereducated.

In the context of Türkiye, these findings align with existing literature. For example, studies using objective methods report overeducation rates ranging from 22% to 34%, while undereducation rates vary between 6% and 24% for Türkiye (Filiztekin, 2011; Acar, 2016; Mercan et al., 2015; Eriş Dereli, 2017; and Duman, 2018). These variations are largely due to methodological differences and sample compositions. However, when compared internationally, the incidence of overeducation in our analysis, which is 31%, is notably higher than the average derived from various country studies reviewed by McGuinness (2006), who reports an average overeducation incidence of 22% based on objective measures for various countries.

This high incidence of mismatch, especially overeducation, suggests that the labor market may not be at equilibrium, indicating either an excess supply of educated labor relative to demand or that available jobs do not fully utilize the education of the workforce. This mismatch extends to skills as well. The analysis of skill mismatch shows that 41% of workers are mismatched in terms of their skills, where 28% of workers are overskilled and 13% are underskilled. This incidence of skill mismatch is higher when compared to findings from other developed countries. For instance, Perry et al. (2014), using PIAAC data, report lower rates of skill mismatch in Germany (16%), Austria (13%), and the USA (14%). Once again, these differences in findings

might be due to variations in the methodologies used in the studies to some extent.

Moreover, a significant portion of individuals classified as overeducated are also identified as overskilled (38.9% in RM and 39.7% in SA), suggesting a dual mismatch. Furthermore, among those who are overeducated, more than half (54.7% in RM and 52.9% in SA) are well-matched in skills. These high ratios suggest that there are inefficiencies in the education system and its alignment with the labor market, suggesting that while the system may produce highly educated individuals, it may not be equipping them with matching skills.

It should be noted that this analysis employs cross-sectional data from PIAAC. Because of the cross-sectional nature of the data, it is not possible to determine whether the observed labor market mismatches are a result of the expansion of higher education in Türkiye. However, the evidence does show that labor market mismatch is an important concern for Türkiye, particularly in the context of its recent educational expansion. The high rates of mismatches suggest that despite increased educational attainment, there is a substantial misalignment between the skills and qualifications workers have and the demands of the labor market.

It is expected that labor market mismatches lead to significant negative outcomes for workers in Türkiye. The high incidence of labor market mismatch, and overeducation in particular, can result in wage penalties for mismatched workers, who may earn less than their well-matched counterparts with similar educational backgrounds. The findings partially support this hypothesis. Overeducated workers receive lower returns on their education compared to well-matched workers in all but one model. Similarly, undereducation shows significant negative effects on wages in all but one model. On the other hand, being overskilled results in a wage penalty in all models, while being underskilled does not have a significant effect on wages.

Regarding job satisfaction, the significant positive effect of undereducation on job satisfaction (based on self-assessment method for detecting over/under-education) indicates that undereducated individuals might still feel satisfied with their work. Similarly, being underskilled has a significantly positive effect on job satisfaction in all models. The significance of this positive effect, even after controlling for wages,

indicates that the influence of being underskilled or undereducated on job satisfaction is independent of wage levels.

This chapter is structured as follows. The next section will present a theoretical literature review on the topic of labor market mismatch. The third section will provide a summary of empirical studies related to the subject. Following that, there will be an extensive section dedicated to the Turkish education system, exploring the relationship between the education system and mismatch. Following this, the focus will shift to the labor market in the subsequent section, examining various labor market regulations and policies. The sixth section will provide information about the OECD PIAAC data, which serves as the dataset for this study, and the methodology employed will be outlined. The subsequent chapters will present the findings of education and skill mismatches. Finally, the concluding chapter will serve as a comprehensive summary, focusing the key results, implications, and conclusions drawn from the research.

2.1.1. Definitions

In the literature, there are several different ways to classify the types of labor market mismatch, and the specific categories and definitions vary depending on the context and research question. Nonetheless, labor market mismatch is commonly classified into three main types, which are education mismatch, field-of-study mismatch and skills mismatch:

1. **Education mismatch** refers to the situation where the level of education of an individual do not match the requirements of the job they hold. This happens when workers have a higher or lower level of education than is required for their job.
2. **Skill mismatch** defines a situation in which skills possessed by an individual are not matched with the skills required by the job. While skill mismatch and education mismatch can occur together, they can also happen separately. For instance, individuals who are overeducated for their current job may not be mismatched in terms of skills if they possess a similar level of skills with their well-matched counterparts.
3. **Field-of-study mismatch**, refers to the situation where workers have studied a subject or field that is not related to the jobs that they have. This

happens when workers have studied a subject or field that is not in demand in the labor market, or when they have studied a subject or field that does not provide the skills and qualifications that are needed for the jobs that are available.

2.2. Labor Market Mismatch in the Theoretical Literature

The theoretical literature on labor market mismatch builds on and incorporates existing labor market theories. The concept of labor market mismatch is often discussed and studied within the broader framework of labor market theories, such as human capital theory, job competition theory and assignment theory, among others. This section discusses aspects of these theories to explain the concept of labor market mismatch, which will serve as a background for the analysis.

2.2.1. The Human Capital Theory

The human capital theory, developed by Becker (1964), is fundamentally related with labor market mismatch because it emphasizes the value of education, training and skills in determining economic outcomes for individuals. The theory suggests that wages are equal to the marginal product of the labor, determined by the level of human capital acquired through investments in education and other forms of training. In this context, "human capital" refers to all productive skills, experience and knowledge that an individual possess that contribute to their productivity. According to the human capital theory, market forces are expected to create an equilibrium in the long run where there is no mismatch, and skills are fully utilized. This implies that there is an efficient labor market where jobs and wages are aligned with workers' qualifications based on their marginal productivity. Hence, it is expected that all human capital will be fully utilized and that the costs of acquiring such capital will be fully compensated.

Under the human capital theory, a wage rate that is below or above the value of the marginal product of a worker is inconsistent. Nonetheless, mismatches can still occur in the short run. If an individual is over-qualified or under-qualified, then either the qualification level does not fully capture the human capital stock of the individual, or it is a temporary phenomenon (Quintini, 2011a). One reason for a worker to be mismatched may be due to the fact that other forms of human capital are overlooked.

For instance, if a worker is lacking some skills or abilities that are required for the job, she may compensate for this with experience. Therefore, being overqualified may be a result of investment in experience, and a temporary period of overeducation may be a part of the career path for some individuals. Alternatively, if a worker is still looking for a new job that suits her better, she may stay overeducated for a period of time. Or, the worker may accept a lower-paying job if the job offers a better chance of promotion in the future (Sicherman and Galor, 1990).

There are other theories that complement the human capital framework, including the Career Mobility theory and the Search theory, which help explain why mismatch may be observed in the short run and may even persist in the long run (Quintini, 2011b).

The Career Mobility theory, for instance, explains why mismatches in the labor market may persist by suggesting that job tasks that a person performs often change throughout their career, and that this occupational mobility is particularly common among younger and highly educated workers. Sicherman and Galor (1990) suggest that wage penalties for overeducated workers are compensated by better promotion prospects. As young workers gain more experience and knowledge, they tend to move into higher-level occupations, and overeducation becomes a temporary phenomenon over the life cycle, declining with age as individuals find jobs that better match their skills.

In this context, overeducation can be viewed as an investment in gaining work experience, which in turn enhances the chances of promotion to higher-level positions. The Career Mobility theory suggests that individuals may choose to accept jobs that are below their skill level or educational qualifications as a strategic career move. These “stepping-stone” jobs may not fully utilize their abilities but can provide work experience, skill development, and networking opportunities. By taking on these jobs, individuals can improve their overall employability in the long run. On the other hand, an individual who chooses not to accept a job for which they are overeducated may face a longer period of unemployment, which might extend the time until they find a suitable job (Sicherman and Galor, 1990).

On the other hand, some researchers object to that argument by proposing that overeducation might become an obstacle when transitioning to a better employment

(Baert el al., 2013). This could occur due to reduced job search intensity while currently employed (Holzer, 1987) or the potential for being stuck in current job due to investments in job-specific skills (Pissarides, 1994). Moreover, the adverse effects associated with unemployment, such as diminished job prospects and scarring effects, can also be applicable to overeducation.

Another explanation for mismatch is related with the costs associated with job matching (Jovanovic, 1979). In this case, the productivity of a worker in a job is initially not known by either the employer or by the employee and a mismatch is revealed in case of a turnover. If the search mechanisms in a labor market are not functioning effectively, individuals with higher qualification levels might be placed in positions that require lower qualification levels, and crowd-out individuals with lower qualifications. Search theory helps to explain mismatch due to imperfect information available to employees and employers regarding job tasks and actual skills. It suggests that job search is costly in terms of time and resources, and that job seekers engage in a process of searching for the best available job given their skills and preferences. In this process, both job seekers and employers face imperfect information about the job requirements and skills and characteristics of applicants. Workers may accept job offers that do not match their qualifications or skills because of incomplete or inaccurate information about the job tasks. Younger workers in particular may not be able to find the right jobs, and some of them may actually need additional training to suit job opportunities but not be aware of it.

2.2.2. Job Competition Theory

The job competition theory shifts the focus from individual skills, as in human capital theory, to the characteristics of jobs and the role of competition in determining an individual's position in the labor market. The job competition theory suggests that job characteristics are the only factor that determines earnings (Thurow, 1975). In this theory, individuals compete for jobs, and their qualifications only serve as a proxy that signals the employers about the training costs they may need to bear in the future and so determine the allocation of workers to jobs, rather than determining the wage level. Higher levels of qualifications in an applicant signal to employers that they would require less training when employed, thus wages depend on the qualifications required

for the job. This differs from the human capital theory, where competition is based on an individual's human capital, which determines the level of wage they would be willing to accept.

The job competition framework is consistent with overeducation. In the job competition theory, where an individual stands on the hiring queue matters. In other words, the relative position of an individual compared to others determine if she will get a matching job or not. It is for this reason that if the competitors of the applicant are investing more in education, it is more likely for the individual to invest more as well in order to protect her place in the hiring queue. In this framework, the returns to excess education (education that is more than the required qualification level, i.e. surplus qualification) will be zero as wages only depend on the level of required qualification. This is different than the human capital theory where if more workers invest in higher education, the supply would increase which means a lower return for investment.

2.2.3. Signaling Theory

Similar with the job competition theory, the signaling theory, proposed by Spence (1973), extends the concept of how education functions in the labor market by framing it as a mechanism for signaling the potential productivity of workers to employers. In a market characterized by imperfect information, where employers cannot directly observe individual skills and productivity, educational credentials serve as a proxy. Because of this, individuals who aim to show that they are ‘more likely to be productive, efficient to train, and more likely to succeed in the job’ try to signal this to the employer by acquiring higher levels of education (Desjardins and Rubenson, 2011).

In this framework, however, the decision to invest in education is based on a comparison of its cost and the expected wage gain. Since acquiring human capital is less costly for more qualified individuals who may learn faster or build upon a better foundational knowledge, investments in education can disproportionately benefit those with initially higher levels of education and skill. Due to this, reducing educational costs can encourage those with lower initial education and skill levels to invest in their human capital, thereby raising the average education level in the labor

market.

Signaling theory relates to skill mismatch through the idea that educational qualifications act as signals to employers about an individual's skills and productivity. However, when these signals are not accurate reflections of actual skills, mismatches can occur. The signaling theory differentiates between education mismatch and skill mismatch, with *qualification inflation* and *grade drift*. 'Qualification inflation' refers to the situation where employers require higher levels of education or qualifications for a job position, even though the job requirements or tasks may not have changed significantly. If, for instance, the average education level in the labor market rises, firms may require higher education levels for the same job positions. This can lead to a situation where applicants need to obtain more qualifications or education in order to get the same job, without necessarily gaining any additional skills that are relevant to the job. As a result, there will be qualification mismatch in the labor market without any skill mismatch.

On the other hand, if the quality of education is diminishing, employers may start to look for higher qualification levels for a given job. This is called a 'grade drift', where the level of knowledge and skills required for a job remains constant, but the qualifications required for that job increase over time. In this case, the human capital level that the qualification level signals changes.

2.2.4. Assignment Theory

The assignment model proposed by Sattinger (1993) serves as a middle ground between the human capital theory and the job competition and signaling models. Sattinger (1993) focuses on the changing relative wages over time, particularly the increasing wage inequality between college and high school graduates, which could not be fully accounted for by the neoclassical framework. Sattinger's (1993) argument is that the neoclassical framework (where the wages depend on the education level and productivity, but not on the characteristics of the jobs that are available in the economy) is unable to explain the increased wage inequality in the labor market, and an adequate explanation for such a change in the wage distribution would need to focus on job characteristics and availability of jobs in the economy, as well as on individual characteristics.

According to the assignment theory, individual earnings depend on both job and individual characteristics, as the decision to invest in education is influenced by how well the individual skills and qualifications match the job requirements. While investing in education leads to higher productivity in general, it is equally important to consider the job's complexity and actual productivity in that specific job. If an individual is working in a job which requires less qualifications or skills than a worker endows, this limits their productivity, and as a result they earn a lower wage. So, the level of job complexity (and the skills or qualifications that the job requires) works like a ceiling on the productivity of the worker.

Moreover, the job assignment model asserts that the level of the wages affects the allocation process as well since the individual chooses the job that she wishes to work in (so the allocation itself is not a 'lottery'). Unlike models that view job allocation as a random or externally determined process, the assignment model argues that individuals choose their jobs based on a combination of wages and job requirements. Higher wages might attract individuals with specific qualifications, aligning employee attributes with job requirements. But if wages do not reflect the complexity or demands of a job, this may lead to mismatches.

Here, the wage level of an individual is both determined by the level of schooling and other individual characteristics (as in human capital theory), and with the job characteristics (as in job competition model). Mismatches can occur if individuals incorrectly assess their own skills or the demands of the job, or if they accept less demanding jobs due to economic needs or a lack of available positions. If a worker figures out that she performs poorly in the job that she had selected, she can look for another job.

In this context, Sattinger (1993) claims that the choice of the job works as an intermediate step between individual characteristics and wages. The earnings function in this framework represents the equilibrium outcome to the solution to an assignment problem. Productivity is maximized when individuals are assigned to jobs that match their skill level, such that the most qualified individual is assigned to the most complex job and the least qualified individual to the least complex job. However, if there is a

surplus of highly skilled workers in the labor market compared to the number of available complex jobs, there will be mismatch in the labor market.

2.3. Empirical Literature on Labor Market Mismatch

Given the economic and social implications, the empirical literature on labor market mismatch is vast and continues to expand. The research on labor market mismatches focuses on how these mismatches effect wages, job satisfaction, and other labor market outcomes. In this section, we aim to explain this extensive empirical literature on labor market mismatches. We will focus on two types of labor market mismatch, including education and skills mismatch, and their effects on wages and job satisfaction. In the last section, we review studies on labor market mismatch in Türkiye so that we can contextualize our findings within the existing body of research and examine how they align with previous empirical evidence for Türkiye.

2.3.1. Education Mismatch

The literature on education mismatch is thought to have started with Freeman's (1976) "The Overeducated American", where he analyses the incidence of overeducation in the American labor market and explains why it occurs. He finds that a significant proportion of workers in the U.S. are overeducated, and that this phenomenon is more common among workers with higher levels of education. He argues that overeducation occurs when workers have overinvested in their education, and when the returns to education are lower than they expected. He states that the education system in the US was creating a large surplus of college graduates with respect to the aggregate demand in the labor market and this surplus caused the wage returns to drop.

Freeman's (1976) work on overeducation was groundbreaking and had a significant effect on this literature. Since then, there has been a growing body of literature on education mismatch. One of the most influential early studies was by Duncan and Hoffman (1981) (DH henceforward). DH (1981) found that overeducation was relatively common in the U.S. labor market with an incidence rate of more than 40%. However, as opposed to Freeman, they claimed that excess education has ‘an economic value’, i.e., the return to the surplus education is positive and significant and therefore, productive (Duncan and Hoffman, 1981).

2.3.1.1. Two Specifications for The Wage Effects of Education Mismatch

DH (1981) distinguished between the required education level of a job and the attained education level of an individual, and by doing so they started a new strand of literature (Hartog, 2000). They analyzed the consequences of overeducation using an earnings function known as the ORU (Over/Required/Undereducation) specification. In this approach, they replaced the variable for years of education in the traditional Mincer earnings equation with three variables: years of overeducation, years of required education, and years of undereducation. The ORU specification is:

$$\log w_i = \delta_R S_i^R + \delta_O S_i^O + \delta_U S_i^U + X_i'\beta + \varepsilon_i \quad (1)$$

where $\log w$ is the natural logarithm of wages, S^R is the years of required education, S^O and S^U are the years of overeducation and undereducation, respectively. X is a vector of other control variables that include experience and ε is the error term. The definitions of overeducation and undereducation, based on actual years of education and required education, are as follows:

$$Education: \quad E = S^R + S^O - S^U$$

$$Overeducation = \begin{cases} E - S^R & if \quad E > S^R \\ 0 & if \quad ow \end{cases}$$

$$Undereducation = \begin{cases} S^R - E & if \quad S^R > E \\ 0 & if \quad ow \end{cases}$$

The ORU specification given in (1) implies that, for well-matched workers, δ_R represents the total return to schooling. For mismatched workers, on the other hand, the combined effects of δ_O and δ_U, when interpreted alongside δ_R, provide estimates of the overall effect of their education. For overeducated workers, the total return to schooling includes both the return for the years of schooling corresponding to the job requirements (δ_R) and an additional contribution for the extra years of education (δ_O). For undereducated workers, the total return to schooling is calculated using the return for the years of schooling corresponding to the job requirements (δ_R) minus the penalty for the missing years of education (δ_U). With the ORU specification, overeducation is evaluated in terms of years, and the comparison is made between individuals who are

overeducated and those who hold the same job but are not overeducated and have a lower level of education (See Table 1). It enables the estimation of returns attributed to surplus schooling, in comparison to returns associated with required education[4].

The ORU specification of the wage equation allows estimating the returns for the years of education required for the job, for the years of overeducation, and for the years of undereducation, separately, and it provides a general equation that can be employed in various contexts (Sloane, 2003). For example, the human capital theory, for which investing in education and skills improves a person's overall human capital, which in turn affects their earnings, implies that in equation (1), we have $\delta_R = \delta_O = -\delta_U$. For Thurow's (1975) job competition model, on the other hand, where wages depend on the qualifications that the job requires and surplus education has no wage return, we have $\delta_O = \delta_U = 0$.

An alternative approach to analyze the impact of education mismatches on wages is also developed during the 1980s and called as dummy variable approach. In this approach, overeducation and undereducation characteristics of individuals are specified by the inclusion of a dummy variable to the wage equation. When dummy variables are employed, the comparison is made between overeducated/undereducated individuals and those with the same level of education who are matched (Verdugo and Verdugo, 1989; Kiker et al. 1997). The specification with dummy variables is:

$$\log w_i = \theta_O D_i^O + \theta_U D_i^U + X_i'\beta + \varepsilon_i \qquad (2)$$

where $\log w$ is the natural logarithm of wages, D^O and D^U are dummy variables for overeducation and undereducation, respectively. X is a vector of other control variables that include education level and experience and ε is the error term.

Studies using the ORU method generally find that there is a positive return from years of overeducation relative to required education. In other words, individuals who are overeducated still tend to earn more than those who are not overeducated, but the return is lower than if they were adequately matched to their education. Employing the

[4] However, as highlighted by Sloane et al. (1999), the ORU specification may overlook the potential occurrence of repeated years and dropout years.

dummy variable approach often reveal a negative sign on the overeducation dummy. In this case, the negative sign on the overeducation dummy means that overeducated individuals earn less than their counterparts who are adequately matched in terms of education. Furthermore, it is important to understand that this method distinguishes education mismatch categories through the use of dummy variables instead of quantifying the difference in years. Hence, the size of this negative coefficient cannot be directly compared to the coefficient for the actual years of education attained, as it is not clear how many years of overeducation the dummy coefficient corresponds to (Hartog, 2000).

Table 1. Methods to measure the effect of education mismatch on job wage outcomes.

Method	**Purpose of Comparison**
ORU specification	Compare overeducated or undereducated individuals to adequately educated (well-matched) individuals performing the same job.
Dummy variable approach	Compare overeducated or undereducated individuals to those with the same education level but who are well-matched to their respective jobs.

It should be noticed that the two specifications measure different effects of education mismatches on wages and the common findings from the ORU studies do not contradict with the general findings of the studies that use dummy variable approach. A negative sign on the overeducation dummy does not mean that additional years of overeducation result in negative returns. Instead, it indicates that overeducated workers are more likely to be in lower-paying jobs compared to individuals who have the appropriate level of education for their job (Quintini, 2011b).

To clarify, consider two types of individuals, A and B, both possessing an identical level of educational attainment where person A is well-matched and person B is

overeducated for their current job. The presence of a negative coefficient on the overeducation dummy variable implies that, on average, person B has lower earnings than person A. This difference in earnings is indicative of an earnings penalty associated with overeducation. However, it is important to clarify that this negative coefficient does not imply a negative effect of the additional years of education on earnings. Instead, it shows the likeliness of overeducated individuals, such as person B, to occupy low-skill jobs and thereby low wage levels. On the other hand, ORU specification is based on the required years of education for different jobs and the positive sign on the excess years of education for person B will indicate positive returns to overeducation. Hence, if the analysis shows that the return to required education is higher than the return for overeducation, it indicates a wage penalty for overeducation. This is because person B, despite being overeducated, receives less return for each extra year of education compared to what is required for the job.

2.3.1.2. Different Approaches to Measure Required Education Level

Freeman's study, which started the literature on education mismatch, investigates the prevalence and consequences of overeducation from a macroeconomic perspective, by analyzing the U.S. labor market using aggregate data sources like the U.S. Census and the Current Population Survey (CPS). These sources provide detailed demographic and employment information, allowing him to assess educational attainment levels across the population and correlate these with employment rates and earnings to see whether the supply of college-educated individuals exceeds labor market demands.

This is different from the micro approach (like the DH model) which would analyze the mismatches at the individual worker level. Although DH approach offers more information compared to the macro approach, it has been criticized that this additional information has resulted in misleading conclusions (Leuven and Oosterbeek, 2011). This is because the ORU model is commonly used to analyze the mismatch between workers' education levels and the education levels required for their jobs and examines the potential efficiency gains that can occur when overeducated and undereducated workers swap jobs to achieve a better match between their education and job requirements. This means that workers who are overeducated for their current job could benefit from moving to a job that better matches their education level but it is

unlikely that these job swaps will occur voluntarily, as undereducated workers may be at a disadvantage in such exchanges since such a move will result in lower wages if the job they transition which matches their lower educational attainment pays less than what they are currently earning.Another criticism was that DH (1981) utilized workers' personal assessments of the educational qualifications necessary for their job to determine if there was a mismatch (Leuven and Oosterbeek, 2011). In the literature, there are different empirical methods used to measure mismatch. The measurement of required level of education mismatch and, consequently, education mismatch can be approached in three ways, comprising a subjective measure and two objective measures. The subjective measure involves worker self-assessment, while the objective measures involve realized matches and job analysis methods.

The worker self-assessment (SA) method involves surveying individuals and asking specific questions to determine their level of qualification match. This can be achieved by directly asking participants if they are well-matched for their job or by indirectly inquiring about the job requirements needed to get or to perform their job and comparing this to their actual level of education. This self-assessment method relies on individuals' subjective assessments of their own qualifications and job requirements. Individuals may tend to be biased about their abilities or qualifications, leading to inaccuracies. Workers may also lack information about their own qualifications, or they may not be aware of the level of education required for their job. In addition, there is no standardized set of questions for self-assessment, which can make it difficult to compare results across different studies. Still, the self-assessment is considered a useful method for measuring qualification mismatch, especially in cases where other methods are not feasible or practical.

Another method used in the literature is the realized matches (RM) method, which derives required education levels from the mean or mode qualification level of workers in a given job or occupation. If an individual is above or below this level of qualification, they are classified as mismatched (see, for example, Verdugo and Verdugo, 1989; Groot and van der Brink, 2000). A criticism against the realized matches method is that the method relies on data that are observed in the labor market. According to Hartog (2000), RM are essentially observations of the current state of

employment where individuals' educational qualifications and their job requirements are matched based on available data.

The job analysis (JA) approach, on the other hand, involves systematic evaluations of job requirements conducted by professional job analysts. An example of this approach is the US Department of Labor's Dictionary of Occupational Titles (DOT). Accordingly, the distribution of education for each occupation is calculated and the required education levels for each occupation are determined. Workers who are above or below the mean or mode qualification level required to perform a specific job are classified as mismatched. While it is often used in the literature, the job analysis approach has been criticized for assuming that all jobs within a given title have the same level of required education and this hold in all countries that have the same occupational classification.

There are two different methods to objectively finding required education level of jobs in the literature: the Verdugo and Verdugo (1989) method (VV henceforward) and the modal method. VV (1989) investigates how overeducation affects earnings by defining overeducated workers as individuals whose educational level significantly exceed the mean education level for their occupations. They define the required schooling as a range of one standard deviation around the mean. For the second method, introduced by Kiker et al. (1997), workers who have educational qualifications that match the modal value within their occupation are considered matched. Workers whose educational attainment is above (below) the modal educational level for their particular occupation are classified as overeducated (undereducated).

The choice between mean and mode depends on the characteristics of the dataset. In general, the mode is suitable for datasets with categorical data, where the values represent distinct categories or educational levels. Furthermore, according to Hartog (2000), the VV approach tends to lower the reported mismatch incidence, as it includes a wide margin of two standard deviations. Typically, such measures find the rates of overeducation and undereducation quite similar, ranging from 10 to 15%, which is what one might expect to find beyond the one standard deviation tails of a normal distribution. Therefore, the VV measure can be seen as identifying the tails of a normal

distribution of actual job matches (Hartog, 2000).

As Sloane (2003) explains the mode might be a better measure than the mean when analyzing mismatch, since the educational attainment levels of workers in an occupation may not follow a symmetrical distribution. On the other hand, the modal method estimates can be influenced by increases in educational attainment, and the prevalence of education mismatch within the country (Quintini, 2011a). If educational attainment rises significantly over time, the modal level of education may also shift, potentially affecting the estimates of education mismatch. Therefore, it is useful to consider the limitations of both methods to obtain a comprehensive understanding of labor market mismatch.

Within the labor market mismatch field, the literature on education mismatch has played a significant role in expanding the discussion surrounding the influence of occupational requirements on wage determination, thus broadening the scope of the human capital framework (Sloane, 2003). There are two stylized facts emerging from the research on education mismatch. Empirical studies indicate that (i) overeducated individuals tend to earn lower wages compared to individuals with the same educational level but work in jobs that match their education levels, and (ii) overeducated individuals earn higher wages than matched individuals who work in equivalent jobs (Sicherman, 1991; Sloane, 2003; Levels et al., 2014).

Consider the previous ORU specification (model 1):

$$\log w_i = \delta_R S_i^R + \delta_O S_i^O + \delta_U S_i^U + X_i'\beta + \varepsilon_i$$

which shows the relationship between wages (w), various forms of education mismatch (years of overeducation and undereducation), and other independent variables represented by the vector X. The consistent findings from cross-sectional wage regressions can be summarized as follows (Korpi and Tahlin; 2009): Overeducated workers tend to earn higher wages than those correctly matched to their job type ($\delta_O > 0$), but still earn less than well-matched workers with the same level of education ($\delta_R > \delta_O$). On the other hand, undereducated workers typically earn lower wages than well-matched workers in a similar job ($\delta_U < 0$). Despite this, undereducated workers can still earn more than well-matched workers in jobs

requiring lower levels of education. This is because of the higher return they receive due to higher educational requirements of their jobs, despite their undereducation.

According to Quintini (2011a), for example, overeducated workers tend to earn approximately 4% more than well-matched workers in similar positions. This means that a tertiary school graduate who is employed in a job that only requires an upper secondary qualification would earn less than if they were in a job that aligns with their tertiary education level. However, they would still earn more compared to an upper secondary graduate in a job that specifically requires upper secondary education. On the other hand, Quintini (2011a) finds that undereducated workers earn an average of around 17% less compared to workers who are well-matched in similar roles. This indicates that being undereducated for a job has a negative impact on earnings, resulting in lower wages compared to those who possess the appropriate education for their positions.

A relevant question is how different definitions of education mismatch impact the results. As mentioned earlier, education mismatch can be defined in different ways, and each definition may yield different results regarding the incidence and the implications for individuals experiencing the mismatch. Groot and Maasen van den Brink (2000) conducted a meta-analysis examining the occurrence of education mismatch within the labor market and found that the definition selected, despite significantly impacting the prevalence of education mismatch, does not have a notable effect on the wage differential estimates. In other words, the choice of definition is important in understanding how prevalent the problem is, but it does not change the basic finding that education mismatch tends to lead to wage penalties.

2.3.1.3. Impact on Job Satisfaction

The literature on labor market mismatches has expanded in recent years, investigating their impact on non-monetary outcomes, including job satisfaction. Job satisfaction is an important indicator as it can influence job turnover rates, especially among individuals who are overeducated. Individuals who are overeducated are found to be more inclined to change jobs compared to well-matched workers with similar education levels (Quintini, 2011b). Moreover, when job satisfaction is low, both employees and employers have reduced motivation to invest in developing job-

specific skills. In fact, studies indicate that overeducated workers are less likely to engage in training compared to their well-matched counterparts with similar educational backgrounds (Verhaest and Omey, 2006). Thus, job satisfaction is useful for estimating the productivity consequences of labor mismatches.

According to Korpi and Tahlin (2009), the relationship between educational mismatch and job satisfaction can be analyzed based on two explanations: the ability explanation and the mismatch explanation. The ability explanation suggests that overeducated workers may actually possess lower abilities, or that the jobs held by overeducated workers may be better than the jobs their educational requirements imply. In this case, mismatched workers should not be less satisfied with their jobs compared to others. On the other hand, the mismatch explanation predicts that overeducated workers are likely to be less satisfied than well-matched workers. The outcome for undereducated workers is less clear, as attaining a job level above one's educational level can be seen as a positive achievement, yet having less schooling than the job typically requires may create challenges.

The findings of Korpi and Tahlin (2009) support the mismatch explanation: Education has a strong and positive relationship with job satisfaction up to the schooling level required for the job. However, beyond that point, education becomes negatively correlated with job satisfaction. In general, the research on the relationship between education mismatch and job satisfaction has ambiguous results, with some studies indicating that education mismatches are associated with lower levels of job satisfaction (Hersch, 1991; Sloane et al., 2000), while others find that educational mismatch do not necessarily result in lower job satisfaction. According to Tsang et al. (1991), having an excess of education negatively affects job satisfaction and the adverse effect of surplus schooling on job satisfaction is higher among individuals with more surplus education. According to Badillo-Amador et al. (2008), on the other hand, workers who are overeducated for their current position do not experience a decrease in job satisfaction compared to those with adequate education. They found that years of overeducation have a neutral effect on job satisfaction, while years of undereducation generally contribute positively, likely due to the higher wages typically associated with being undereducated. Badillo-Amador et al. (2008) also find that the impact of educational mismatches on job satisfaction largely depends on the

similarity of educational requirements within specific job roles. When workers are in occupations where educational requirements are similar, educational mismatches do not significantly influence job satisfaction. Moreover, Mateos-Romero and Salinas-Jiménez (2018) find that while educational mismatch has a stronger impact on wages, the effects of labor mismatch on job satisfaction are primarily driven by skill mismatches.

2.3.1.4. Studies Focusing on The Persistence of Education Mismatch

For policymakers, understanding whether education mismatch is a temporary or persistent issue is important. While beyond the scope of this thesis, persistence of education mismatch has been explained briefly in this part due to its relevance, as it is a topic of interest within the existing literature. If education mismatch is persistent, it means that some workers remain overeducated for an extended period, even after gaining work experience. This indicates that despite accumulating experience, these individuals are still unable to find jobs that fully utilize their educational qualifications, leading to a prolonged mismatch between their education and the job requirements. On the other hand, if education mismatch is temporary, it means that workers who are initially overeducated tend to eventually find jobs that better align with their educational qualifications as they gain experience in the labor market. Therefore, overeducation may be more common among new entrants to the job market, but it decreases over time as workers gain work experience and move to jobs that require higher levels of education.

The evidence on the persistence of education mismatch is mixed. Some earlier studies suggest that overeducation is mostly temporary and decreases with work experience, supporting the claims of career mobility (Sicherman, 1991; Alba-Ramirez, 1993; Robst, 1995b). However, recent research indicates that a considerable proportion of workers continues to experience education mismatch for longer periods, suggesting a more persistent problem in certain cases (Dolton and Vignoles, 2000; Büchel and Mertens, 2004).

2.3.2. Skill Mismatch

A point often mentioned in the education mismatch literature is that workers who are

considered overeducated may not be identical as it is possible for overeducated workers to have lower skill levels. This indicates that being overeducated does not necessarily imply being overskilled (Allen and Van der Velden, 2001). Education mismatch can be partially attributed to heterogeneity in skills among workers who possess same level of education. Several studies, including Chevalier (2003) and McGuinness (2006), have argued that education mismatch might not accurately reflect skill mismatch as education mismatch could be concealing skill heterogeneity among workers (Quintini, 2011b).

Skill mismatch analysis has been used as an alternative method for evaluating labor market mismatch, complementing education mismatch approach. The explanation behind this lies in the assumptions made by each approach. Education mismatch analyses assume that job requirements accurately reflect the actual skill content of the job and that worker qualifications adequately represent their total human capital (McGuinness and Wooden, 2009). Moreover, this perspective overlooks the possibility that job entry requirements might only loosely correlate with the actual requirements of the job (McGuinness et al., 2018). Additionally, a worker's human capital includes not only formal qualifications but also skills gained through non-formal means, such as experience and training (Mavromaras et al., 2009), which are not fully considered in the education mismatch approach.

The concept of skill mismatch requires the assessment of all skills regardless of whether they were acquired through formal education or on-the-job experience, and then compare these with the actual skill requirements of their current job. This enables an accurate evaluation of how well workers' abilities align with the demands of their job. In other words, skill mismatch uses a more direct comparison between an individual's skills, which may include formal education, on-the-job training, or innate ability, with the actual skill requirements of the specific job under consideration (Mavromaras et al., 2009; McGuiness and Sloane, 2011). In the literature, there are several methods that are commonly used to measure skill mismatch. These are: worker self-assessment, direct measure, and a combination of these two methods.

In the self-assessment method, workers are asked to assess themselves on their skills and compare it with the required skill level of their jobs. Information on self-assessed

skill mismatch can be easily retrieved with a survey, but on the downside, individuals may tend to not being objective when it comes to answering questions about themselves and they may not know the requirements of their jobs. The direct measure, on the other hand, is done by measuring the skills of the workers directly by proficiency scores and comparing them with the skill use at their jobs. Direct measures can be costly since this type of data is available in large-scale assessments.

The OECD PIAAC data used in this thesis offers an extensive background information of respondents as well as information on cognitive skills and workplace characteristics (for example, skill use at work). This extensive information that PIAAC provides allows us to use a third method, which we will call the hybrid method (OECD, 2013). The hybrid method combines the two methods that are explained above. It uses both the self-reported information and information on proficiency in different areas (Adalet McGowan and Andrews, 2015) since PIAAC offers both a direct measure and a self-assessed measure of skill mismatch. This method is comprised of three steps, which are explained in detail in the "methodology" part in section 6.

2.3.2.1. Effect on Wages

While there is extensive research on the impact of education mismatch on wages, the consequences of skill mismatch have received relatively less attention. Still, existing evidence suggests that workers who are overskilled for their jobs generally experience a wage penalty[5], while those who are underskilled tend to receive a wage premium (Carlos and Sequiera, 2014). To estimate the effect of skill mismatch on wages, the following earnings function is estimated in the literature:

$$\log w_i = S_i^O \theta_1 + S_i^U \theta_2 + X_i' \beta + \eta_i$$

which shows the relationship between wages (w), two dummy variables ($S^O$and S^U) for being overskilled and underskilled respectively, and other independent variables including education represented by the vector X and η is the error term.

[5] McGuiness et al. (2018) compiled the findings from the skill mismatch literature that investigate the relationship between skill mismatch and wages, and found that the average overskilling wage penalty, based on 38 estimates, is approximately 7.5%.

The relation between education mismatch and skill mismatch has attracted some attention in the literature. Allen and van der Velden (2001) investigate the relation between education and skill mismatches and their impact on wages. Their findings suggest that while education mismatches significantly affect wages, skill mismatches do not. Allen and van der Velden (2001) suggest that high-skilled workers are more likely to find jobs that align with their skills, even if those jobs do not match their educational qualifications. This implies that the effects on wages are more directly linked to the actual skills workers have rather than a mismatch in education levels.

2.3.2.2. Impact on Job Satisfaction

Empirical literature has indicated that when considering both educational and skill mismatches together, skill mismatches tend to have a more significant effect on explaining the variations in workers' job satisfaction levels compared to educational mismatches (Shevchuk et al., 2019). Several studies, such as Badillo-Amador et al. (2013), Allen and van der Velden (2001), and McGuinness and Sloane (2011), have consistently found that skill mismatches play a more prominent role in understanding job satisfaction. Badillo-Amador and Vila (2013) find that skill mismatches have a significant impact on workers' job satisfaction, while education mismatches have relatively weaker effects. Allen and van der Velden (2001) also find that skill mismatches are more accurate predictors of job satisfaction and on-the-job search compared to educational mismatches. McGuiness and Sloane (2011) analyzed the influence of education and skill mismatch variables together and found that only overskilling consistently lead to a decrease in job satisfaction for both males and females.

2.3.2.3. Studies Focusing on The Persistence of Skill Mismatch

Although this aspect falls outside the scope of this thesis, it is important to consider the presence of state dependence, where the current state of being overskilled can affect the likelihood of remaining overskilled. State dependence refers to the persistence of skill mismatch, where individuals remain in a situation where their skills do not align with the requirements of their jobs. Various theories propose that labor market mismatches are temporary in nature. Job search theories, for example, suggest that mismatched workers can gradually improve their job matches through repeated

job search. Additionally, career mobility theories predict that individuals may intentionally accept positions below their qualification level in order to acquire further skills through on-the-job training so that they can promote faster.

Mavromaras and McGuiness (2012) explores whether overskilling tends to persist as a long-term condition and whether this persistence differs between different levels of education. Their results show that workers with higher education not only experience the strongest state dependence in overskilling but also face the highest wage penalties associated with it. On the other hand, workers who complete vocational education and training experience a relatively lower wage penalty and show less state dependence.

2.3.2.4. Cognitive and Non-Cognitive Skills

One of the challenges with the skill mismatch analysis is that it is not easy to define skills, yet the categorization of different abilities and skills makes it easier to measure the effects of skills. In the most general sense, skills are abilities that individuals develop through learning, practice, and experience, enabling them to effectively perform tasks. There are various names and terms used to describe different types of skills. Firstly, there are hard skills, which refer to specific, measurable abilities that are often teachable and can be quantified. Hard skills and cognitive skills are related but distinct concepts. Hard skills are often job-specific and can be measured and demonstrated through tasks or assessments. Cognitive skills, on the other hand, are mental abilities that involve processing information, thinking, and problem-solving. These skills are related to how a person's mind processes and analyzes information, makes decisions, and learns new concepts. These skills are not tied to specific tasks but are instead foundational for various activities that require mental processing. Similarly, foundational skills are the fundamental abilities and knowledge that serve as the basis for acquiring more advanced skills. These skills are often considered essential for building a strong foundation upon which more complex skills can be developed (Heckman and Kautz, 2012; Kautz et al., 2014).

There are also soft skills, also known as interpersonal or people skills, that refer to non-cognitive, social, and emotional abilities that help individuals interact effectively with others. In the literature, the names soft skills, non-cognitive skills and personality traits can sometimes be used interchangeably. Non-cognitive skills, often referred to

as soft skills or personality traits, are increasingly recognized as important factors in shaping outcomes in the labor market. These skills include a range of attributes, such as motivation, problem-solving ability, adaptability, and emotional intelligence. Non-cognitive skills complement cognitive skills and enable individuals to effectively apply their knowledge. Empirical studies have demonstrated the economic benefits associated with them such as higher wages (Heckman and Rubinstein, 2001) and improved employment opportunities and occupational status (Waddell, 2006; Borghans et al., 2006; Heckman and Kautz, 2012).

Heckman and Rubinstein (2001) found evidence from the General Educational Development (GED) testing program[6], which certifies an alternative high school degree for dropouts, which highlighted the importance of non-cognitive skills. When comparing GED recipients to high school graduates who do not pursue higher education, GED recipients displayed similar cognitive abilities as measured by the Armed Forces Qualification Test (AFQT) score[7]. However, when cognitive ability was controlled, GED recipients earned the same or even lower hourly wages compared to high school dropouts. The findings from Heckman and Rubinstein (2001) suggest that while the GED serves as an alternative certification of high school equivalency and GED recipients display similar cognitive abilities to traditional high school graduates, but this does not translate into higher earnings for them. These results challenge the "diploma effect" since the credential itself is not sufficient to increase earnings if it does not include the skill set valued by employers.

Traditionally, there has been a widely held assumption that when it comes to cognitive abilities, they can be effectively summarized or represented by a single latent factor (Jensen,1998; Heckman, 1995). However, Heckman, Stixrud, and Urzua (2006) employed the Roy model to incorporate non-cognitive skills into the examination of economic outcomes and conducted an analysis of the influence of cognitive and non-

[6] The GED test is a series of exams in the United States and Canada that provides an alternative way for individuals who did not complete traditional high school to earn a high school equivalency credential. The GED test covers subject areas such as language and arts (reading and writing), mathematics, social studies, and science (Heckman et al., 2006).

[7] The AFQT score focuses on four main areas of the larger Armed Services Vocational Aptitude Battery (ASVAB) test: Arithmetic Reasoning, Mathematics Knowledge, Paragraph Comprehension, and Word Knowledge.

cognitive skills on multiple aspects of individuals' lives, including their income, educational choices, work experience and career decisions.

The central argument in the article is that a model that incorporates one latent cognitive skill and one latent non-cognitive skill can effectively explain a wide range of human behaviors. In fact, the authors suggested that cognitive skills are not the primary determinants of socioeconomic outcomes as previous studies suggested. Instead, they claim that, for many dimensions of behavior and outcomes in the labor market, non-cognitive skills can have an impact equivalent to or greater than that of cognitive skills. They find that non-cognitive skills play a significant role in shaping decisions about education and so impact earnings based on those educational choices (Heckman et al., 2006).

2.3.3. Literature on Türkiye

The subject of the first chapter of this thesis, i.e. the incidence, determinants, and consequences of labor market mismatch in Türkiye, has increasingly gained attention in recent literature (Table 2). Mostly, the research concerning labor market mismatches in Türkiye has concentrated on education mismatch. The studies of Filiztekin (2011) and Orbay and Aydede (2015) have paved the way for understanding the education mismatch in Türkiye. Filiztekin (2011) investigates the education mismatch within the Turkish labor market, utilizing data from Household Budget and Expenditure Surveys conducted in 1994 and 2002. The study focuses on individuals who are employed full-time in permanent positions within the non-agricultural sector between 20 and 64 years old.

Filiztekin (2011) uses the RM approach to assess mismatch and to enable comparisons between different methods, both the mean and mode approaches are used. To examine the impact on earnings, this study employs the ORU method. The results show that in 1994, 20.3% of the workforce was overeducated according to the mode method, and 13.4% according to the mean method. By 2002, these figures had increased to 24.6% (mode) and 15.1% (mean). Furthermore, the study reveals that overeducated workers earn more than their well-matched, lower-educated counterparts in current jobs, yet their earnings are less than those of equally educated workers in well-matched positions.

Orbay and Aydede (2015) looks at educational mismatch and the cost of underutilization in Turkish labor markets, finding a 54% education mismatch rate in Türkiye. This was based on data from Labor Force Surveys from 2009 to 2012. The study employs an ORU model by using the Realized Matches (RM) and VV methods to investigate the implications of educational mismatch within the Turkish labor market. It finds that overeducation leads to wage losses and undereducation leads to unexpected wage gains.

Mercan et al. (2015) take a sector-based approach to analyze the education-occupation mismatch in the Turkish labor market, finding significant levels of undereducation and overeducation within sectoral job groups. They note that while undereducated individuals are penalized, the overeducated gain some rewards, though not extensively. Acar (2016) explores the effects of education mismatch on wages through a panel analysis of the Turkish labor market. The findings suggest no significant impact of either overeducation or undereducation on earnings, based on the Survey of Income and Living Conditions panel data from 2006-2010.

Eriş Dereli (2017) focuses on education mismatch in Türkiye, using evidence from Household Labor Force Surveys between 2009 and 2014. The study examines the prevalence of overeducation among high school and university graduates and its variation over time and finds that there has been a rise in undereducation rates since 2009, while the prevalence of overeducation has been on the decline.

Duman (2018) investigates education mismatches in the labor markets and their impact on wages across different sectors in Türkiye, using data from the European Working Conditions Survey and Household Labor Force Survey of 2015. The research indicates that overeducation yields lower returns than required education in both public and private sectors, with a smaller wage gap in the private sector.

Yenikkaya and Tat (2019) use data from the Household Labor Force Survey and Annual Industry and Service Statistics from 2004 to 2015 to analyze the effect of educational mismatch on the Turkish manufacturing industry, finding that labor productivity is positively correlated with level of overeducation whereas it is negatively affected by the level of undereducation.

Table 2. The literature analyzing the incidence, determinants and consequences of labor market mismatch for Türkiye

Study	Focus	Data	Result
Filiztekin (2011)	Education mismatch	HBES conducted in 1994 and 2002	Over-educated workers earn more than well matched lower educated workers in their current jobs, but less than workers with the same level of education that are well matched to their jobs.
Orbay and Aydede (2015)	Education mismatch (ORU model)	LFS from 2009 to 2012	The education mismatch rate is around 54 percent in Türkiye, which is considerably higher than most European countries.
Mercan et al. (2015)	Education mismatch	2009 LFS	• Significant levels of undereducation and overeducation have been identified within sectoral job groups. • Educational mismatch is prevalent among several sectoral job groups. • Undereducated are penalized, while overeducated receive some rewards, but not to a great extent.
Acar (2016)	Education mismatch	SILC panel data from 2006-2010	There is no statistically significant impact of either overeducation or undereducation on earnings.
Eriş Dereli (2017)	Education mismatch	LFS for 2009 to 2014	There has been a rise in undereducation rates since 2009

Duman (2018)	Education mismatch	European Working Conditions Survey (EWCS) and LFS, 2015.	• In both the public and private sectors, the returns on overeducation are lower compared to those for required education. • The wage gap between overeducated and well-matched is smaller in the private sector.
Yenikkaya and Tat (2019)	Education mismatch	HLFS and Annual Industry and Service Statistics for the period 2004-2015.	The labor productivity is positively affected by the mode of education and the average level of over-education, while it is negatively impacted by the average level of under-education.
Özer and Suna (2020)	Field-of-study mismatch	Employment Ratios from Turkstat	Although graduates of VTAH have high employment rates, many of them end up working outside of their field of education
Şahin (2020)	Skills mismatch	Data retrieved from Türkiye's Productivity Development Map Project in 2016	• More than 50% of employers are content with their employees' skills. • 39.2% of employers feel that white-collar employees lack some crucial skills • 43.7% of employers feel that blue-collar employees lack essential skills

Özer and Suna (2020) discuss the employability and education mismatch in the context of vocational education and labor market in Türkiye. By using Employment Ratios from TURKSTAT, they find that despite the high employment rates among vocational education graduates, many work outside their field of study. Lastly, Şahin (2020) provides an analysis of skills mismatch in Türkiye and offers suggestions for vocational education and training policies. Data from Türkiye's Productivity

Development Map Project in 2016 suggest that while over 50% of employers are satisfied with their employees' skills, a significant portion perceives a lack of crucial skills among both white-collar and blue-collar workers.

The literature on labor market mismatches in Türkiye has offered substantial insights into mismatches and their implications. Nevertheless, these studies mainly concentrate on specific aspects of mismatches. This thesis intends to delineate itself from the existing research by using a comprehensive approach to labor market mismatches in Türkiye, simultaneously examining education mismatch and skill mismatch. Additionally, this thesis will extend beyond wages to include job satisfaction as a measure of labor market success and as a proxy for labor productivity. This is particularly significant as most studies primarily concentrate on the wage aspect. This dual focus is expected to yield a more complete view of the labor market mismatches in Türkiye. Furthermore, employing different identification methods, including both objective and subjective measures, will enable a more complete analysis of mismatches.

2.4. The Turkish Education System

Education plays a crucial role in empowering individuals with knowledge, skills, and capabilities to pursue their goals, participate actively as citizens, and demonstrate critical thinking abilities (Council of Higher Education (YÖK in Turkish abbreviation) Strategy, 2007). Obtaining a higher education degree is often driven by the desire to secure better job opportunities in the future. Individuals recognize that investing in their education enhances their human capital, including their accumulated knowledge, skills, and abilities (Rios-Avila and Caballero, 2019). Furthermore, education equips individuals with practical skills that can be effectively applied in the labor market. Robst (2007) emphasizes that the successful utilization of acquired education in future employment is necessary in achieving positive outcomes in the labor market.

The education system of a country not only prepares individuals for the workforce but also acts as a powerful tool for reducing labor market mismatches. The seminal work by Goldin and Katz (2008), "The Race between Education and Technology," underscore the importance of historical shifts in the demand for skills and accentuate the need of an adaptive education system. If the education system keeps pace with

technological changes, it can effectively reduce mismatches in the labor market by ensuring that the workforce is adequately trained for the available and potential jobs. This means that educational institutions and the job market are affecting each other. The adaptability of education system can reduce labor market mismatch by ensuring that individuals are equipped with the right skills, knowledge and adaptability to meet the demands of the job market.

In Türkiye, education is perceived as a key driver of social mobility. Parents often believe that providing their children with higher education opens up opportunities for better employment prospects and a higher standard of living. In 2021, 72.5% of education expenditures were funded by the state, while households contributed 22% to education expenses according to TURKSTAT data. This percentage signifies a substantial financial dedication that households in Türkiye directed towards education, given that there is a state-funded education alternative at every stage.

Table 3. The structure of the education system in Türkiye

EDUCATION LEVEL	**Age range**	**Duration**	**Compulsory**
Early Childhood Education	3 to 6	-	No
Primary Education	6 to 14	12 years	Yes
-Primary Schools	6 to 10	4 years	
-Middle Schools	11 to 14	4 years	
Upper Secondary Education (General or vocational)	15 to 18	4 years	
Higher Education	After	Varies	No
-Associate Degree	secondary	2 years	
-Bachelor's Degree	education	4 years	
Graduate Programs	After	Varies	No
-Master's Degree	Bachelor's	2 years	
-Doctoral Degree	degree	4-6 years	

According to the "Education at a Glance" report published by the OECD in 2017, Türkiye has the second-highest share of the overall spending on schools sourced by

households among OECD countries and surpasses the OECD average by more than double. However, despite households investing significantly in education, the presence of labor market mismatch can hinder the realization of returns on these investments as it creates challenges for individuals making the transition from education to the workforce. Therefore, understanding the relationship between education system and labor market mismatch becomes crucial not only for individual career success but also for the overall effectiveness of the education system. In this section, main characteristics of the education system in Türkiye is described and the relationship between labor market mismatch and education system is discussed.

2.4.1. The Structure of The Turkish Education System

The education system in Türkiye is based on a formal structure and is regulated by the Ministry of National Education (MoNE). It consists of several stages starting from pre-primary education and progressing to primary education, upper secondary education, and higher education (Table 2.3). The government offers free formal education at all levels, although private schools also exist alongside the public education system.

2.4.1.1.Primary to Upper Secondary Education in Türkiye

Primary education is compulsory for all children between the ages of 6 and 14. It comprises four years of primary school (elementary school) and four years of lower secondary school (middle school). During primary school stage, students study Turkish, mathematics, science, social studies, and physical education. This phase aims to build a solid educational base for students. Lower Secondary education in Türkiye refers to the educational stage known as middle schools. It is a mandatory level of schooling that spans grades 5 to 8, typically covering students aged 11 to 14. In lower secondary education, students continue to study a broad range of subjects, building upon the foundational knowledge acquired in primary schools.

The High School Transition System (LGS) has been implemented by the MoNE since 2018 to facilitate the transition of students from lower secondary education to upper secondary education. Through LGS, the placement of students into upper secondary education institutions is conducted through two types: exam-based and non-exam-based placement. The Central Exam is used for admission to schools that accept

students based on exam results and is administered to assess students' academic achievement in six different subjects.

The aim of upper secondary education is to provide students with a common general knowledge and prepare them for higher education, professions, life, and career fields. Upper Secondary education in Türkiye encompasses both general and vocational high schools. General high schools offer a broad curriculum and prepare students for higher education. General education institutions include Anatolian high schools, science high schools, social sciences high schools, fine arts high schools, and sports high schools. Vocational high schools, on the other hand, provide specialized education in various fields, equipping students with skills and knowledge for specific career paths or further vocational training. VET comprises vocational and technical Anatolian high schools, multi-program Anatolian high schools and vocational training centers. Additionally, there are Anatolian imam-hatip high schools that focus on religious education within the secondary education system.

2.4.1.1.1. Vocational Education and Training in Türkiye

In Türkiye, Vocational Education and Training (VET) is an integral part of the education system and plays a significant role in preparing individuals for the labor market. VET institutions aim to train qualified human resources in accordance with national and international professional standards and to prepare vocational education students for employment in collaboration with economic sectors (MoNE, 2018, p.21; and the Regulation of the Ministry of National Education on Secondary Education Institutions).

Upon completing a VET program, students receive a vocational qualification certificate, which is recognized nationally. The certification validates the skills and knowledge acquired by students and enhances their employability prospects in their respective fields. VET programs in Türkiye cover a wide range of fields, including technical, industrial, commercial, and service sectors. The Ministry of National Education (MoNE) oversees the VET system and is responsible for curriculum development, program accreditation, and quality assurance. In 2014, different types of institutions in the VET system were consolidated under the names of Vocational and Technical Anatolian High Schools (VTAH), Multi-Program Anatolian High Schools

(MPAH), and Vocational Training Centers (VTC).

Vocational and Technical Anatolian High Schools:

Within VTAH schools, two distinct programs are offered. These are Anatolian Technical Program and Anatolian Vocational Program. Both programs are vocational secondary education programs that lead to the title of technician. Admission to the Anatolian Vocational Program is based on non-examination transition and local placement, while the Anatolian Technical Program admits students through a centralized exam. While both programs focus on vocational education, the Anatolian Vocational Program includes general knowledge courses alongside profession-specific knowledge and skills. On the other hand, the Anatolian Technical Program places a strong emphasis on mathematics, physics, chemistry, and biology throughout the four-year curriculum.

Multi-Program Anatolian High Schools:

In settlements with a low population and a small number of students, high schools that consolidate programs from Anatolian High Schools, Vocational High Schools and Technical High Schools are referred to as MPAH Schools. Graduates from MPAH schools who have completed vocational and technical education programs have the same rights as graduates from schools that solely provide vocational or technical education. Furthermore, internship opportunities are also provided for students studying in the vocational and technical departments of MPAH schools.

Vocational Training Centers:

VTCs under MoNE operate in all provinces of Türkiye. These centers offer training programs in various fields with the aim of equipping students with vocational skills. Unlike VTAH and MPAH schools, school education in this context takes place one day a week. On the other days, vocational training is carried out in businesses. The training in businesses continues from the first year to the final year. At the end of the third year, students take the Journeyman (kalfalık) exam, and at the end of the fourth year, they take the Master Craftsman (ustalık) exam. Successful students receive certificates upon passing these exams.

Religious Education:

In Türkiye, Anatolian Imam-Hatip High Schools (AIHH) are specialized vocational high schools that focus on religious education. The curriculum of AIHH schools includes both general subjects and specialized religious studies. AIHH also offer vocational training programs that are related to religious professions and aim to provide the necessary knowledge and skills that will contribute to the fulfillment of religious services such as imamate, preaching, and Quran course instruction. Graduates of AIHH schools can work as religious officials in mosques and official Quran courses by meeting the requirement of the Public Personnel Selection Examination (KPSS in Turkish abbreviation). Graduates are also eligible to pursue higher education in any department offered by universities and can work in their field of study after completing their higher education.

2.4.1.2. Higher Education in Türkiye

Established in 1981, the Council of Higher Education (YÖK in Turkish abbreviation) in Türkiye serves as the regulatory and supervisory body responsible for overseeing and coordinating higher education institutions across the country. YÖK's primary objective is described as to ensure the quality, efficiency, and effectiveness of higher education. One of the key roles of YÖK is to accredit and ensure the quality assurance of higher education institutions and programs. YÖK also assumes the responsibility of planning and coordinating higher education in Türkiye. It formulates strategic plans and guidelines for the establishment of new universities, determines student quotas for various disciplines, and allocates resources among universities to promote equitable distribution (Higher Education Law No. 2547).

In addition, YÖK establishes regulations pertaining to student admissions, enrollment procedures, and graduation requirements. In Türkiye, upon completion of upper secondary education, students can pursue higher education. Admission to higher education institutions is based on the results of the Higher Education Entrance Examination (YKS in Turkish abbreviation). YKS is a standardized exam administered by the Student Selection and Placement Center (ÖSYM in Turkish abbreviation), under the supervision of YÖK. It is the collective name given to three sessions of exams: The Basic Proficiency Test (TYT in Turkish abbreviation), the

Field Proficiency Test (AYT in Turkish abbreviation), and the Foreign Language Test (YDT in Turkish abbreviation).

The higher education system in Türkiye follows the Bologna Process, which divides higher education into three cycles: undergraduate (4 years), graduate (2 years), and doctoral (4-6 years). There are also associate degrees (önlisans) which typically last two years. Associate degree refers to an educational level that falls between secondary education and bachelor's degree level. These programs are typically offered by vocational schools or higher education institutions, providing specialized vocational or technical education. The degree is awarded upon the successful completion of these programs. Associate degrees are distinct from bachelor's degrees, which require a longer duration of study and a broader academic curriculum.

2.4.1.2.1. Open Education and Secondary Higher Education

Even though the public perception of university education in Türkiye has evolved over the years, it has always been highly valued in Türkiye, as it has been seen as a path to social and economic mobility. Today, higher education system is composed of a diverse range of institutions, including open education, vocational schools, state and private universities, which vary greatly in terms of their student populations and educational capacities. A potential reason for this diversity is that governments in Türkiye have constantly felt the pressure of the public's demand for increasing the capacity in higher education. Indeed, the statistics released by the Council of Higher Education in Türkiye (Figure 1) show that the number of universities and graduate programs opened has increased significantly in the last few decades.

In Türkiye, there are both public (state) and private (foundation) universities, with public universities being more common. Public universities are established and operated by the state, with funding primarily coming from the government budget. Since meeting the demand for higher education requires large investments, governments in Türkiye have been looking for solutions that can increase capacity without making large investments, and have reached two main solutions. The first of these is the development of open education. Open education started in Türkiye in 1982 at Anadolu University. Today, it serves a very high percentage of higher education students in Türkiye. The number of registered students in open education faculties

within Anadolu University is above 2 million in 2023 and the share of the students in open education in total higher education is 44.3% (See Table 4).

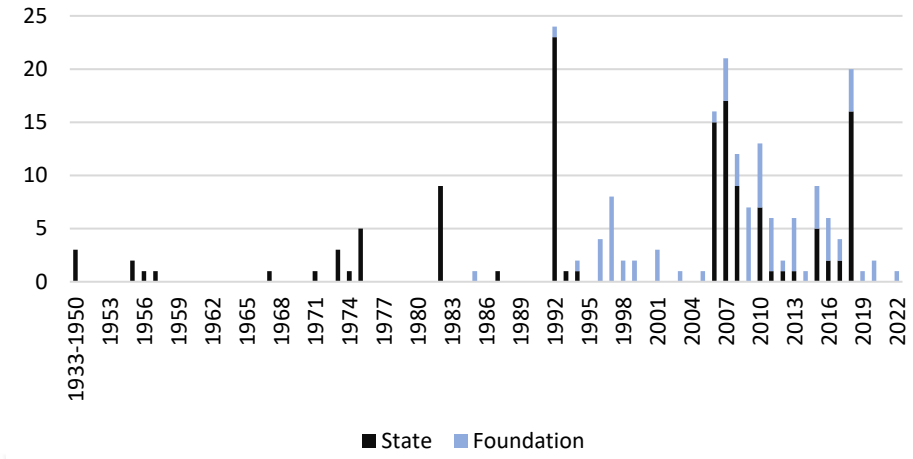


Figure 1. The number of state and private universities opened yearly (1933-2022)

Source: CoHE database

The second solution found was to develop secondary higher education (in Turkish, "ikinci öğretim") programs that will be carried out in the evenings. These programs, at both the associate and undergraduate levels, follows the same principles as the regular (daytime) education programs regarding the duration of instruction, the structure of the curriculum, attendance requirements, the number of mid-term exams, their contribution to the final grade, requirements for practical applications, make-up exams, and other matters related to teaching and learning. There is no difference between the secondary higher education program and the regular education program in these aspects (Law on the Implementation of Dual Education in Higher Education Institutions – Law No. 3843).

This solution is based on the principle of saving on investments that should be made to increase the student capacity of a higher education system. With the same physical infrastructure and space, secondary education is conducted by the current academic staff after regular daytime education. The assignment of instructors in the secondary education program at a higher education institution is determined by the board of directors, taking into account the viewpoint of the department council. Instructors who have fulfilled the required course load in the regular program will be compensated for each course they teach in the evening program. On the other hand, instructors who

have not fulfilled the course load will receive compensation for the courses they teach only after fulfilling the remaining load. The compensation includes an additional payment, which cannot exceed three times the prescribed amounts for extra lessons, mid-term exams, semester exams, and final exams (Law on Higher Education Personnel - Law No. 2914).

Table 4. Total number of students enrolled at the associate degree and bachelor's degree levels (2022-2023 academic year)

	Male	**Female**	**Total**	**%**
Associate degree	**1.285.803**	**1.361.251**	**2.647.054**	**100,0%**
Formal Education	471.657	405.256	876.913	33,1%
Secondary Education	102.267	73.589	175.856	6,6%
Distance Education	18.745	15.490	34.235	1,3%
Open Education	693.134	866.916	1.560.050	58,9%
Undergraduate level	**1.845.587**	**1.908.508**	**3.754.095**	**100,0%**
Formal Education	1.071.805	1.149.693	2.221.498	59,2%
Secondary Education	134.730	91.479	226.209	6,0%
Distance Education	13.357	17.395	30.752	0,8%
Open Education	625.695	649.941	1.275.636	34,0%
Total	3.131.390	3.269.759	6.401.149	

Source: Published within the scope of the Official Statistics Program under TURKSTAT, collected from YÖK statistics website.

2.4.2. The Relationship Between the Education System and Labor Market Mismatch?

Labor market mismatch is a topic closely intertwined with the education system. The enhancements in the education system plays an important role in addressing the potential mismatches. Evidence indicates the positive impact of educational match on productivity, as well as the effect of education itself. Therefore, enhancing the education system is one of the key elements in economic development.

The discussions about enhancing the education system are centered on ensuring an equitable access to education for children from diverse social backgrounds (Froomkin et al., 1976). While equitable education access might not entirely resolve labor market mismatch, it does promote fairness in the system, as equity in education extends beyond its economic implications. When education is equitable, individuals can pursue careers based on their interests rather than limitations imposed by their social background. This, in turn, leads to a more skilled workforce that is better equipped to adapt to changing economic conditions, which can indirectly reduce labor market mismatch. Equality in education is therefore a contributing factor for tackling labor market mismatch as it ensures that individuals have equal opportunities to acquire the skills and qualifications demanded by the job market.

The OECD (2020) identifies specific practices within education systems that can promote equality, such as extending the period of compulsory education, reducing grade repetition, and minimizing academic tracking. In 2012, Türkiye implemented changes to its education system, increasing the duration of compulsory education to 12 years. This move positioned Türkiye among the countries with the longest compulsory education periods in the OECD. As a result, there has been a steady growth in the mean years of schooling in Türkiye between 2011 and 2022, as reported by TURKSTAT's National Education Statistics Database. The overall average years of schooling increased from 7.3 years in 2011 to 9.2 years in 2022. Both men and women benefited from this progress. In 2011, men had an average of 8.3 years of schooling, while women had an average of 6.4 years. Over the following years, these figures increased steadily. By 2022, men had an average of 10.0 years of schooling, while women had an average of 8.5 years. In terms of grade repetition, approximately 11% of 15-year-old students in Türkiye reported repeating a grade, which aligns with the OECD average.

However, the Turkish education system differs significantly from the OECD average in terms of tracking students into different educational paths at an earlier age. Tracking in education refers to the practice of grouping students based on perceived academic abilities or achievement levels. Students are sorted into different classes or educational tracks, each with a distinct curriculum or level of difficulty. The intention is to tailor the education to the perceived abilities of the students in each group. Tracking students

influences skill accumulation through peer effects and curriculum content, so that there is a positive complementarity among peers with similar abilities. On the other hand, it may exacerbate socio-economic disadvantages. Türkiye is one of the countries with high tracking (Liu, 2018). While the OECD average age for academic tracking is 16, Turkish students are sorted into different paths at the age of 13. This has the potential to contribute to academic segregation among schools (OECD, 2020).

Academic segregation can have implications for labor market mismatch, particularly concerning skill development of general education and vocational education students. General education typically refers to a comprehensive curriculum that aims to provide students with a broad range of knowledge and skills across various subject areas. However, within this area, several factors can give rise to differences in academic achievement and access to better education within schools such as school quality and resource allocation. To assess the extent of this segregation, isolation indices are used. These indices measure the concentration of students with low or high academic achievement levels within specific schools, indicating the level of grouping based on abilities. In the case of Türkiye during the PISA 2018 assessment, the isolation indices for both low achievers and high achievers were the highest among OECD countries. Specifically, the isolation index for low achievers was 0.35 (compared to the OECD average of 0.22), and the isolation index for high achievers was 0.39 (compared to the OECD average of 0.21). These high values indicate a significant level of segregation in Turkish schools based on academic performance.

Traditional tracking systems, by segregating students into different ability groups, can contribute to disparities in skill development. Educational reforms include several strategies to improve the education system, and two approaches include de-tracking and the establishment of new universities. While both de-tracking and opening up universities have the goal of promoting educational equity, they address different levels of the education system. De-tracking concentrate on changing the organization of existing primary and secondary educational institutions. These reforms seek to move away from traditional tracking systems, towards inclusive classrooms to promote equity. On the other hand, opening up new universities addresses the capacity and accessibility of higher education institutions. This approach focuses on broadening access to tertiary education, especially in regions with limited opportunities, aiming to

accommodate a larger student population (Woessmann, 2009).

Expanding access to higher education aim at increasing the number of individuals who have the opportunity to pursue higher education. However, the quality of education is an important factor that influences the effect of higher education on individuals' economic prospects. Expanding access to higher education does not necessarily lead to better economic outcomes if the quality of education is poor (Hanushek et al., 2008). High-quality education ensures that students receive effective instruction, relevant and up-to-date curriculum, and acquire the necessary knowledge and skills to succeed in the job market.

For example, Robst (1995a) reports that individuals who are overeducated, despite having attended higher education, typically have lower skills and come from lower-ranked institutions compared to their adequately educated counterparts who also attended higher education. McGuiness (2006) raises concerns regarding the degree's reliability as an indicator of ability, considering the broader participation in higher education, which may have resulted in a wider range of abilities among graduates entering the job market.

Expanding access to higher education and increasing the number of universities may lower the effects of academic segregation. However, as more educational institutions emerge, there can be significant differences in the quality of education provided. This means that graduates from different institutions, or even different programs within the same institution, may end up with varying levels of knowledge and skills. According to Chevalier (2003), the expansion of higher education access can result in increased heterogeneity among graduates. He suggests that the increased accessibility of higher education has resulted in an increased heterogeneity of graduates, largely due to the inclusion of lower-ability students in higher education and a rise in student-staff ratios.

Blanden and Machin (2013) also show evidence to suggest that widening access to higher education can lead to increased heterogeneity among graduates. They find that while the expansion of higher education did result in greater overall attainment, it also contributed to a widening gap in educational outcomes between students from different socio-economic backgrounds. This widening gap suggests that the expansion of higher education may not have benefited all students equally.

Expanding access to higher education can also lead to an oversupply of highly educated workers (Card, 1999). If there is a significant increase in the number of individuals with higher education degrees, it can lead to a situation where the supply of highly educated workers exceeds the demand in the labor market. This oversupply can result in challenges for graduates in finding employment opportunities that match their qualifications and skills and may cause mismatch. To prevent these, the increase in the number of programs and institutions must be balanced with the quality of education and programs must be relevant to the needs of the labor market so that students are equipped with the skills and qualifications that are needed.

2.4.2.1. Vocational vs. General Education

Within this context, an important aspect to consider is whether individuals with vocational education are more likely to be well-matched to their jobs in comparison to those with a general academic education. From human capital theory perspective, vocational education is often associated with a specialized form of human capital that is specific to a particular field or occupation within the labor market. Initially, one could argue that workers with vocational skills are more likely to have job-specific competences, making them well-matched to their job compared to workers with general education. However, vocational courses often prioritize technical skills over numeracy and literacy (Quintini, 2011b). As a result, vocational graduates may face deficits in these fundamental skills, potentially putting them at a higher risk of being underskilled for certain positions. In other words, by focusing primarily on specific vocational skills, students may lack other transferable skills necessary for the labor market. This can hinder their ability to meet the demands of employers. In fact, Acemoglu and Pischke (1998, 1999) argue that firms tend to prioritize investment in general education since general education equips individuals with a diverse set of skills and knowledge that can be adaptable and transferable across various occupations and industries.

Türkiye's adoption of a dual training model in VET education represents a strategic approach to bridging the gap between educational outcomes and industry needs. The dual training model combines academic education with on-the-job training in the workplace. Students typically spend part of their time in school and part in workplaces

or apprenticeships, gaining practical skills and industry knowledge. Local partnerships are formed between schools and companies to ensure that the curriculum is aligned with current industry demands. This model aims to enhance the alignment between education and industry needs by providing students with hands-on experience in real work environments.

However, the "Education Outlook 2020: Monitoring and Evaluation Report" by Eğitim-Bir-Sen finds that there is a substantial difference, equivalent to 6-7 academic years, on average scores between students in science high schools (considered the most successful school type) and students in vocational high schools (Eğitim-Bir-Sen, 2020). This disparity is important as it can perpetuate the perception that vocational education is of lower value compared to general education. This may discourage individuals from pursuing vocational careers, resulting in a shortage of skilled workers in specific sectors. Consequently, employers may struggle to find qualified candidates with the necessary skills, exacerbating labor market mismatch.

In fact, although the dual system is likely to have positive effects on reducing mismatch in the labor market, there is evidence to suggest that graduates of VET schools experience mismatch. For example, according to a survey conducted by TURKSTAT and reported in the 'Report on Workforce Qualifications Needed in Industry' by the Turkish Ministry of Industry and Technology in 2017, approximately half of the surveyed VET graduates (47%) expressed the belief that the education they received did not have a strong impact on their professional lives. This signals a disconnection between the skills and knowledge acquired through vocational education and their practical use in the workplace. Further insights into the challenges faced by VET graduates are provided by Suna et al. (2015), who conducted face-to-face interviews with 4,863 graduates from VET high schools.

The main reason provided by VET graduates for working outside their field of study is the difficulty in employment in their specific field. Other factors mentioned include low wages, insufficient vocational skills in their chosen field, lack of necessary experience, unfavorable working conditions, and personal disinterest in their field of study.

From the viewpoint of employers, the main concern is whether VET programs are

equipping students with the skills that are needed at the workplace. The report titled 'Vocational Education in Türkiye,' prepared by Korkmaz (2015) in collaboration with the Izmir Chamber of Commerce (ITO), provides insights into the status of vocational education from an industry perspective. The report highlights observed problems and proposes solutions to address them. One issue identified is that VET graduates fail to meet industry requirements. It is noted that the current curriculum in vocational education falls short in equipping students with the necessary skills for sectors employing modern technologies. These findings align with the research by Hanushek et al. (2017), which emphasizes that vocational education, while initially offering early employment advantages, may lead to reduced employability in the long term. This is attributed to the limited adaptability of vocational education graduates to emerging technological advancements. The specialized skills acquired in vocational education may not adequately prepare individuals to keep up with evolving industry demands and changing labor market requirements. As a result, their long-term career prospects could be negatively affected.

If vocational programs fail to accurately reflect the current needs of employers or lack coordination with industry, this further contributes to labor market mismatch. According to the results of Manpower's 2023 Talent Shortage Survey, a significant 72% of employers in Türkiye report difficulties in finding skilled workers. Among their main concerns, employers highlight the scarcity of workers with technical skills related to manufacturing and production (30%), followed by sales and marketing skills (28%). This unmet demand for skilled professionals in Türkiye's manufacturing and production sectors suggests the need for further advancements in vocational and technical education.

In fact, the 11th Development Plan (2019-2023) of Türkiye underscores the enhancement of skills as one of its three main goals. It specifically underscores the importance of aligning the education system more effectively with the requirements of the job market. Aligning education with the labor market ensures that students acquire skills and knowledge that are directly applicable to the workforce. This is necessary for a successful transition from education to employment. To achieve this objective, there is a focus on reforming the curriculum, implementing a transition system based on the interests and skills of students, and adopting a standards-based

evaluation framework that places a central emphasis on student learning.

The emphasis placed on improving skills and aligning the education system with the needs of the labor market, as delineated in Türkiye's 11th Development Plan, carries significant importance in mitigating labor market mismatch. Firstly, the focus on skill relevance ensures that individuals acquire skills directly applicable to available job opportunities. Secondly, by shifting towards a curriculum less fixated on exams and more centered on practical skills, the plan aims to bridge the divide between academic qualifications and the actual skills sought by employers. This can contribute to more effective job placement. Last but not the least, aligning education with skills and interests enhances the likelihood of individuals finding fulfilling and meaningful careers, contributing not only to the efficiency of the labor market but also to overall job satisfaction and well-being.

2.5. The Structure of The Turkish Labor Market in The Context Of Labor Market Mismatch

The structure of the labor market refers to the various components and dynamics that collectively define and characterize the job market within a specific economy. The structure of the labor market includes the demographic characteristics of the workforce, employment dynamics, wages, distribution of employment across different occupations, labor market institutions and regulations, the broader economic conditions that shape the demand for labor and other external factors. Therefore, it is important to understand how these different components influence the labor market, as a change in any of these components can have implications for labor market mismatch.

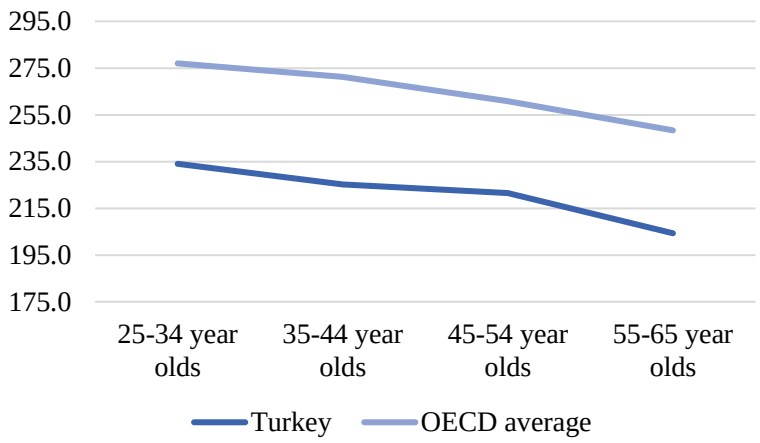
2.5.1. The Demographic Characteristics of the Workforce

The demographic characteristics of the workforce include a range of factors that define the composition of individuals contributing to the labor market. These factors include the age distribution, gender distribution, educational backgrounds, and skill sets of the workforce. These factors influence the adaptability of the labor force. For instance, a young and educated workforce may be more adaptable to industries driven by technological advancements. Türkiye has a relatively young population, with a

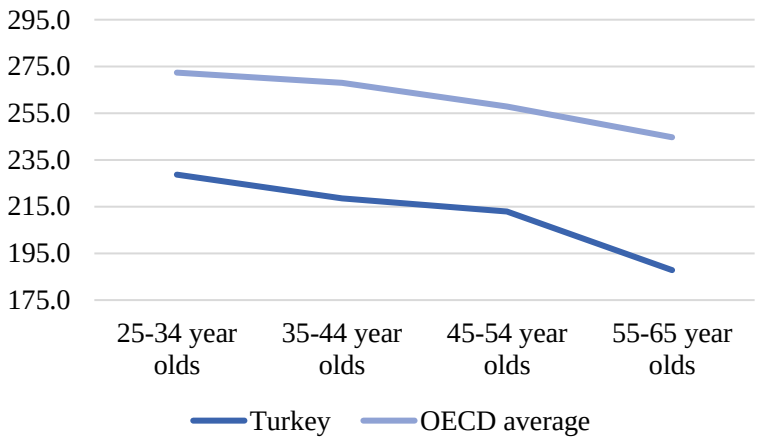
significant percentage of people under the age of 24. As of the end of 2022, Türkiye's total population reached 85 million, with the youth population (15-24 age group) constituting 15.2% of the overall population. A young population has the potential to create what is referred to as a "youth bulge", which offers benefits to economic development if effectively managed, as the presence of a larger working-age population can increase productivity and contribute to overall economic growth. However, as noted by Yifu Lin (2012), while the youth bulge is an opportunity for economic advancement, it also creates the need for a robust educational system. Adequate education programs are needed to equip the younger generation with the competencies demanded by the job market. A mismatch between educational outcomes and the actual demands of the job market can undermine the potential benefits of the youth bulge.

Moreover, a young population may possess different skill sets compared to an older one (see Figure 2 below). Figure Panel 1 shows mean literacy proficiency scores across different age groups in Türkiye in comparison to OECD average. There is a notable trend of decreasing proficiency with advancing age, particularly sharp in Türkiye. Among 25-34 year-olds, the mean score stands at 234.0, gradually declining to 204.3 for the 55-65 year-old cohort. This suggests a potential generational gap in literacy skills.

A similar trend is observed in Figure Panel 2, which shows mean numeracy proficiency scores across different age groups in Türkiye in comparison to OECD averages. The mean numeracy score for 25-34-year-olds is 228.7, progressively diminishing to 187.8 for those in the 55-65-year-old category, emphasizing a considerable 40.9-point gap between the youngest and oldest adults. This decline, notably more substantial than the 29.7-point difference observed in literacy proficiency between the youngest and oldest adults, suggests significant educational problems in numeracy development for Türkiye. These comparisons indicate that the skills acquired by older individuals during their education may not be aligning with the demands of the labor market. Older adults with lower proficiency levels may be facing challenges in securing employment or transitioning to new job opportunities, which might lead to labor market mismatch.



Panel 1. Mean literacy



Panel 2. Mean numeracy

Figure 2. Mean PIAAC proficiency scores of Türkiye and OECD averages, by age groups

Source: OECD PIAAC

In addition to age, gender and education level are two other factors that play an important role in determining individuals' skills. It is expected that the differences in skill levels are influenced by variations in the educational attainment of both men and women. Figure 3 provides a comparison of the distribution of educational levels across age groups and genders in Türkiye and the average of OECD countries. The data shows that for Turkish women in 25-44 age group, a high percentage (65.8%) have an

educational level lower than upper secondary, which is substantially higher compared to the OECD average (16.9%). On the other hand, a smaller percentage of Turkish women (15.2%) have tertiary education, while a much higher percentage of women in the OECD (42.9%) have reached this level. Turkish men in this age group also have a higher percentage with education lower than upper secondary (55.5%) compared to the OECD average (18.3%).

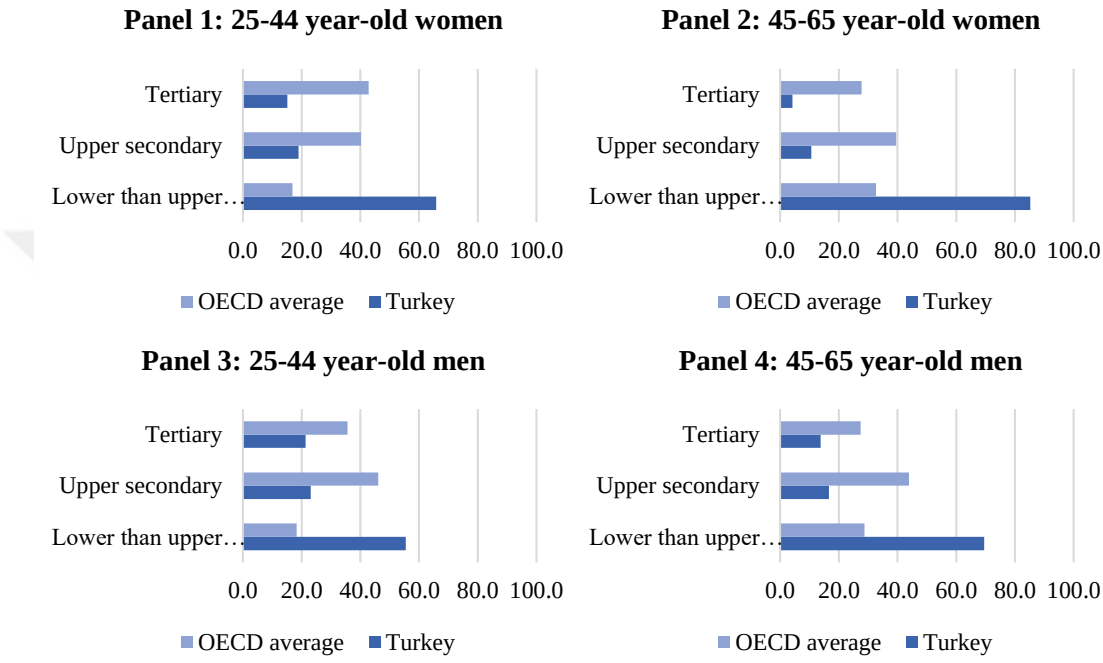


Figure 3. Distribution of educational levels across age groups and gender, 2015

Source: OECD PIAAC
Note: The data does not include open or distance learning programs in the tertiary education percentage

In the 45-65 age group, the difference in educational attainment between Turkish men and women is even more significant. A higher percentage of Turkish women (85.2%) have educational attainment lower than upper secondary compared to Turkish men (69.5%). A high percentage of Turkish women have an educational level lower than upper secondary, while the OECD average is significantly lower at 32.7%. Additionally, Turkish women have a much lower percentage with tertiary education (4.2%) compared to the OECD average (27.7%) in this age group. These data suggest that educational attainment in Türkiye, particularly among older age groups, is lower

than the OECD average. The gender differences in education are quite pronounced, particularly in the 45-65 age group, with Turkish women being less likely to attain higher levels of education compared to Turkish men and the OECD average. However, this is not the case for all age groups. Among the younger population, especially women aged 25-44, there is a higher rate of university attendance compared to men, signaling a shift in educational attainment patterns.

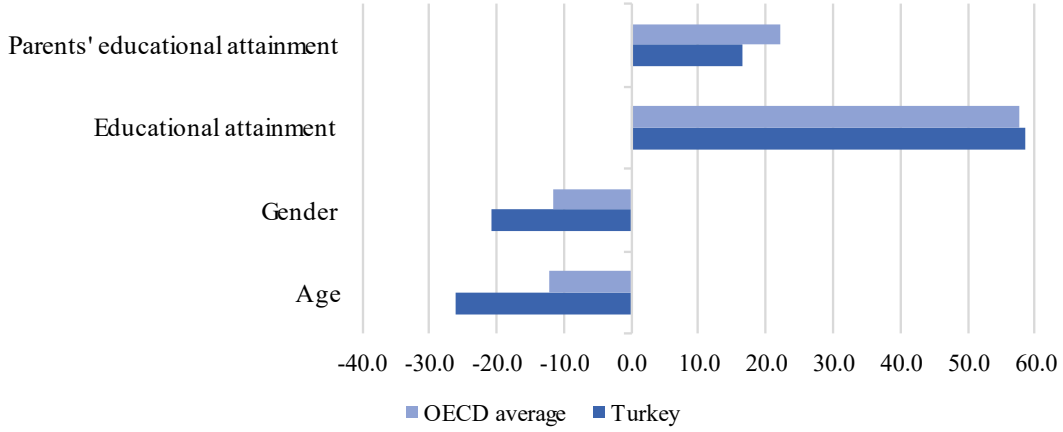


Figure 4. Comparison of Numeracy Skills Disparities across four categories: Türkiye vs. OECD Average (2015)

Source: OECD PIAAC
Note: In this graph, 'Gender (women - men)' indicates the numeracy skill difference favoring men over women, 'Age (older - younger)' shows the numeracy skill disparity favoring younger adults (25-34 years) over older adults (55-65 years), 'Educational attainment' compares numeracy skills of adults with tertiary education to those with less than upper secondary education, and 'Parents' educational attainment' assesses the impact of higher parental education levels on numeracy skills.

Overall, the PIAAC data reveals substantial disparities in numeracy skills between Türkiye and the OECD average across various demographic indicators (Figure 4). Firstly, Türkiye exhibits a significantly larger difference in numeracy skills between its youngest (25-34) and oldest (55-65) adults compared to the OECD average, with a value of -26.2 for Türkiye and -12.1 for the OECD. This suggests potential variations in educational attainment or access to numeracy-related training across different age groups. Additionally, when considering numeracy skills, there is a more pronounced gender gap in Türkiye, with men outperforming women by 20.9 points, compared to the OECD average gender gap where men outperform women by 11.7 points. On the other hand, the difference in numeracy skills between adults with tertiary education and those with lower than upper secondary education is similar in Türkiye and the

OECD (Türkiye's value stands at 58.7, while the OECD average is 57.7). Finally, the data reveals a smaller difference in numeracy skills based on parents' educational attainment in Türkiye compared to the OECD average (Türkiye's value is 16.6, while the OECD average is 22.2).

2.5.1.1. A Discussion on Age, Cognitive Abilities, Digital Skills and Labor Market Mismatches

Two factors may link the phenomenon of declining numeracy and literacy proficiency with age and potentially higher levels of mismatches in the labor with increasing age. The first one is the cognitive abilities (or intelligence) of an individual and its relation with age. Intelligence is generally considered important as it influences various aspects of life and it plays a significant role in the abilities to perform tasks and adapt to new job requirements. Psychologists make a distinction between two types of intelligence: fluid intelligence and crystallized intelligence (Heckman, 2011).

Fluid intelligence refers to the capacity to learn new information and adapt to new situations quickly. It is essentially the ability to solve problems and think logically in novel and unfamiliar contexts. On the other hand, crystallized intelligence involves the knowledge and skills that a person has acquired over their lifetime (Almlund et al., 2011). A study by Raven (1988) suggests that fluid intelligence plays a role in facilitating the acquisition of crystallized intelligence. In simpler terms, the ability to solve problems and learn quickly contributes to building a foundation of knowledge over time.

There are discussions on how cognitive abilities change with age (Heckman and Kautz, 2012). Studies show that the recession in fluid intelligence is notably more pronounced compared to the decline in crystallized intelligence (Horn, 1970). A research conducted by Schaie (1994) suggests the cognitive processing of adults decline in with age. This decline is generally observed after individuals reach the age of 55 (Borghans et al., 2008).

The second aspect which complicates the discussions on age and labor market mismatch is the use of technology. The ways in which different age groups interact with technology vary significantly. For the younger generation, technology is an

integral part of everyday life, influencing how they learn and communicate. Educational tools provide tailored learning experiences, and digital platforms shape their social interactions. On the other hand, older age groups may engage with technology in different contexts. The integration of technology into the lives of older individuals is to improve their daily tasks. These differences in technology proficiency, known as the digital divide, can exacerbate labor market mismatch. Individuals who lack access to digital resources may find themselves at a disadvantage in a job market that increasingly relies on digital literacy (Aissaoui, 2022).

Of course, age is not the only reason for a lack of access to technology and the digital divide. Financial constraints can be a significant barrier to technology access. According to the World Development Report published by the World Bank in 2016, some countries have imposed tariffs on specific goods related to information and communications technology (ICT) including computers and smartphones, which increased the cost of these devices for consumers and slowed down the adoption of digital technologies. The report mentions Türkiye as an example where taxation adds a significant cost to ICT devices, causing them to be treated as luxury goods. This can have implications for the labor market as individuals with limited financial means may struggle to invest in the necessary technology, impacting their ability to access better job opportunities and potentially resulting in labor market mismatches.

The digital divide can impact job seeking in several ways. Digital skills are increasingly important in the modern job market and many employers expect workers to have at least basic digital literacy skills. But additionally, job seekers without digital skills face barriers when searching for and applying for jobs. For example, in regions with limited digital infrastructure, individuals may not have access to job openings in other areas. This can result in a geographical mismatch, where individuals are unable to access job markets that better align with their skills and qualifications. If individuals lack access to the internet or a computer, they may miss out on a wide range of job opportunities. This can limit their ability to find suitable employment and can contribute to labor market mismatch.

In this regard, the internet is important as it allows for a greater number of individuals and companies to connect with each other. This means that a larger pool of potential

employees and employers can find each other easily. Additionally, the internet provides a more cost-effective way for both job seekers and employers to connect. On the other hand, traditional methods of finding job candidates or jobs, such as newspaper advertisements, can be costly and less efficient. The online platforms that consolidate job vacancies from various sources makes it easier for firms and for job seekers to find and apply for these positions.

This can extend to international job searches, making it easier for individuals to explore opportunities in other countries. In addition to international platforms, there are similar services for local job markets, like "kariyer.net" in Türkiye. These online platforms play a significant role in improving labor market efficiency and reducing mismatches. They are especially important for developing countries with a wide informal sector, where traditional methods of job searching and hiring may not be as effective.

2.5.2. Employment Dynamics

Employment dynamics refer to the changes and fluctuations in the job market and workforce over time. Several statistics are commonly used to analyze employment dynamics, which include labor force participation rate (LFPR), employment rate and unemployment rate. Figure 5 shows these statistics for employment dynamics in Türkiye between 2014 and 2023. Data indicates that the seasonally adjusted LFPR in Türkiye has shown variations over the years, with a high of 53.90% in November 2022 and a low of 46.50% in April 2020. There is a noticeable decline during the initial months of the COVID-19 pandemic (March to June 2020). This decline reflects the effect of lockdowns and economic disruptions during that period. However, the participation rate gradually recovers, reaching 53.90% in November 2022.

The employment rate fluctuates throughout the years as well, reaching a peak of 48.40% in November 2022 and a low of 40.30% in April 2020. Similar to the LFPR, the employment rate experiences a dip during the early months of the COVID-19 pandemic and subsequently increases. The unemployment rate also shows variations, with a peak of 14.20% in July 2020 and a low of 9.20% in January 2014. The highest unemployment rates coincide with the early months of the COVID-19 pandemic, showing the challenges during that period.

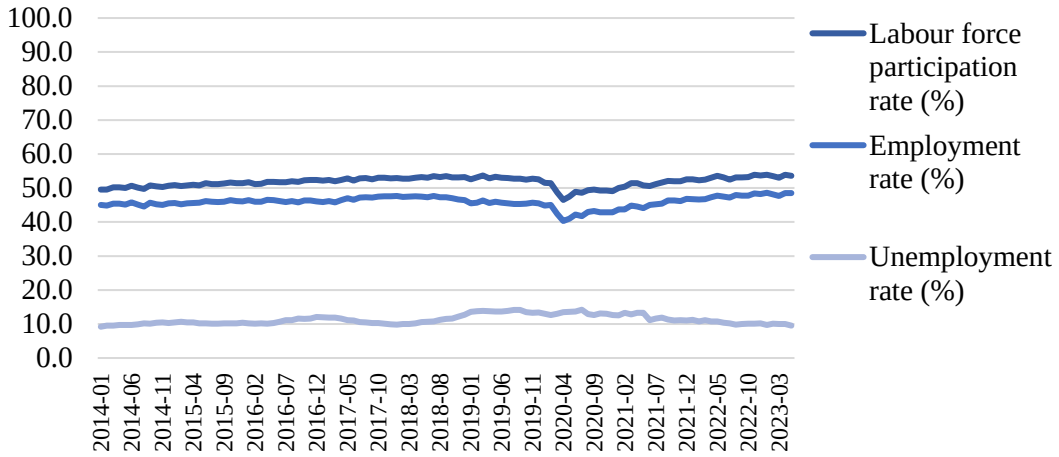


Figure 5. Seasonally adjusted main labor force indicators (15+ age), 2014-2023

Source: Electronic Data Delivery System (CBRT)

Table 5. Main labor force indicators by educational level, 2022 (%) (Age: 15+)

	Illiterate	Less than high school	High school	Vocational high school	Higher education
ALL					
LFPR	16.8	46.6	55.5	66.7	77.3
Employment rate	15.7	42.3	48.4	59.1	68.6
Unemployment rate	6.2	9.2	12.7	11.3	11.3
MEN					
LFPR	30.6	65.9	72.1	81.5	85.1
Employment rate	27.1	60.0	64.9	74.4	78.0
Unemployment rate	11.6	8.9	10.0	8.7	8.3
WOMEN					
LFPR	13.9	27.1	36.1	43.0	68.8
Employment rate	13.4	24.4	29.2	34.8	58.3
Unemployment rate	3.8	10.0	19.1	19.1	15.2

Source: TURKSTAT

Table 2.5. provides further detail from TURKSTAT data on the LFPR, employment rate, and unemployment rate based on different educational attainment levels for Türkiye for 2022. Overall, higher levels of education are associated with higher labor

force participation rates and employment rates. Among all individuals, the LFPR ranges from 16.8% for illiterate individuals to 77.3% for those with higher education. Similarly, the employment rate varies from 15.7% for illiterate individuals to 68.6% for individuals with higher education. For men, the data suggests that higher educational attainment consistently lowers the risk of unemployment, aligning with the expected benefits of education in enhancing employment prospects. For women, however, the dynamic is more complex. Particularly among educated women, the unemployment rates observed do not necessarily reflect a straightforward effect of higher education but rather the selective nature of labor force participation among this group. Educated women participating in the labor force may represent a distinct subset. Many less educated women may opt out of the labor force entirely or face barriers to entry, leading to their lower representation in unemployment statistics.

Overall, the data from Table 2.5 indicates that higher educational levels correlate with higher labor force participation and employment rates. However, high unemployment rates (11.3% for both men and women with higher education) at higher educational levels suggests that there is a potential mismatch in the labor market. This could mean that although more educated individuals are entering the labor force, there is a high unemployment rate for this group, indicating an oversupply of higher-educated individuals relative to the demand in the job market. Furthermore, despite a higher LFPR for women with higher education, it remains lower than that for men, and the unemployment rate for educated women remains high (8.3% for men vs. 15.2% for women), suggesting a gender-specific labor market mismatch.

2.5.2.1. The Female Labor Force Participation in Türkiye

The dynamics of female labor force participation in Türkiye can be explained through the U-shaped female labor force participation, also known as the “feminization U” hypothesis, which explains the relation between economic growth and the labor force participation of women (Sinha, 1967; Çağatay and Özler, 1995, Goldin, 1995). Goldin (1995) identifies a U-shaped curve as a pattern in women's labor market participation through different stages of economic development. According to Goldin (1995), initial economic development tends to reduce female labor force participation. This is attributed to the diminishing role of agriculture in a developing and modernizing

economy. Historically, women have been a significant part of the agricultural workforce. As economies develop, contribution of agricultural sector to national output and employment decreases, often without providing equal employment opportunities for women, especially those with lower education levels, in other sectors. This transition leads to a decline in women's labor force participation. However, this trend reverses as economies continue to develop, leading to an increase in female labor force participation. This increase is due to improvements in women's education and declines in fertility rates, enabling women to secure jobs outside the agricultural sector.

Tunalı, Kırdar, and Dayıoğlu (2021) corroborate this hypothesis for Türkiye. They explore the U-shaped pattern of female labor force participation in Türkiye from 1988 to 2013 using a synthetic panel approach and age-cohort-period (APC) methods to understand changes in participation rates. Their findings show that Türkiye is currently positioned on the ascending part of the U-shaped curve and experiencing an increase in female labor force participation. The analysis shows that changes at the societal level, seen through yearly data, have positively influenced the participation of women in the labor force between 2003 and 2013. The study suggests that the increase in female labor force participation is likely to continue due to inertia of key factors such as education levels and fertility rates.

Tunalı, Kırdar, and Dayıoğlu (2021) further show that women's participation in the labor force has an M-shaped pattern. This pattern indicates a decline in participation rates after the age of 25, followed by a rebound and a second peak around the mid-40s. This trend suggests that many women temporarily leave the workforce, primarily due to childbearing responsibilities, and re-enter later in life. The observation of an M-shaped pattern in women's labor force participation, as discussed by Tunalı, Kırdar, and Dayıoğlu (2021), shows the significant effect of childbearing on women's employment decisions in Türkiye and the importance of maternal leave policies and childcare support for encouraging women's continuous participation in the labor force.

In Türkiye, like in many countries, labor laws provide a framework that both public and private sector employers must follow. Certain benefits can be more generous in the public sector due to collective bargaining agreements or specific public sector regulations. One such benefit is the provision of maternal leave. In Türkiye, the

regulation titled "Regulation on Part-Time Work After Maternity Leave or Unpaid Leave" is based on and refers to Article 13 of the Labor Law numbered 4857. This indicates that the regulation applies to employees and their employers under the scope of the Turkish Labor Law. This regulation outlines the rights of women in Türkiye regarding maternity leave and part-time work. The Labor Law numbered 4857 does not distinguish between public and private sector employees. Therefore, the maternity leave entitlements and provisions for part-time work following maternity leave or unpaid leave should apply to female workers in both the public and private sectors. According to this law, women workers are entitled to a total of 16 weeks of maternity leave, with 8 weeks before and 8 weeks after the birth. In the case of multiple pregnancies, an additional two weeks are added to the pre-birth period. However, with a doctor's medical report, a woman worker can choose to work up to three weeks before the birth, and those days will be added to her post-birth leave. Women workers have the right to unpaid leave after maternity leave for up to 6 months.

This is relevant for labor market mismatch for two reasons. Firstly, the period of absence due to maternity can lead to a skills gap, as in many industries a break can render one's knowledge and abilities less relevant. Secondly, the potential for women to take maternity leave for childcare purposes can lead to hesitation among employers about hiring female employees, particularly those of childbearing age. This is because of the concern that women will eventually leave the workforce temporarily, which could disrupt ongoing projects and require the hiring of temporary replacements or the redistribution of the absent employee's workload among existing staff. Such concerns may result in a hiring bias against women, which not only affects gender diversity in the workplace but can also contribute to the labor market mismatch. Women may find themselves passed over for roles for which they are qualified, or they may be offered positions that do not fully utilize their skills or offer fewer opportunities for advancement.

Childcare is another important factor for labor market mismatch for women for several reasons. Firstly, women are often the primary caregivers in families. Therefore, lack of accessible and affordable childcare can influence their decision to either not participate in the labor force or to work in less demanding jobs that may not match their qualifications. Secondly, without reliable childcare, women may be forced to

seek part-time work or flexible schedules that are often lower-paid. Furthermore, the lack of childcare options can push women into "female-dominated" sectors or roles that are perceived as more family-friendly but may not correspond to their actual skills or experience.

In Türkiye, childcare and preschool services are offered by entities in both the private and public sectors, with accreditation from the Ministry of National Education (MoNE) or the Ministry of Family and Social Policies (MoFSP). A 2015 World Bank report indicates that, in Türkiye, despite the growth in service availability, a significant portion of children and families do not have access to these services. Furthermore, these services are constrained not only by the age range but also by the service hours available to parents. Full-day childcare is predominantly available through private providers, whereas public preschools typically run for half a day, either in two shifts or just a single half-day session. Among the few providers that cater to the 0-2 age group, private facilities are the majority. The operating hours of public services are not supportive enough for mothers looking to return to work post-maternity leave. For children aged 3-6, full-day care is again largely the domain of private providers (World Bank, 2015).

In Türkiye, even with significant growth since the early 2000s, the participation of working-age women into the labor market remains relatively low. The World Bank report (2015) emphasizes that improving access to affordable, high-quality Early Childhood Education and Care (ECEC) services not only increases women's participation in the workforce, but also enhances early childhood development (World Bank, 2015). High-quality early childhood education can have substantial, long-lasting benefits for the children which are not just limited to educational outcomes; but also include socio-economic advantages and improved life chances.

2.5.3. The Distribution of Employment Across Different Sectors

Typically, an economy is divided into two primary sectors: public and private. The public sector includes government-owned organizations and institutions such as government agencies, public schools, healthcare facilities, and law enforcement, while the private sector comprises privately-owned businesses from large corporations to small enterprises. These sectors are distinct not just in their structure but also in the

aspects that can contribute to labor market mismatch. The differences in employment conditions, job stability, and career advancement opportunities may contribute differently to labor market mismatch in the public sector and the private sector.

To begin with, the public sector generally offers higher job security due to civil service protections and regulations, whereas the private sector often has less job security, with greater exposure to market fluctuations. For example, in Türkiye, the status of a state civil servant cannot be terminated, and their salary and other rights cannot be confiscated except for the situations specified in Law No. 657 on State Civil Servants. In other words, the public sector typically experiences lower job mobility due to job security. The private sector, on the other hand, offers more mobility, with employees often changing jobs and industries throughout their careers (Sanchez and Fernandez, 2021).

Secondly, public sector earnings are often characterized by stability and predictability. Salary structures in the public sector have clear pay scales based on factors like job classification, years of service, and education. As a result, public sector tends to have a more stable and transparent salary structure, but it may offer lower salaries compared to the private sector. On the other hand, earnings in the private sector can vary widely depending on the industry, company, and individual performance. In addition to base salaries, the private sector often offers non-salary compensation, such as performance bonuses. However, while the private sector may offer higher earnings, it can also bring income volatility and less job security compared to the public sector. On the other hand, while career progression may be slower and more structured in the public sector, the private sector offers a wider range of career paths, with rapid advancement based on performance.

Thirdly, the public sector is known for offering better work-life balance and predictable working hours. Public sector employees often report higher job satisfaction due to factors like job security, work-life balance, and the sense of contributing to the public good (Tschirhart et al., 2008). In the private sector, job satisfaction can be influenced by factors such as career advancement opportunities, innovative work environments, and performance-based rewards (Karl and Sutton, 1998). Moreover, public sector employment often provides more robust maternity leave benefits and job

security, which are typically guaranteed by law or strong collective bargaining agreements. The stability and supportive policies in the public sector not only facilitate work-life balance but also contribute to a significant presence of women in this sector. Indeed, in many countries, the public sector is a major employer of women, reflecting these more favorable conditions.

The differences between the private and public sectors extend to their respective job application processes as well. These processes show distinct characteristics in terms of application methods, job listings, selection criteria, interview procedures, timelines, background checks, and compensation structures. In the private sector, the application process is typically more flexible, with various methods such as online portals, email, direct applications, and recruitment agencies. The process is often quick to match the dynamic nature of the business. In contrast, the public sector generally has a more structured and formal application process. Applications often require completion of specific forms, strict adherence to application guidelines, and may include civil service exams or other standardized tests.

In Türkiye, becoming a public sector employee typically involves a few steps, which are somewhat similar to public sector recruitment processes in many other countries, but with specific elements unique to Türkiye. The initial step involves meeting the educational prerequisites for the aimed public sector position. Then, candidates must take the Public Personnel Selection Examination (KPSS in Turkish abbreviation). The administration of KPSS is overseen by The Measuring, Selection and Placement Center (ÖSYM in Turkish abbreviation), which manages tasks such as receiving applications, conducting the examination, and evaluating the results. Applicants are required to pay a registration fee when applying to take the KPSS. The fee amount can vary depending on the level of the examination[8].

The KPSS includes standardized exams tailored to different job categories and to educational background of the candidates. It comprises multiple tests, each targeting different groups of government positions. These cover a range of subjects, including

[8] As of May 2023, the fee was approximately $7.5 USD for Level A Test and an additional $5 USD for Level B Test.

general culture, general ability, educational sciences, and field-specific knowledge depending on the job type. Candidates are scored based on their performance in these tests. These scores are critical in determining the eligibility and ranking of candidates for various public sector positions, emphasizing a merit-based and transparent selection process. The examination is held periodically, often annually, allowing candidates multiple opportunities to improve their scores (General Regulations on Examinations for Initial Appointments to Public Duties, Related Law Date: 14/7/1965; Official Gazette Publication Date: 3/5/2002).

In Türkiye, public sector jobs are categorized into Group A (found in ministries, related organizations, etc.) and Group B (all positions in various public institutions, except for professions in Group A). To determine the eligibility of candidates for positions in Group A and to make placements for positions referred to as Group B, KPSS is conducted to generate the scores that will be used. For Group A positions, institutions organize their own entrance examinations according to their regulations to appoint candidates afterwards. On the other hand, KPSS scores can be used directly by the relevant public institutions and organizations for appointments to Group B positions without the need for an entrance examination. Any candidate who takes the section of KPSS that consists of general knowledge (i.e. Level A – Mathematics and Turkish language) can participate in this process for the Group B positions.

In this respect, the KPSS is the primary means through which candidates are assessed for eligibility and suitability for public sector jobs in Türkiye. It aims to provide an objective and standardized method of evaluating the qualifications of a large number of applicants. High scores increase the chances of securing a government job. However, even though success in the KPSS is a significant factor in a public worker's career trajectory in Türkiye, there have been criticisms about the KPSS system, including concerns about fairness, the pressure it places on candidates, and its effectiveness in truly identifying the best candidates for public service roles. Furthermore, preparing for the KPSS is a major endeavor for many candidates, with a large industry of preparatory courses, books, and materials available, which requires a good amount of investment.

As the third and the last step following the exams, candidates who have passed are

required to apply within a specified timeframe to the public institution or organization where they have been placed. The public institutions and organizations form an examination evaluation commission (“mülakat komisyonu” in Turkish). This commission is tasked with evaluating the candidates who have been nominated for appointment and it reviews the qualifications and characteristics of the nominated candidates to ensure that they meet the required criteria. Candidates who receive the recommendation of the commission proceed to appointment in the public sector based on this evaluation. (General Regulations on Examinations for Initial Appointments to Public Duties”, Related Law Date: 14/7/1965; Official Gazette Publication Date: 3/5/2002).

According to the data from the Presidency of Strategy and Budget on public sector employment in Türkiye for the third quarter of September 2023, the total number of people employed in the public sector is 5,101,689. Out of the total, 3,467,443 employees are classified as civil servants, who are typically permanent government employees. As of 2021, based on OECD data, public sector employment in Türkiye constitutes 13.4% of the total workforce, while the OECD average is higher at 18.6%. Furthermore, a report titled "Public Sector and General Employment Sector Employment Report," published by the Confederation of Progressive Trade Unions of Türkiye (DİSK) in November 2023, reveals that the average female employment rate in the public sector across OECD member countries stands at 57.8%. However, women make up 25% of the public sector workforce in Türkiye (DİSK, 2023). This shows that many countries have a higher representation of women in the public sector compared to their overall workforce than Türkiye. These data suggest that although the public sector offers better opportunities for women compared to the private sector, there are inequalities in gender representation within the public sector.

2.5.4. The Broader Economic Conditions That Shape the Demand for Labor

Türkiye has experienced substantial economic growth since the 1990s, reflecting sustained economic growth over more than three decades. (Figure 6). However, this growth has not consistently translated into a corresponding rise in employment (Telli et al., 2016). According to Yeldan and Ünüvar (2016), an important feature of the post-2001 period in Türkiye was the emergence of patterns characterized by growth

without a corresponding increase in employment. Despite rapid economic expansion, high unemployment rates and reduced participation rates were evident. Following the 2001 crisis, the unemployment rate increased to over 10 percent, and even with subsequent robust growth, it has not returned to its pre-crisis levels, which were at 6.5 percent in 2000 (Yeldan and Ünüvar, 2016). This is referred to as "jobless growth", which points to a situation in which an economy experiences economic growth without a proportionate increase in employment opportunities. In other words, even though the overall economic output and productivity of a country are expanding, the growth is not translating into a significant creation of new jobs.

According to Telli et al. (2016), two contributing factors to jobless growth in Türkiye were the rigid regulatory framework and the perceived burden of taxes in the labor market. Tunalı (2003) suggests that laws protecting employment in Türkiye may have increased job insecurity among workers, as employers attempt to avoid severance payments by redirecting their labor demand to informal market workers. The presence of a rigid regulatory framework and employment protection laws can contribute to labor market mismatch by creating incentives for employers to shift their labor demand towards informal markets. Additionally, the country has one of the highest tax burdens in its labor markets compared to the OECD averages (Tunalı, 2003).

The 'Youth Unemployment in Türkiye' report by the ILO in 2007 highlighted that nearly 30 percent of Türkiye's workforce was engaged in agriculture, surpassing global averages, as agricultural subsidies kept this population in rural areas. But their discontinuation has led to a notable trend towards urbanization (Ercan, 2007). In 2022, the ratio of agriculture in total employment has decreased to around 15 percent. However, in Türkiye, the trajectory of employment shifting from low-productivity agriculture to higher-productivity industry and services has encountered deceleration, potentially hindering associated productivity gains (World Bank, 2019). This shift shows the importance of aligning workforce skills with the demands of the job market to mitigate potential labor market mismatches.

Furthermore, compounding these concerns are demographic trends that have implications for labor market dynamics. Despite its relatively young population, Türkiye, like many other countries, is undergoing significant demographic shifts,

characterized by an increasing aging population. TURKSTAT's forecasts suggest a decrease of youth population to 14.0% by 2030, followed by a further decline to 13.4% in 2040, 11.8% in 2060, and 11.1% in 2080. Furthermore, the median age of Türkiye's population, a key measure of population aging, was 31.0 in 2015 and it rose to 32.7 in 2020. Türkiye's population is projected to peak around 2050, with a shifting dependency ratio.

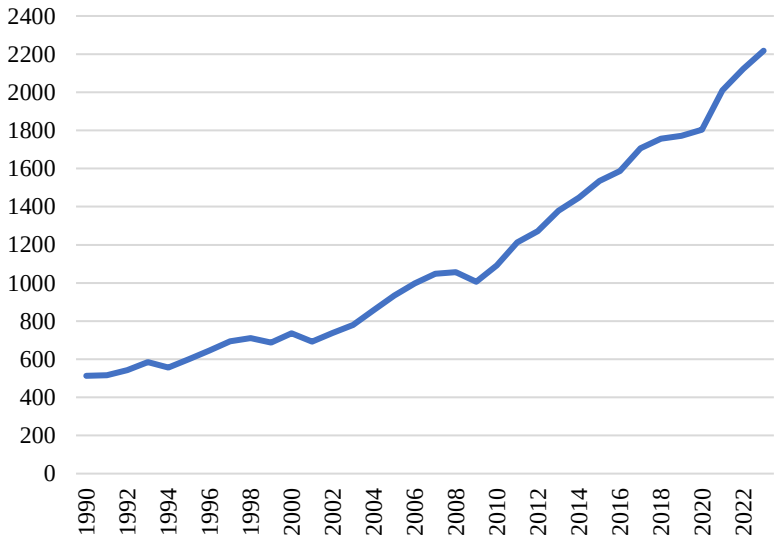


Figure 6. Gross domestic product in chain linked volume, index (Billions TL) (Base Year: 2009)

Source: World Bank database.

This means that Türkiye must generate jobs at a rate sufficient to accommodate the increasing numbers of individuals joining the workforce. According to World Bank (2014), approximately 700,000 new jobs are needed annually to address this challenge. Balancing these demographic shifts with suitable employment opportunities becomes very important in reducing the risk of labor market mismatch. The expansion of higher education in Türkiye further complicates this situation. As more individuals attain higher education, the labor market faces the challenge of creating jobs that match the skill levels and education level of this growing educated population. This shift towards higher educational attainment can lead to an oversupply of graduates, increasing the risk of educational inflation and labor market mismatches.

2.5.5. Labor Market Institutions and Regulations

Labor market regulations have the aim of securing welfare and standard of living for

workers. The discussions surrounding labor market regulations primarily focuses on their impact on employment levels (Katz and Krueger, 1992; Card and Krueger, 1993; Meer and West, 2013; Villanueva and Adamopoulou, 2022). However, Acemoglu (2001) claims that these measures can also significantly influence the composition of employment, in addition to the quantity of jobs available. According to Acemoglu (2001), in a standard labor market, policies such as unemployment insurance and minimum wages encourage firms to generate a greater number of high-wage jobs. Both minimum wages and unemployment insurance contribute to an increase in labor productivity by redirecting employment towards more capital-intensive and higher-quality jobs. In the absence of these labor market regulations, there is a scarcity of good jobs, which can be addressed by implementing such policies that may even enhance overall welfare (Acemoglu, 2001).

Table 6. Indicators of collective bargaining (% of employees)

Trade union density	9.9	2019
Adjusted union coverage rate	8.5	2019
Employer organization density	57.2	2018

Source: OECD and AIAS (2021), Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts

In Türkiye, wage bargaining primarily takes place at the local or company level, indicating that negotiations regarding wages tend to occur within specific organizations. Collective bargaining over wages is mainly conducted at the enterprise level, involving individual companies or specific units within them. However, it is important to note that there are no legal provisions for mandatory extension of collective agreements to non-organized employers, which implies that these agreements do not apply to employers who are not part of trade unions or employer organizations. On the other hand, Türkiye does have statutory minimum wage rates that cover all or most employees, ensuring a baseline level of wage protection for workers across the country (OECD, 2021). In Türkiye, the minimum wage is determined by a committee composed of representatives from the government, employee unions, and employer unions. This committee collaboratively establishes the

minimum wage, taking into account various factors and considerations from each of these stakeholder groups (Gürcihan Yüncüler and Yüncüler, 2016).

Table 6 summarizes the indicators of collective bargaining for Türkiye. Trade union density refers to the measurement of trade union membership relative to the total number of employees, excluding individuals who are not actively part of the labor force, unemployed, unpaid family workers, or self-employed. In other words, it quantifies the proportion of net union members within the wage-employed workforce. In Türkiye, the relatively low trade union density of 9.9% in 2019 implies that a significant portion of the workforce not actively involved in trade unions. Moreover, the adjusted union coverage rate of 8.5% in 2019 indicates that a relatively small proportion of employees are covered by collective agreements or represented by trade unions. This suggests potential gaps between the legal framework giving employees the right to engage in collective bargaining and the actual realization of these rights in practice. On the other hand, the employer organization density of 57.2% in 2018 shows the substantial presence and influence of employer organizations in Türkiye. This implies that employers have a strong organizational representation and influence over labor-related matters.

Figure 7 provides insights into the trade union[9] membership rates in Türkiye and the OECD countries. Analysis of the data from 2000 to 2019 reveals that Türkiye consistently maintained a lower percentage of employees with the right to bargain compared to the average of the OECD countries. This persistent difference suggests a relatively lower level of employee representation in Türkiye, which might be limiting workers' participation and influence in collective bargaining activities. Figure 5.6 also shows an increase in the percentage of employees in trade unions since 2014. One possible explanation for this rise could be the decline in the informal sector, where unionization is typically less prevalent. Additionally, the reduction in workforce

[9] A trade union is an organization composed of employees, and its main functions include negotiating and advocating for favorable pay rates and working conditions on behalf of its members. This definition encompasses employee organizations and professional associations, even if collective bargaining is not their primary focus (OECD, 2021). Unions advocate for minimum wages and other regulations, emphasizing their role in improving job quality since effectively enforced minimum wages raise the wages of low-quality jobs, making them less profitable and resulting in a favorable change in the job composition.

numbers in smaller firms, which generally have lower union membership rates, could be contributing to this trend. Furthermore, the expansion of the public sector in Türkiye after 2018, which traditionally has higher rates of unionization, might also explain the continued increase in union membership.

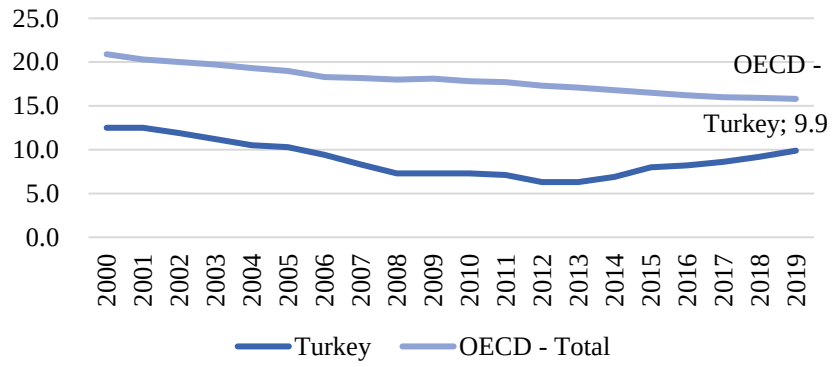


Figure 7. Percentage of employees in trade unions

Source: OECD. Note: OECD is an estimation based on the employee-weighted average of the 38 member countries.

Research has demonstrated that unionism decreases the likelihood of worker separations, since workers who are dissatisfied with their working conditions have the ability to express their concerns (Freeman, 1980). Additionally, unionism has positive effects on the duration of on-the-job training which has a notable positive influence on reducing undereducation, although it does not have the same effect on overeducation (Groot, 1997). Aleksynska and Tritah (2013) finds that individuals who are members of trade unions have a greater likelihood of experiencing overeducation, which can be attributed to their comparatively lower job turnover. Moreover, Sloane et al. (1999) claims that unions may attempt to motivate employers to modify job specifications or implement more stringent entry requirements to improve the match between workers and job positions. However, although they find that while trade union membership appears to decrease the likelihood of mismatch, this effect lacks statistical significance.

2.5.6. Other Factors Related with The Labor Market Mismatch in Türkiye

2.5.6.1. Informality

The prevalence of informal employment is a common phenomenon in many countries,

including Türkiye, and arises due to a combination of economic, social, and structural factors. Informal employment is often associated with lower wages and limited access to social benefits. Individuals in informal jobs may be willing to accept lower wages due to the perceived lack of alternatives or mismatch in the availability of formal job opportunities that match their skills. Furthermore, workers who have experienced labor market mismatch and subsequently entered informal employment may face challenges when attempting to transition back into formal, well-matched positions. The lack of regulation and documentation in the informal sector may hinder their ability to demonstrate their skills and qualifications to potential formal employers.

According to Bağır et al. (2023), between 2004 and 2021, there was a decline in the percentage of informal employment in Türkiye, from 50.6% to 29%. The authors explain that a significant portion of the reduction in informal employment can be attributed to factors such as an increase in the education levels of workers, the size of the firms, and a shift of workers from the agricultural sector to the service sector. On the other hand, they find that informal employment is more common among women, individuals with lower levels of education, as well as both younger and older people.

In Türkiye, being female increases the likelihood of informal employment (Bağır et al., 2023). Başlevent and Acar (2015) finds that this impact of gender on informal employment is sizeable and persistent across the years examined (2000, 2006, and 2012). The authors suggest that part of the gender gap in informality may be due to more women gaining indirect access to social security benefits as a dependent (e.g., as the insured's wife, mother, or daughter), which decreases their incentive to seek formal employment. This effect is absent in the case of never-married women and larger for those who are married, divorced, or widowed, consistent with the "indirect access" argument.

The shift from non-wage employment (such as self-employment in agriculture or informal day labor) to wage employment (formal employment with a regular wage) marks a move towards formal employment. This transition from non-wage to wage employment, coinciding with the migration of labor from agriculture to other sectors, has been accelerated by government policies, such as the 2008 Employment Subsidy Program introduced by Law No. 5763 ("Law on Amending the Labor Law And Some

Other Laws").

The 2008 Employment Subsidy Program was designed to increase formal employment by offering financial incentives to employers for hiring specific groups of people. The aim was creating more jobs in the formal sector by lowering the financial barriers to hiring, thereby reducing the attractiveness of the informal sector, and improving overall employment rates for these specific groups within the formal economy (Ayhan, 2013). It targeted young males between the ages of 18 and 29 and all women over the age of 18, providing a subsidy that covered the employer's share of social security contributions for these new hires on a decreasing scale over five years, starting at 100% coverage in the first year and decreasing by 20% each year. To qualify, these employees had to be newly hired, not previously employed as tax-registered workers in the last six months, with a requirement to stay employed for at least a year after the policy announcement (Emre İnan, 2018).

Initially introduced on 1 July 2008, the Employment Subsidy Package in Türkiye was designed to last for one year, aiming to increase employment among young males and females by subsidizing employers' social security contributions for these groups. However, as the global economic crisis adversely affected the Turkish labor market, the government responded by introducing a second employment package in 2009 (Law No. 5838) to extend the incentives for an additional year, seeking to counteract negative effects of the crisis on policy effectiveness. Further broadening the support, in August 2009, the government introduced additional incentives under a provisional article added to the Unemployment Insurance Law no. 4447, offering subsidies for all new hires irrespective of gender and age for a six-month period (Ayhan, 2013). According to Uysal (2013), while these measures were designed to mitigate the labor market downturn caused by the crisis, they also risked diluting the effectiveness of the original policy that targeted specific demographics, by spreading the subsidies more across a wider range of new hirings.

The 2008 Employment Subsidy Program specifically addressed demographic groups that might be at higher risk of informal employment or unemployment, thus attempting to ensure that the benefits of formal employment reach those most in need. According to Balkan, Cilasun and Turan (2014), the program was successful in enhancing

employment opportunities for older women and those with lower levels of education. However, it did not have a significant positive effect on improving employment prospects for younger male demographics. In other words, while the program helped increase job chances for one target group (older, less educated women), it did not achieve the same level of success for another target group (younger men).

Despite progress, informality remains a significant challenge within the Turkish labor market. In 2008, informal employment in Türkiye accounted for a significant 43.5% of the workforce. By 2012, following various reforms implemented by the Turkish government, the rate of informal employment decreased to 38.4%. Furthermore, while the majority of informal employment is concentrated in the agricultural sector, a considerable portion also exist within non-agricultural sectors. Specifically, 29.8% of the informal labor force was in non-agricultural sectors in 2008, which reduced to 25.8% by 2012. This indicates that, although agriculture remains a primary area of informality, non-agricultural sectors also have similar issues (Balkan, Cilasun and Turan, 2014).

2.5.6.2. Job Quality

Job quality refers to different aspects of a job that affect job satisfaction of workers. It includes factors such as the level and fairness of wages, job security, working conditions, work-life balance, and the nature of the work itself, including opportunities for development and the work environment. High job quality can lead to greater worker satisfaction, higher productivity, and improved economic performance. The OECD has a framework for job quality which assesses three key dimensions: earnings quality, job strain, and labor market security. Earnings quality reflects how well earnings support workers' well-being, focusing on average earnings and their distribution (OECD Jobs Strategy, 2018). Türkiye is positioned as the second lowest among OECD countries in terms of earnings quality in 2015, a metric that shows the overall reliability and stability of income earned by individuals.

Secondly, the OECD report reveal that a significant portion of Türkiye's workforce, specifically 42.9% of wage earners, experienced job strain in 2015 (OECD, 2018). Job strain is a concept used to describe the percentage of workers who have jobs characterized by a combination of high job demands and a lack of adequate job

resources to meet those demands effectively. In work environments with high job demands, employees often face heavy workloads, tight deadlines, or tasks that require substantial effort and time. High levels of job strain and low levels of earnings quality could indicate that workers are facing challenges in finding roles that align with their skills and preferences. It may also suggest a disconnect between the skills demanded by employers and those possessed by the workforce, contributing to the practice of working extra hours.

Thirdly, OECD Jobs Strategy (OECD, 2018) reports that Türkiye faces high labor market insecurity, ranking as the third highest among OECD countries in 2016. Labor market insecurity and earnings quality are different concepts, where earnings quality refers to the characteristics and attributes of an individual's earnings whereas labor market insecurity refers to the uncertainty experienced by workers in relation to their employment situation. It covers various aspects such as job stability, the likelihood of job loss, access to social benefits, and overall economic stability (OECD, 2018).

In 2016, labor market insecurity in Türkiye is surpassed only by Greece and Spain, both of which experienced severe crises during the first part of the 2010s, indicating a notable level of uncertainty and instability in Türkiye. In the context of labor market mismatch, high insecurity may discourage workers from seeking opportunities that align with their skills and qualifications. Workers may settle for certain positions or face challenges in pursuing long-term career development, contributing to labor market mismatch.

2.5.6.3. Refugees

The topic of labor market mismatch and the competition between foreign- and native-born individuals has been a subject of interest in the literature. Studies have highlighted the challenges refugees face when integrating into the labor market due to factors such as language barriers, skill recognition issues, and limited access to formal employment opportunities (Bevelander and Pendakur, 2014; Borjas, 2017). These challenges can lead to underemployment and lower wages for refugees, which may, in turn, affect native-born individuals as they may face increased competition for certain job positions (Altonji and Card, 2018).

The literature on the effect of refugees on Turkish labor market has been expanding. Türkiye, being a country that has provided refuge to a large number of individuals from neighboring regions in recent years, faces with challenges in its labor market regarding the integration and employment of the foreign-born individuals. One significant area is the effect of the large number of Syrian refugees that Türkiye has been hosting since the Syrian civil war began in 2011.

This inflow of refugees has put considerable pressure on the Turkish labor market, as the demand for jobs has increased, leading to higher competition for limited employment opportunities (Akgündüz et al., 2015). Studies have shown that the integration of refugees in Türkiye has been hindered by various factors, including language barriers, a lack of formal education, and difficulties in recognizing the qualifications and skills of refugees (İçduygu and Şimşek, 2016). These challenges can lead to informal work arrangements and wage disparities between refugees and native-born individuals (İçduygu and Diker, 2017).

Refugees are important for labor market mismatch in Türkiye for several reasons. To begin with, due to their status and often limited access to formal employment opportunities, refugees may be willing to accept lower wages and work in the informal sector. This can create wage disparities and may lead to native-born individuals being crowded out of certain job positions or industries. Secondly, labor market mismatch can occur if refugees and native-born individuals are channeled into different job sectors. Refugees may be more likely to find employment in lower-skilled or less desirable positions, and this can cause labor market mismatches. Finally, employers these individuals to access on-the-job training (Özer et al.,2021).

The panels (i) to (vi) of the Figure 2.8 below provides data regarding foreign-born individuals in the Turkish labor market in comparison with the OECD. To begin with, the employment rate for foreign-born individuals in Türkiye is 40%, which is lower than that of native-born individuals, which stands at 48%. In the OECD countries, the difference is less pronounced, with foreign-born individuals having an employment rate of 68%, and native-born individuals at 67%. This suggests that foreign-born individuals in Türkiye face a greater difference in employment rates compared to the OECD.

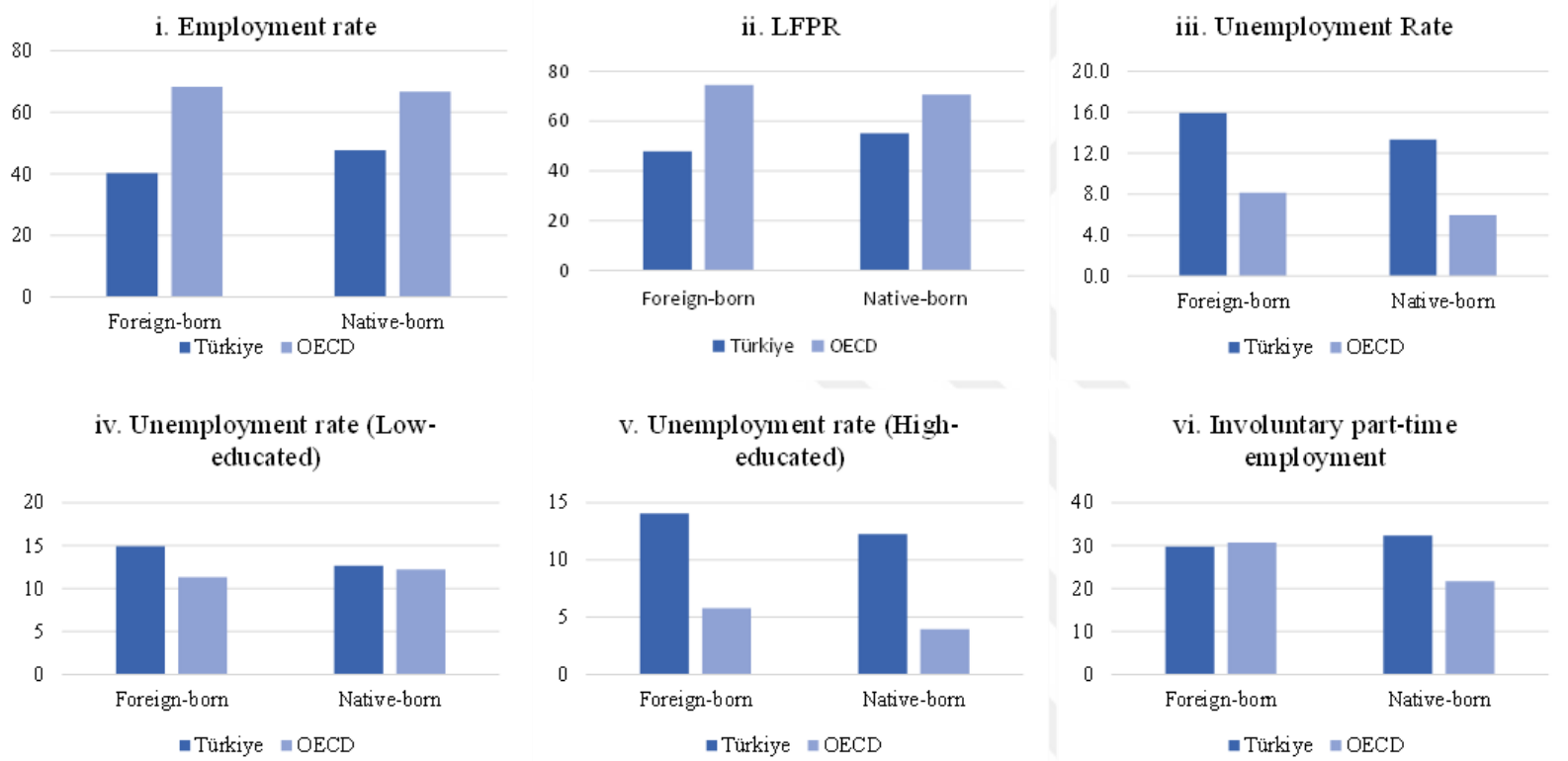


Figure 8: Labor market indicators for foreign-born and native-born individuals in Türkiye (%) (2021)

Source: OECD Indicators of Immigrant Integration

may have unfavorable opinions towards immigrants and refugees, making it harder for

Similar to the employment rates, foreign-born individuals in both Türkiye and the OECD countries have lower participation rates than native-born individuals. In Türkiye, the LFPR for foreign-born individuals is 48%, compared to 55% for native-born. In the OECD, foreign-born individuals have a LFPR of 75%, while native-born individuals have a lower rate at 71%. On the other hand, the unemployment rate in Türkiye for foreign-born individuals is higher at 15.9%, while native-born individuals also have a relatively high unemployment rate of 13.3%. In the OECD countries, the unemployment rate for foreign-born individuals is 8.2%, and for native-born individuals, it's 5.9%. Both foreign-born and native-born individuals in Türkiye face higher unemployment rates compared to their counterparts in the OECD countries. This trend is further exacerbated in the case of low-educated workers[10]. In Türkiye, low-educated foreign-born individuals have a slightly higher unemployment rate (15%) compared to high-educated foreign-born individuals (14%). Similarly, among native-born individuals in Türkiye, those with lower education (13%) face a slightly higher unemployment rate compared to their high-educated counterparts (12%).

Additionally, Türkiye has a higher proportion of foreign-born workers in involuntary part-time employment compared to the EU total. According to the "Integration of Migrants in OECD Regions" report, there are immigrants who work part-time for two main reasons. First, they might not be able to secure a full-time job, possibly due to factors like limited job opportunities or qualifications. Second, they might be working part-time to fulfill family obligations or expectations, which could include taking care of children or other family members. Involuntary part-time work results in decreased income and they prefer to work more hours if given the opportunity to improve their income (OECD, 2018). Considering these points, it is reasonable to claim that the Turkish labor market poses challenges for foreign-born individuals, particularly refugees who may be more likely to have lower educational backgrounds or face obstacles such as language barriers.

[10] Low-educated individuals belong to ISCED groups 0-2 and their educational level do not exceed lower-secondary education, whereas highly-educated individuals completed at least the initial stage of tertiary education.

2.6. Data and Methodology

2.6.1. Data

The data used in this study come from the Programme for the International Assessment of Adult Competencies (PIAAC) by the Organization for Economic Co-operation and Development (OECD). PIAAC is a large-scale international study that assesses the skills and knowledge of adults in participating countries in three domains: literacy, numeracy, and problem solving in technology-rich environments (PS-TRE). It is an individual-level assessment that focuses on the skills and competencies of adults aged 16 to 65. Within the context of the PIAAC, individuals are chosen at random within participating countries to form a representative sample of the adult population. Each individual takes an individual assessment to measure their skills. The PIAAC study assesses these skills through direct assessments, which are administered to study participants, and there are background questionnaires, which collect information about participants' educational attainment, work experience, and other factors. The data from the study can be used to compare the skills of adults, as well as to identify factors that are associated with differences in skill levels.

In the context of the PIAAC, latent variables are the underlying skills or competencies that are being assessed, such as literacy, numeracy, and PS-TRE. Because these skills cannot be directly measured, they are estimated based on the responses to the tasks and questions that are included in the study. In PIAAC, the skills in each of these domains are assessed on a scale from 0 to 500, with higher scores indicating a higher level of proficiency. The scale is divided into six proficiency levels, ranging from Level 1 (lowest) to Level 6 (highest).

- Literacy is the capacity to comprehend, assess, use, and interact with written texts for active participation in society, the achievement of personal objectives, and the nurturing of one's knowledge and potential. Within the PIAAC framework, literacy proficiency is assessed by a variety of tasks that necessitate individuals to read and understand written materials, as well as utilize and assess the information.
- Numeracy is the ability to access, apply, interpret, and convey mathematical information and concepts to effectively handle the

mathematical challenges presented by a variety of real-life situations. In the context of PIAAC, numeracy competence is measured through a series of tasks that require individuals to understand and employ mathematical information and concepts to solve problems.

- PS-TRE is the ability to utilize digital technology, communication tools, and networks to obtain and assess information, communicate with others, and carry out practical tasks. In the PIAAC assessment, this proficiency is evaluated through a set of tasks that necessitate individuals to use digital technology.

The PIAAC was first conducted in 2011-2012. In the first round of PIAAC, there were 24 participating countries. These are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland) and United States. In the second round, which was conducted in 2014-2015, there were 9 more participating countries which are Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia and Türkiye. In the third round, which was conducted in 2018, there were 6 countries. These are Ecuador, Hungary, Kazakhstan, Mexico, Peru and United States.

This analysis focuses only on Türkiye, with a deliberate exclusion of other countries involved in the PIAAC. This decision aligns with the specific goals of our study, which is to examine labor market mismatches in Türkiye. Furthermore, since the focus of this study is labor market mismatch, we narrow down the group we are analyzing to respondents from the survey who are currently employed full-time, meaning they work at least 30 hours per week. We further narrow down our sample to include individuals in the prime working age range, which is defined as those between 20 and 54 years old. The lower age boundary is set at 20 years to avoid including those who are likely still in education and not yet fully active in the labor market. The upper age limit is set at 54 years to account for the increased likelihood of individuals transitioning into retirement, due to the social security system's structure in Türkiye, where there is a increase in retirement rates beyond this age.

PIAAC is designed as a computer-based assessment (CBA). The background

questionnaire (BQ) was conducted in a computer-assisted personal interview (CAPI) format, with an interviewer assisting. For the majority of participants, the cognitive assessment, which evaluates literacy and numeracy skills, was conducted in CBA format under the supervision of an interviewer. However, individuals with limited computer experience were provided with a paper-based (PBA) version for the literacy and numeracy components. Respondents with weak literacy and numeracy skills were directed to complete the reading component on paper, with the computer application used to track completion time. The test sequence, core sections, and adaptive stages within the PBA and CBA frameworks are explained in Table 6.1. Participants were allowed to use as much time as needed, although interviewers were trained to offer guidance to those who took a long amount of time or faced challenges in progressing through the assessment.

To ensure the reliability of measurements in the specified domains, PIAAC employs a complex survey design which comprises two fundamental aspects. Firstly, it adopts a matrix sampling approach in which a group of assessment items is given to test-takers in a way that shortens the time it takes for individual testing. In more specific terms, each test-taker interacts with only a subset of these items; however, these subsets are interconnected within the design to create a unified measurement scale for each domain.

To achieve consistent test results across all three cognitive domains for various sample groups, all items are calibrates within a specific domain onto a single standardized scale. To do so, a process of linking was necessary to connect items across different test booklets (containing subsets of questions) and assessment modes. This linking was achieved through the use of common sets of items across various booklets and assessment modes. Consequently, certain questions were presented in both the PBA and CBA for literacy and numeracy domains, with problem-solving items exclusively available in the CBA (Yamamoto et al., 2013).

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Table 7. Overview of Module Details in Literacy, Numeracy, and PS-TRE Skills Evaluation

Branch Type	Sequence of Assessments	Description
PBA Branch	**1.** 10-min core assessment of literacy and numeracy	- Individuals who achieve or exceed a specified minimum proficiency level proceed to subsequent stages. - Individuals who exhibit subpar performance on the core items are guided toward the reading component.
	2. Random assignment to a 30-min literacy or numeracy items, followed by a 20-min reading component	
CBA Branch	1. CBA core section consisting of two 5-min stages: - Core Stage 1: Items related with ICT - Core Stage 2: Cognitive items	- Individuals who do not meet the requirements of Core Stage 1 are rerouted to the PBA. - Those who successfully pass Core Stage 1 but fail in Core Stage 2 are administered only the reading component items.
	2. Those who perform well on both CBA core sections are directed to one of the following: 1. Literacy and numeracy modules 2. PS-TRE module combined with either a literacy or numeracy module 3. Only PS-TRE modules	(Each taking approximately 50 min) **Literacy and numeracy modules** each have two adaptive stages. - Each stage comprises several blocks with varying difficulty levels. - The blocks within a stage are interconnected through a shared item unit to ensure consistent item parameter estimates. **PS-TRE modules** are not adaptive

Note: This table has been organized based on the framework presented in the study by Maehler and Rammstedt (2020).

each test-taker interacts with only a subset of these items; however, these subsets are interconnected within the design to create a unified measurement scale for each domain. To achieve consistent test results across all three cognitive domains for various sample groups, all items are calibrates within a specific domain onto a single standardized scale. To do so, a process of linking was necessary to connect items across different test booklets (containing subsets of questions) and assessment modes. This linking was achieved through the use of common sets of items across various booklets and assessment modes. Consequently, certain questions were presented in both the PBA and CBA for literacy and numeracy domains, with problem-solving items exclusively available in the CBA (Yamamoto et al., 2013).

Secondly, the evaluation framework adopts a multistage adaptive testing scheme (MST). This approach aligns the administration of assessment items with the difficulty levels that correspond to the proficiency of the test-takers. The initial adaptive phase guides test-takers toward either the paper-based or computer-based assessment branch based on their computer-related experience and skillset. Following that, the second adaptive phase tailors the difficulty of presented items, offering more or less difficult questions based on the test-takers' responses to previously answered items (Maehler and Rammstedt, 2020).

In the context of PIAAC, the calculation of the scores in the three cognitive domains relies on generating 10 plausible values[11] that are independently drawn for each of these domains for every respondent. The PIAAC study uses a statistical technique called item response theory (IRT) to estimate the plausible values for skill domains. The IRT model accounts for differences in the difficulty of the items and other factors that may affect an individual's performance on the test. Hence, the plausible values estimated by the PIAAC study provide a more accurate estimate of an individual's skill level than a simple average of their responses to the tasks and questions in the study. (Yamamoto et al., 2013).

Yamamoto et al. (2013) further conducts an exercise in which they provide data on the

[11] In statistical analysis, a plausible value is an estimated value of a latent variable that is derived from the observed data.

estimated average correlations among the domains of literacy, numeracy, and PSTRE for various countries. In the case of Türkiye, they find that for literacy and numeracy, there is a positive correlation (0.846), indicating a strong relationship between an individual's literacy skills and their numeracy skills. Literacy and PS-TRE are less strongly correlated (0.589), suggesting a moderate positive relationship between literacy skills and problem-solving skills in technology-rich environments. Numeracy and PS-TRE also show a moderate positive correlation (0.524), implying that individuals with strong numeracy skills tend to have relatively strong problem-solving skills in technology-rich environments, although this correlation is somewhat weaker than the other two (Yamamoto et al., 2013).

Table 8. Comparative Demographic and Employment Statistics from PIAAC and LFS (20-54 years old), 2015

		PIAAC	**LFS**
Gender	Male	51.42	50.01
	Female	48.58	49.99
Age	Entry Age (20-29)	30.31	30.02
	Prime Age 1 (30-44)	46.63	46.39
	Prime Age 1 (45-54)	23.06	23.58
Marital Status	Married	74.50	72.22
Education	Lower sec. and below	61.52	60.55
	Upper secondary	22.56	21.23
	Tertiary	15.91	18.22
Employment Status*	Employed	49.81	57.69
	Unemployed	7.86	10.42
Economic Sector**	Private sector	83.22	86.14
	Public sector	16.78	13.86
Obs		4,223	240,841

Note: (*) Employed ratio represents the proportion of employed individuals relative to the total population, and unemployment ratio reflects the proportion of unemployed individuals within the total labor force. (**) The economic sector is calculated only for employed individuals, and 'private sector' includes non-governmental organizations (NGOs) alongside traditional enterprises.

While Türkiye tested PS-TRE as part of the PIAAC assessment, we opted not to

include this proficiency in our analysis. This decision is due to data limitations, as including it results in a reduction of the sample size available for analysis. Furthermore, similar to previous researchers (Hanushek et al., 2015; Forster et al., 2016), we use only the scores related to numeracy skills in our models. This choice is based on the fact that various skill measurements exhibit a high degree of correlation, and numeracy skills are generally regarded as the most consistent and comparable skill set (as highlighted by Hanushek et al., 2015). Further rationale for our preference is that numeracy skills are foundational skills, meaning that they serve as the foundation for more advanced and complex learning. Besides, literacy and numeracy skills are interconnected, as they often complement each other. For instance, understanding written instructions, interpreting data, and solving problems may require a combination of literacy and numeracy skills. In fact, we also find a positive correlation between average literacy skills and average numeracy skills in our data set where the correlation coefficient is 0.842. The fact that these two variables have a positive correlation suggests that individuals with higher average literacy skills tend to have higher average numeracy skills, and vice versa. In other words, there is a strong tendency for these skills to go hand in hand; if someone performs well in one, they are likely to perform well in the other.

Numeracy is a highly valued skill in many contexts. It contributes to quantitative literacy, which is the ability to understand and interpret quantitative information presented in different forms, such as charts, graphs, tables, and statistics. Numeracy proficiency does not only involve mathematical skills but also require positive cognitive and psychological traits. In other words, it is also related to how people think and make decisions. Empirical studies on decision-making suggest that numeracy skills have implications for different aspects of individuals' lives (Liberali et al., 2012; Peters et al., 2006). Individuals with well-developed numeracy skills show a reduced susceptibility to cognitive biases such as framing effects[12] (Jonas, 2018). People with high numeracy skills are also better at making objective decisions based on the actual numerical information. Furthermore, they show less susceptibility to non-numerical factors like emotional states and display an good capacity to assess and consider

[12] Framing effects occur when the way information is presented (the "frame") influences decision-making.

various levels of risk within decision-making processes (Peters and Levin, 2008; Reyna et al., 2019; Jasper et al., 2013; Jonas, 2018).

In this analysis, the representativeness of the PIAAC data for Türkiye, which includes 4,223 observations, is substantiated through a comparative examination with TURKSTAT's Labor Force Survey (LFS) 2015 data, including a larger sample of 240,841 observations (Table 8). Although the PIAAC and the LFS datasets show close alignment in demographic distributions such as gender, age, and education levels, slight variations are observed in employment and unemployment rates. These differences can in part be attributed to seasonality. Additionally, the slightly younger average age of PIAAC participants could further influence these employment figures. Therefore, despite its smaller sample size relative to the LFS, the alignment of demographic distributions between the PIAAC and the LFS dataset corroborates the PIAAC's comprehensiveness and representativeness.

2.6.2. Methodology

2.6.2.1.Analyzing the Prevalence of Labor Market Mismatch

To assess labor market mismatch for this study, several methods are employed. Table A1 (See Appendix) outlines these different methods used to measure labor market mismatch. For education mismatch, two approaches are used. The first is the self-assessment (SA) method, which assesses the education mismatch using a survey question[13] to find what individuals believe is the required education level for their job. The answer is then compared with the actual level of education of the individual. This method relies on individuals' perceptions of the education required for their current jobs, rather than objective measures.

The second method to measure education mismatch is the realized-matches (RM) method, which assesses education mismatch in an objective way. The RM method uses occupational data by using the International Standard Classification of Occupations (ISCO08) codes, to assess the match between individuals' educational attainment and

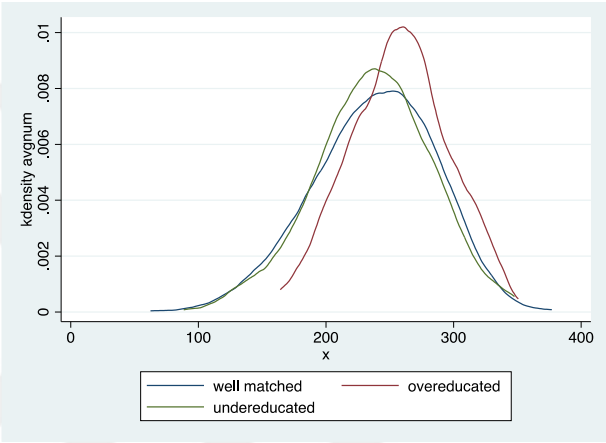
[13] Question D_Q12a: If applying today, what be the usual qualifications, if any, that someone would need to GET this type of job? Responses: ISCED levels

the education typically required for their jobs. This method identifies the most common level of education within an occupation as a benchmark for determining if individuals are well-matched. In this thesis, this involves calculating the modal education level for each occupation. This serves as the required education level for that occupation, assuming that the most common education level reflects a standard. Figure 9 presents the distributions of numeracy skills across different categories of educational match, employing both the self-assessment and realized-matches methods. The similar distributions of numeracy skills for two definitions of education mismatch indicate that in terms of numeracy skills, the two methods yield comparable results for the individuals being evaluated. In addition, the positioning and order of mismatch categories in each method provide information about the nature of the mismatch as defined by these methods. In the RM method, the co-location of undereducated individuals with well-matched individuals suggests that, in this approach, undereducated individuals are close to those who are well-matched in terms of their numeracy skills. This implies that, in the RM method, the distinction between undereducated and well-matched individuals is not strongly reflected in numeracy skills.

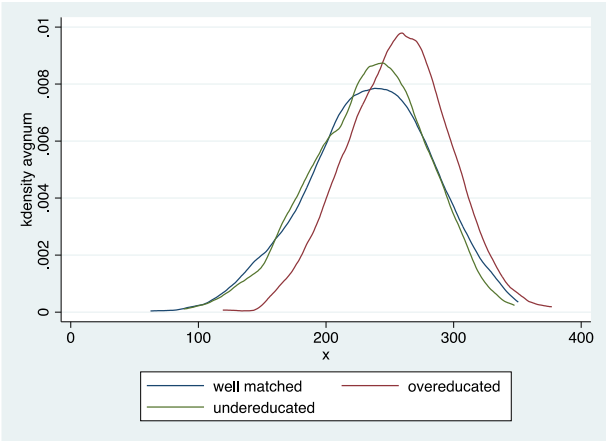
In the context of skill mismatch, a three-step method is used following the method developed for the OECD (Pellizzari and Fichen, 2017). Firstly, a quantitative scale of skills is created by calculating proficiency scores. To assess skill mismatch using the PIAAC, individuals first determine if they perceive themselves as well-matched. This is done through two self-assessment questions: the first (F_Q07A) asks whether they feel capable of handling more demanding tasks than those required by their current role, and the second (F_Q07B) asks if they need further training to perform their job effectively. Answering "No" to both questions suggests that individuals perceive themselves as well-matched.

Self-assessment can be influenced by personal biases. Individuals may overestimate or underestimate their skills or the job requirements. Thus, the next step is establishing minimum and maximum thresholds for each occupation based on the lowest and highest skill scores of self-reported well-matched workers. The 20th percentile (p20) is used as the minimum threshold and the 80th percentile (p80) is used as the maximum threshold of numeracy skills required for a job category (see Figure 6.2.1 for the

minimum and maximum threshold levels for average numeracy skills). The choice of p20 and p80 as thresholds is not entirely arbitrary, but rather depends on the objectives of this study as this is a country-level analysis where workforce diversity and the range of occupations are vast. Choosing p10 and p90 would narrow the criteria for identifying skill mismatches, leaving out individuals whose skills are not aligned with their job requirements but who do not fall into the extreme categories. On the other hand, p20 and p80 identifies a larger group, including those with moderate skill mismatches, which are likely to constitute a significant portion of the workforce in any country, including Türkiye.



(i) Self-assessment method



(i) Realized-matches method

Figure 9. The distributions of numeracy skills for two definitions of education mismatch

Source: OECD PIAAC.

Note: The x-axis represents the average of 10 plausible values for each individual's numeracy skills.

In the third step, workers are categorized as well-matched if their numeracy score falls within the defined minimum and maximum thresholds for their occupation. If a worker's score is above the maximum or below the minimum level, they are considered overskilled or underskilled, respectively. This method helps to identify outliers and provides a less subjective measure of skill mismatch. For example, if a worker answer "No" to both self-assessment questions, it indicates that they do not think they are skill mismatched. However, if their numeracy skill score, as measured objectively, falls above the 80th percentile threshold for their occupation, they are categorized as overskilled, even though they perceive themselves as well-matched.

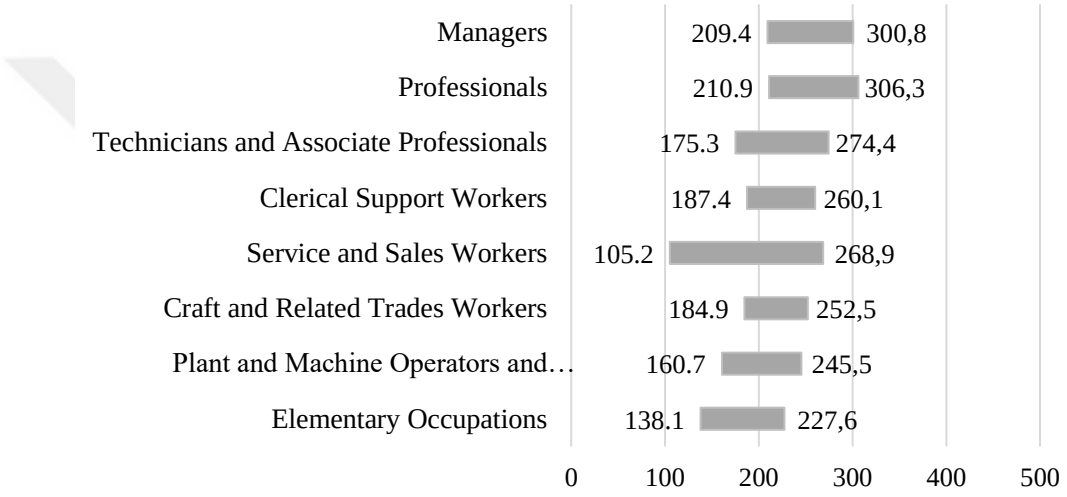


Figure 10. Average numeracy skill minimum and maximum threshold levels of occupational groups (1-digit ISCO categories)

The minimum and maximum thresholds (in Figure 10) for skill mismatch across different occupational groups show that there are significant variations between thresholds. This variation suggests that the level of numeracy skills required for well-matched employment differs substantially depending on the occupation. Skilled roles, such as professionals and managers, have relatively high minimum thresholds. This implies that individuals in these roles are expected to possess a certain level of numeracy skills to be considered well-matched. However, measurement errors in the context of assessing skill mismatch using broad occupational categories like 1-digit ISCO codes can affect the reliability of these findings, as they aggregate a wide range of professions under single categories.

For example, service and sales workers exhibit a wider range between the minimum and maximum thresholds. This suggests that while numeracy skills may be important in these roles, there is a broader acceptance of skill levels. It might indicate that individuals in these roles could have diverse skills and still be considered well-matched. Occupations like service and sales workers may include a wide range of jobs that have very different skill requirements. This heterogeneity means that while some positions may require minimal numeracy skills, others might demand higher levels. The aggregated data across such a diverse group can mask these differences. This suggests that the heterogeneity signified by the occupational classifications can mask the specific skill requirements within each occupational group.

2.6.2.2. Analyzing the Correlates of Labor Market Mismatch

To examine the determinants of labor market mismatch, we employ multinomial probit models that take into account various worker and job characteristics. To do so, we estimate the probit equation, which seeks to find the determinants of being in a mismatched employment situation, that is derived from the following latent variable model:

$$y_i^{M*} = X_i^M \beta + \varepsilon_i^M \text{ and } y = I[y^* > 0]$$

where y^* is the outcome variable for labor market mismatch. It is a latent variable since directly observing and measuring the degree of mismatch between the skills and qualifications possessed by individuals and those demanded by jobs is not possible. M stands for labor market mismatch (OE for overeducated; UE for undereducated; OS for overskilled; US for underskilled), I[.] is an indicator function that takes on the value 1 if the event is true and 0 if otherwise; X_i are the control variables (shown in table 6.2.1); and ε is the error term.

We assume that the error term has standard normal distribution. According to Wooldridge (2003), this assumption of normality is common in the literature, despite several specification problems. This is because, in the context of binary response models, the main objective is typically to elucidate the impact of the variable X_i on the probability $P(y = 1|x)$. While the latent variable approach might suggest a focus on the effects of each X_i on y^*, Wooldridge (2003) notes that y^* often lacks a clearly

defined unit of measurement. Consequently, the individual magnitudes of β_j, by themselves, lack practical utility.

Table 9. Control variables included in probit models for labor market mismatch

Variables	**Description**
Gender	1 if female, 0 if male
Experience	Years of paid work during lifetime
Experience squared	Experience squared divided by 100
Entry age (20-29)	1 if age is between 20-29, 0 otherwise
Prime age 2 (40-54)	1 if age is between 40-54, 0 otherwise
Vocational education	1 if received vocational education, 0 if ow
Public sector	1 if job employed is in the public sector, 0 if ow
Dropout	1 if dropout, 0 ow.
Manual	1 if perform physical tasks regularly, 0 ow.
Numeracy skill	Score between 0-500 showing numeracy skill
Readiness to learn	Index of readiness to learn, categorized
Computer experience	1 if yes, 0 if no

Table 9 describes the control variables used in multinomial probit models for analyzing labor market mismatch. To begin with, gender is included as a binary variable. This variable is important for understanding potential gender-based disparities in labor market mismatch. Secondly, both age and experience variables are included. This is because younger workers might face challenges related to undereducation due to a lack of experience, while older workers might experience mismatches due to changes in skills demand over time. While experience typically increases with age, the rate at which it accumulates can vary significantly between individuals. These two measures may not increase at the same rate due to factors like education, career changes, or periods of unemployment. Furthermore, age can affect factors such as expectations, career aspirations, and job preferences. It can also be associated with other life events, such as family responsibilities, health considerations, and retirement plans, all of which can impact labor market choices and outcomes. The coefficient for the experience variable (years of work) is expected to have a negative

sign, suggesting that as individuals gain more work experience, the risk of labor market mismatch should decrease. This aligns with the general expectation that experience leads to better job matching. The coefficient for the squared experience term may have a positive sign. This indicates that at some point, as individuals accumulate more experience, the risk of mismatch may start to increase due to factors like skill obsolescence.

The dropout variable is used to identify individuals who have not completed their formal education or have left their school before receiving a diploma. The inclusion of this variable is related with the diploma effect[14]. From a signaling theory perspective, diplomas serve as a signal to employers about an employee's potential productivity. Dropouts may be seen as less productive in the labor market, affecting their employment opportunities, job matches, and wages. Furthermore, for certain jobs or sectors (for example, public sector jobs), a diploma may act as a barrier to entry, where formal qualifications are a prerequisite for employment. This can lead to education mismatch among dropouts. Employment in the public sector is also expected to lower the risk of labor market mismatch, as public sector jobs are often considered more standardized.

There is a variable for the skill level of individuals based on numeracy skills, which is used to assess how foundational cognitive skills influence labor market mismatch. Higher skill levels are generally associated with a lower risk of labor market mismatch, as individuals with better skills may have access to a broader range of job opportunities. We also include a computer experience variable that indicates whether individuals have experience with computers, which is important in understanding the role of digital literacy in labor market mismatch. Those with computer experience are less likely to experience technological skills-based mismatches and may have better access to a broader range of job opportunities, thus a negative sign is expected.

Finally, we included the readiness to learn index, which measures individuals' readiness to learn and is categorical. It can help determine whether willingness to learn

[14] The diploma effect refers to the advantages related with holding a formal educational credential, such as a diploma, beyond the actual skills or knowledge acquired through education.

and adaptation to new skills affects labor market mismatch. There is a growing recognition among researchers that non-cognitive traits such as 'readiness to learn' are key drivers of labor market success. The OECD, for instance, has published various reports that mention the importance of learning. Similarly, ILO emphasizes the importance of lifelong learning and skills development to adapt to the changing world of work. In the 'Work for a Brighter Future' report, lifelong learning is explained as the ongoing process of formal and informal education. It includes learning basic skills, as well as developing other skills, such as the ability to 'learn how to learn' (ILO, 2019). Individuals who are less ready to learn and less motivated to engage in learning activities may be more likely to experience labor market mismatches. Without learning, they may find themselves unable to meet the demands of the labor market, which can result in lower wages and fewer job opportunities. Hence, their readiness to learn might be important to acquire the necessary skills and knowledge.

The PIAAC survey includes a range of questions related to individuals' engagement in learning activities, motivation to learn, and confidence in their learning abilities, which can be used to construct a measure of readiness to learn. The background questionnaire, although not described in detail, incorporates a Readiness-to-Learn scale. This scale is used to assess an individual's readiness and ability to engage in learning and named as "metacognitive abilities"[15] in the conceptual framework of the background questionnaire. The PIAAC study introduced a 6-item Readiness-to-Learn scale aimed at measuring the extent of deep learning[16]. These are:

1. Connecting new ideas to real-world situations
2. Enjoying the process of learning new things
3. Relating new information to existing knowledge
4. Delving into and understanding complex concepts

[15] Metacognitive abilities relate to one's capacity to think about and control their own cognitive processes. These abilities involve understanding, monitoring, and managing one's thinking and learning (Gorges et al., 2016).

[16] In the context of education, deep learning refers to a type of learning approach and cognitive processing that emphasizes understanding and making meaningful connections between concepts, as opposed to surface learning that may involve rote memorization without a deep understanding.

5. Enjoying the challenge of integrating diverse ideas
6. Actively seeking additional information to clarify understanding

The readiness-to-learn scale combines two theoretically and empirically distinct constructs: motivation to learn and learning strategies (Gorges et al., 2016). In educational psychology literature, motivation to learn relates to the willingness to engage in learning, while learning strategies are the methods individuals use to learn effectively. In other words, the scale comprises two theoretically distinct components. This raised questions regarding whether the readiness-to-learn scale could accurately be considered a unidimensional measurement. Smith et al. (2015) conducted an evaluation of the 6-item scale in the PIAAC US sample to examine the scale's reliability and validity. Despite the concerns about unidimensionality, it exhibited strong measurement invariance across gender, age groups, and employment status in the study. This means that the scale performed consistently across these demographic variables. However, the scale did not show the same invariance across educational levels, indicating that its performance varied based on participants' educational backgrounds.

2.6.2.3. Analyzing the Outcomes of Labor Market Mismatch

2.6.2.3.1. Wage Outcomes

The wage data for Türkiye is presented only in deciles by PIAAC. Given that the wage data for Türkiye is categorized into ten deciles, the analysis employs OLS regression, rather than using an ordered probit model. Both OLS and ordered probit models were initially employed and the results from both models were consistent, supporting the decision to proceed with OLS for the analysis. This approach simplifies the interpretation of results while maintaining the robustness of the findings. When assessing the effect of labor market mismatches on wages, two approaches can be employed: the ORU model and the dummy variable approach. The model specifications for these two approaches are as follows:

For **the ORU approach,** the model is represented as:

$$Y_i^* = \alpha + \beta_1 RE_i + \beta_2 OE_i + \beta_3 UE_i + \beta_4 OS_i + \beta_5 US_i + \gamma' \mathrm{X}_i + \varepsilon_i$$

where Y_i^* is the wage outcome for individual i, RE_i is the number of years of education that is typically required to perform individual i's job. Overeducation (OE_i) and undereducation (UE_i) are included as continuous variables representing the number of years by which individual i's education level is above or below the required level for their job (RE_i). OS_i and US_i are the overskilled and underskilled dummy variables for individual i. X_i represents other control variables (see Table 6.2.4) included in the model, and ε_i is the error term.

For **the dummy variable approach**, the model can be expressed as:

$$Y_i^* = \alpha + \delta_1 AE_i + \delta_2 OD_i + \delta_3 UD_i + \delta_4 OS_i + \delta_5 US_i + \gamma' \mathrm{X}_i + \varepsilon_i$$

where Y_i^* is the wage outcome for individual i, AE_i is the actual number of years of schooling that individual i has completed. OD_i and UD_i are the overeducation and undereducation dummy variables for individual i, respectively. Here, δ_2 and δ_3 show the average wage differential associated with being overeducated or undereducated, respectively. OS_i and US_i are the overskilled and underskilled dummy variables for individual i. X_i represents other control variables included in the model, and ε_i is the error term.

2.6.2.3.2. Job Satisfaction

To analyze the outcomes of labor market mismatch on job satisfaction, we use ordinal probit models that incorporate both worker and job characteristics. The ordinal probit model is used when analyzing dependent variables that are categorical with a clear ordering but where the distances between categories are unknown or not equal. This model is useful for variables which are ranging across categories. Hence, ordinal probit models are suitable given the nature of the outcome variable job satisfaction, which is ordinal, ranging from 1 ("extremely dissatisfied") to 5 ("extremely satisfied").

The theoretical foundation of the ordinal probit model posits the existence of a latent continuous variable underlying the observed ordinal outcomes. For instance, there is an unobservable level of satisfaction that, upon crossing certain thresholds, falls into the observed categories: the observed satisfaction category for individual i, denoted as S_i, is determined by the position of the individual's latent job satisfaction, JS_i^*, in

relation to a series of threshold parameters (cut points). These thresholds, $\tau_1, \tau_2, \ldots, \tau_k$, separate the continuous scale of JS_i^* into discrete categories that correspond to the observed satisfaction brackets. For example, an individual is categorized into the lowest satisfaction bracket, '1', if JS_i^*, is less than or equal to the first threshold τ_1 (Greene and Hensher, 2008). In an ordinal probit model, coefficients represent the change in the z-score of the latent variable for a one-unit change in the predictor. Because of this, the coefficients can be interpreted in terms of the direction of the association but not the exact magnitude of the effect on the probability of observing a particular category of the dependent variable (Greene and Hensher, 2008; Long and Freese, 2014).

(ii) For job satisfaction; let JS_i^* represent the latent level of job satisfaction for individual i, which is not directly observable:

$$JS_i^* = X_i^{JS}\beta + \epsilon_i^{JS}$$

and $JS = m \;\; if \;\; \sigma_{m-1} < JS_i^* \leq \sigma_m$ for $m = 1,2, \ldots ,5$

where $\sigma_0, \sigma_1, \ldots \sigma_5$ are the threshold parameters with $\sigma_0 = -\infty$ and $\sigma_5 = \infty$. X_i^{JS} are the control variables (see Table 6.2.4) and $\epsilon_i^{JS}$is the error term assumed to follow a standard normal distribution. The model aims to estimate the impact of education and skill mismatches on the probability of an individual reporting each category of job satisfaction. The observed job satisfaction JS_i is an ordinal variable representing different levels of reported job satisfaction. The job satisfaction variable shows the self-reported level of satisfaction that individuals experience in their jobs, measured on a five-point Likert scale. This scale ranges from "Extremely dissatisfied" at one end to "Extremely satisfied" at the other, with intermediate options. The model is written as:

$$S_i^* = \alpha + \mu_1 AE_i + \mu_2 OD_i + \mu_3 UD_i + \mu_4 OS_i + \mu_5 US_i + \gamma' \mathrm{X}_i + \epsilon_i$$

where AE_i is the actual education in years of individual i, $OD_i(UD_i)$ is the overeducation (undereducation) dummy, taking a value of 1 if individual i is overeducated (undereducated), 0 otherwise. OS_i and US_i are the overskilled and underskilled dummies, respectively. X_i is a vector of additional control variables, and

ϵ_i is the error term.

Table 10. Control Variables used in the Analysis of Outcomes of Labor Market Mismatch

Variables	Description
Required education	In years (Continuous)
Actual education	In years (Continuous)
Overeducation	• For ORU model: In years (Continuous) • For dummy approach: 1 if overeducated, 0 ow
Undereducation	• For ORU model: In years (Continuous) • For dummy approach: 1 if undereducated, 0 ow
Overskilled	1 if overskilled, 0 otherwise
Underskilled	1 if underskilled, 0 otherwise
Female	1 if female, 0 if male
Entry age (20-29)	1 if age is between 20-29, 0 otherwise
Prime age 2 (45-54)	1 if age is between 45-54, 0 otherwise
Experience	Years of paid work experience (Continuous)
Experience squared	Experience squared divided by 100.
Numeracy score	Score of numeracy skills (Continuous)
Vocational education	1 if education is vocationally-oriented, 0 ow
Readiness to learn	Continuous index score
Public sector	1 if employed in the public sector, 0 if ow
Medium-sized enterprise	1 if employed in a medium-sized enterprise, 0 ow
Large-sized enterprise	1 if employed in a large-sized enterprise, 0 ow

Table 10 outlines the list of independent variables that are used to analyze the outcomes of labor market mismatch in both wage and job satisfaction specifications. In the literature, the relationship between age and wage is often discussed within the framework of the human capital theory and the sign of the coefficient for age is generally expected to be positive. This is based on the idea that as individuals age, they accumulate experience, skills, and knowledge, making them more productive and thus earning higher wages.

Similarly, studies often find a positive relationship between age and job satisfaction. This can be due to several factors, including higher wages or finding roles that better match their skills (Janson and Martin, 1982; Mincer, 1991) Like age, the coefficient for experience is expected to be positive. This is because more experience is associated with the accumulation of job-specific skills which increases an individual's productivity. The expected sign for the experience squared variable is negative, indicating diminishing returns to additional years of experience. This means that while wages increase with experience, the rate of increase slows down over time.

Numeracy skills are fundamental components of an individual's human capital and are expected to have a positive relationship with wages since foundational skills increase an individual's productivity. Higher skills can also lead to employment in better-paying jobs. On the other hand, while these skills are important for employment and wage levels, which can influence job satisfaction indirectly, the direct relation between these skills and job satisfaction may not be as clear.

Working in the public sector can affect wages differently. Lower-skilled workers may earn more in the public sector than they would in the private sector, while high skilled workers might earn less than their private sector counterparts. While the public sector may offer higher entry-level wages and better job security, it often has lower wage ceilings compared to the private sector. Hence, high-skilled individuals might earn more in the private sector, where wages can be more closely tied to individual productivity. Similarly, job satisfaction in the public versus private sector can might be influenced from factors like job security, work-life balance, and the nature of the work itself.

The relationship between firm size and labor market outcomes has been extensively

studied in the literature. The literature generally finds that larger firms tend to pay higher wages than smaller firms, whereas the relationship between firm size and job satisfaction is less clear. Some studies find that employees in smaller firms report higher job satisfaction, due to closer personal relationships and a greater sense of impact. Other studies suggest that the benefits, stability, and professional development opportunities in larger firms contribute to higher job satisfaction among their employees.

2.7. Incidence and Correlates of Labor Market Mismatch in Türkiye

2.7.1. Education Mismatch

Table 11 shows the incidence of education mismatch among full-time employed workers in Türkiye, categorized by gender. It compares two approaches to measuring education mismatch: the subjective approach (SA) and the objective approach (RM). The results show that there is a high incidence of education mismatch in Türkiye. According to subjective assessments, 29.01% of workers perceive a mismatch between their education and their job requirements. This includes both overeducation (16.27%) and undereducation (12.74%). The objective approach indicates that 42.12% of workers are mismatched in terms of their educational qualifications relative to their job requirements. This approach results in a higher rate of overeducation at 30.71% and a lower rate of undereducation at 11.41%. These results suggest that the labor market may not be at equilibrium. High rates of mismatch, especially overeducation, imply that the market has excess supply of educated labor relative to demand, or that the jobs available do not fully utilize the skills and education of the workforce.

In the SA method we see that both men and women have similar rates of being well-matched, overeducated, and undereducated. This suggests that they have a similar assessment of how their education aligns with their job requirements. The differences between genders become more apparent with the RM method. Men have a higher incidence of overeducation compared to women. This may be because the group of women who are full-time wage earners may represent a selective subset of the females. Women who choose or are able to work full-time may have made more deliberate educational and career choices, leading to a lower incidence of overeducation.

The difference between the SA and RM methods regarding the incidence of overeducation may seem interesting at first. Typically, one might expect individuals to overstate their qualifications (resulting in higher rates of overeducation and lower rates of undereducation under the SA). One possible explanation would be that the subjective approach relies on individuals' perceptions of their alignment, which may not always accurately reflect objective reality. Some individuals might not be fully aware of the requirements of their job. This lack of awareness can lead to underestimating their own overeducation because they might believe a higher education level is necessary, even if it is above the requirements for their job. According to the literature, it is a common observation that overeducation tends to be reported lower when using subjective (SA) methods compared to objective (RM) measures. In fact, McGuinness, Pouliakas, and Redmond (2018) reviews 296 estimates for the incidence of overeducation using different measurement approaches. They find that the average incidence rates of overeducation tend to be lower when assessed through subjective methods (21.5%) compared to objective measures (25.9%).

Table 11. The incidence of education mismatch in Türkiye, full-time employed workers, 2015

	Men (74.17%)	**Women (25.83%)**	**All**
Self-Assessment Method			
Well-matched	70.10	70.66	70.99
Overeducated	16.19	16.52	16.27
Undereducated	12.71	12.82	12.74
Realized matches method			
Well-matched	57.40	59.26	57.88
Overeducated	32.08	26.78	30.71
Undereducated	10.53	13.96	11.41

How do workers' self-assessments (SA) compare with an objective classification (RM)? Table 12 presents a comparative analysis of education mismatch measurement

methods, focusing on the subjective approach versus the realized match method. When comparing the subjective approach with the realized match method, it is seen that there is a certain degree of alignment between SA and RM methods. For example, 83.3% of those considered well-matched according to the RM are also classified as well-matched by the SA. This indicates a high level of consistency between individuals' perceptions of the education typically required to secure their type of job and the educational level identified for their occupation through objective analysis.

However, there are also differences in the distribution of individuals across mismatch categories. For instance, in the subjective approach, 68% of individuals who considered themselves well-matched were also classified as well-matched by the realized match method. However, 22.3% of those who perceived themselves as well-matched in SA were categorized as overeducated according to the RM method. Another interesting finding is that only 31.8% of those who consider themselves undereducated according to SA are also classified as undereducated by RM, whereas a significant portion (59.5%) are categorized as well-matched under RM. This suggest that many individuals feel they lack necessary education, but according to the RM method, their qualifications align well with their job's requirements. On the other hand, from the RM perspective, 35.5% of those classified as undereducated are identified as undereducated in SA, whereas 60.7% are found as well-matched in SA. This shows that there are individuals who, despite not having the required education levels, believe their education is adequate for their type of job. This could be due to various factors such as experience, on-the-job learning, or a misalignment between formal education requirements and the practical skills needed for job performance. Overall, these results imply that some individuals may not recognize their education as fitting the job's needs despite meeting the objective standards. This might be due to a lack of awareness about the education requirements or their qualifications, as SA reflects individual assessments of what education is necessary for their job. Or, it could indicate that the required education level identified for an occupation may not reflect the variety of jobs within that occupation, or that the nature of job requirements may change over time.

Which occupations have the highest and lowest education mismatch? Figure presents 11 the distribution of education mismatch across different occupational skill levels based on the ILO's (2012, p.14) categorization using the ISCO-08 classification. The

four skill levels according to the ILO categorization are:

- Skill Level 1: Includes elementary occupations requiring the completion of primary education, typically ISCO major group 9.
- Skill Level 2: Includes ISCO major groups 4 through 8. These occupations usually require secondary education or equivalent vocational training.
- Skill Level 3: Includes ISCO major group 3, typically require post-secondary education.
- Skill Level 4: Includes managers and professionals who generally need a university degree or higher, typically ISCO major groups 1 and 2.

Table 12. Comparative Analysis of Education Mismatch Measurement Methods

		Subjective Approach		
		Undereducated	Well-matched	Overeducated
Realized Match Method	Undereducated	**31.8**	9.8	2.7
	Well-matched	59.5	**68.0**	12.7
	Overeducated	8.7	22.3	**84.6**

		Realized Match Method		
		Undereducated	Well-matched	Overeducated
Subjective Approach	Undereducated	**35.5**	13.1	3.6
	Well-matched	60.7	**83.3**	51.6
	Overeducated	3.9	3.6	**44.8**

In low-skilled occupations, which constitute 4.3% of the full-time wage-earner sample, 22.0% of workers are overeducated, whereas 78.0% of workers are well-matched. No workers are undereducated in this category, reflecting that the educational requirements for these jobs are low and met by all workers. In medium-low skilled occupations, which make up 57.8% of the sample, the majority (58.3%) are still well-matched whereas 33.8% are overeducated. In medium-high skilled

occupations, which account for 13.2% of the sample, 42.8% of workers are overeducated, the highest among all categories. Only 40.6% of workers are well-matched, the lowest proportion, suggesting a high mismatch. Finally, in high-skilled occupations, 18.6% of workers are overeducated, suggesting that even in jobs that require higher education, a large portion of workers are overeducated.

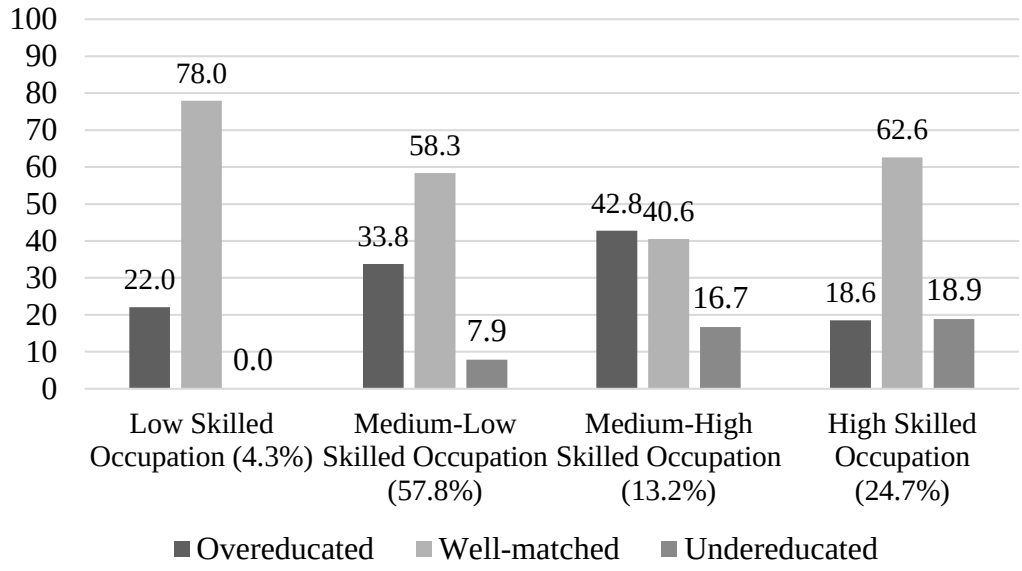


Figure 11. Percentage Distribution of Education Mismatch by Occupational Skill Level Among Full-Time Wage Earners in Türkiye (2015)

2.7.1.1.Correlates of Education Mismatch

What are the factors associated with being overeducated (OE) or undereducated (UE), and how do these factors affect the likelihood of education mismatch? Table 13 presents the results from multinomial probit models analyzing the correlates of education mismatch with two different methods: self-assessment and realized match. Furthermore, Table 14 shows the marginal effects (ME)[17] of these variables on the probability of being overeducated or undereducated.

In the RM method, female variable has a statistically significant negative coefficient for OE, indicating that women are less likely to be overeducated than their male

[17] Marginal effects (dy/dx) indicate how a small change in the independent variable affects the predicted probability of the outcome, holding other variables constant.

Table 13. Multinomial Probit Analysis of Education Mismatch, by SA and RM

	Overeducated		**Undereducated**	
Variable	**SA**	**RM**	**SA**	**RM**
Female	0.051	-0.296*	0.274	0.071
	(0.166)	(0.166)	(0.177)	(0.188)
Entry age (20-29)	-0.157	-0.255	0.683***	0.076
	(0.174)	(0.160)	(0.215)	(0.223)
Prime age 2 (45-54)	0.039	0.210	0.585***	0.348
	(0.196)	(0.181)	(0.190)	(0.228)
Experience	-0.044	-0.071***	0.091***	0.010
	(0.028)	(0.026)	(0.032)	(0.037)
Exp. squared (1/100)	0.062	0.096	-0.155*	-0.044
	(0.089)	(0.085)	(0.094)	(0.113)
Vocational education	1.114***	2.045***	0.126	1.051***
	(0.150)	(0.157)	(0.177)	(0.185)
Numeracy skill score	0.006***	0.007***	-0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Dropout	-0.313	-0.381*	0.544**	-0.258
	(0.265)	(0.207)	(0.221)	(0.255)
Readiness-to-learn	-0.007	0.069	0.029	-0.194**
	(0.066)	(0.062)	(0.074)	(0.079)
Computer experience	-1.211***	-0.804***	-0.478**	-1.080***
	(0.265)	(0.211)	(0.237)	(0.316)
Public sector	-0.210	0.031	-0.390**	-0.222
	(0.174)	(0.162)	(0.182)	(0.197)
Manual job	0.166	0.105	-0.359**	-0.823***
	(0.155)	(0.145)	(0.165)	(0.181)
Constant	-1.419**	-1.312**	-1.571**	1.358*
	(0.620)	(0.548)	(0.642)	(0.796)
Obs.	1,354	1,354	1,354	1,354

Table 14. Marginal Effects of Worker Characteristics on Education Mismatch

Panel 1: SA method	**Overeducated**			**Undereducated**		
Variable	**dy/dx**	**std. err.**	**Signif.**	**dy/dx**	**std. err.**	**Signif.**
Female	-0.001	0.023		0.042	0.027	
Entry age (20-29)	-0.042	0.022		0.110	0.036	**
Prime age 2 (45-54)	-0.012	0.028		0.085	0.028	**
Experience	-0.009	0.004	*	0.016	0.005	**
Experience squared	0.014	0.012		-0.027	0.014	
Vocational education	0.154	0.019	***	-0.014	0.026	
Numeracy skill	0.001	0.000	***	0.000	0.000	
Dropout	-0.061	0.036		0.096	0.033	**
Readiness-to-learn	-0.002	0.009		0.005	0.011	
Computer experience	-0.157	0.038	***	-0.039	0.036	
Public sector	-0.018	0.024		-0.056	0.028	*
Manual job	0.035	0.021		-0.062	0.025	*
Panel 2: RM method	**Overeducated**			**Undereducated**		
Variable	**dy/dx**	**std. err.**	**Signif.**	**dy/dx**	**std. err.**	**Signif.**
Female	-0.061	0.030	*	0.027	0.027	
Entry age (20-29)	-0.051	0.027		0.023	0.031	
Prime age 2 (45-54)	0.023	0.034		0.041	0.033	
Experience	-0.014	0.005	**	0.005	0.005	
Experience squared	0.021	0.015		-0.012	0.016	
Vocational education	0.342	0.020	***	0.051	0.022	*
Numeracy skill	0.001	0.000	***	-0.001	0.000	**
Dropout	-0.060	0.037		-0.019	0.036	
Readiness-to-learn	0.024	0.011	*	-0.033	0.011	**
Computer experience	-0.099	0.040	*	-0.121	0.045	**
Public sector	0.018	0.029		-0.035	0.028	
Manual job	0.064	0.025	*	-0.130	0.025	***

counterparts when objective measures are considered. The ME results show that being female decreases the probability of being OE by 6.1 percentage points. The negative coefficient for women implies that, within the full-time wage earner group, women might have a better alignment between their education and job requirements compared to men. This could be due to selectivity. Women in the labor force, especially those in full-time jobs, may face more rigid criteria in their job search, leading to situations where only those with closely matched education levels secure employment. Alternatively, occupational segregation by gender could play a role in this finding. If women are more likely to be employed in occupations that traditionally require specific education levels (e.g., education, healthcare), this could lead to a lower incidence of OE among women in full-time jobs.

Age is another factor that might influence education mismatches. Both models show negative overeducation coefficients for the entry age group, but they are not statistically significant. On the other hand, they are significantly more likely be undereducated according to SA. This might be due to qualification inflation, where even entry-level positions require higher levels of education. For the 45-54 age group, the significant and positive coefficient for being undereducated in the SA model suggests that individuals in this age group are more likely perceive themselves as being undereducated in their jobs. This might be because as the average level of education within the workforce rises, what was once considered a required level of education might change. Furthermore, the RM results show that more experience significantly decreases the likelihood of overeducation, while its effect on undereducation is positive in SA results. This suggests that while experience influences mismatches, this effect is not symmetrical.

To examine the effect of different educational backgrounds on education mismatch, variables for vocational education and dropout status are included in the analysis. The SA and RM coefficients for vocational education is positive and significant, suggesting that vocational education increases the likelihood of being overeducated. The coefficients for undereducation are positive and significant in the RM model, suggesting that individuals with vocational education are more likely to be undereducated. ME results show that vocational education significantly increases the probability of being overeducated by 34.2 (15.4) percentage points and the probability

of being undereducated by 5.1 percentage points, suggesting a strong impact of vocational training on education mismatch in the RM (SA) method. The significance of vocational education for both overeducation and undereducation in both methods suggests that receiving vocational education increases the likelihood of mismatch, possibly due to a difference between the specialized skills acquired through vocational education and the requirements of available jobs. Moreover, in the RM model, dropping out decreases the likelihood of perceiving oneself as overeducated, while in the SA model it increases the likelihood of being undereducated, suggesting that those who do not complete their education are more likely to feel undereducated.

To assess how foundational skills (numeracy skills) and soft skills (readiness-to-learn) influence individuals' alignment with their job requirements, two variables are used. The results show that higher numeracy skills have a statistically significant effect on the likelihood of OE, whereas the numeracy skill coefficient for undereducation are negative but not significant. The readiness-to learn variable do not show a significant effect in SA model, but has a significant negative effect on UE in the RM model, meaning that being more open to learning decreases the likelihood of being undereducated.

Computer experience is a routing variable for CBA test of the PIAAC. It does not assess the ability to use specific software or devices but shows a general ability to use computer technologies. The results show that, in the SA model, individuals with computer experience are significantly less likely to perceive themselves as OE. Similarly, in the RM model, computer experience significantly reduces the likelihood of being classified as OE or UE. These results show that computer experience contribute to a better alignment between individuals' education level and the needs of their jobs.

To analyze how job characteristics effect education mismatch, variables for manual work and employment in public sector are included in the model. The results show that the manual variable has a significant negative relationship with being UE in SA and RM models. Manual jobs might demand specific skills and knowledge that are not obtained through formal education, leading to less undereducation. This might be because the modal education level for these jobs might be set at a lower threshold,

reflecting the skills and training necessary to perform the job, which are often more focused on hands-on abilities rather than educational qualifications. For the public sector, the SA results show that workers in the public sector have a significantly lower likelihood of perceiving themselves as UE, indicating that public sector jobs may better match individuals' educational levels or that these jobs have more stringent education requirements.

Overall, these results show the factors influencing education mismatch, with differences in how these factors are effective across subjective (SA) and objective (RM) assessments. It is important to note that neither the SA nor the RM results are "wrong" when it comes to analyzing education mismatches. They provide different perspectives on education mismatch, each having its own limitations. For example, if both methods indicate a high level of agreement on the prevalence of OE for a certain variable, it strengthens the interpretation of the results.

2.7.2. Skill Mismatch

Given the influence of education and skills on each other, it is natural to expect some overlap in the incidence and correlates of skill and education mismatches. Still, skill mismatch and education mismatch might have different correlates due to the nature of what they measure. An individual can be well-matched in terms of education level but still experience a skill mismatch if their specific skills do not meet the job's requirements. For example, individuals may acquire new skills over time, reducing skill mismatch without changing their formal education level.

Table 15. The incidence of skill mismatch in Türkiye (%), full-time employed workers (2015)

	Men	**Women**	**All**
Overskilled	28.37	25.36	27.59
Well-matched	60.22	55.27	58.94
Underskilled	11.41	19.37	13.47

Table 15 shows the incidence of education mismatch among full-time employed workers in Türkiye, categorized by gender. This analysis categorizes individuals into three groups: well-matched, overskilled (OS), and underskilled (US). The analysis indicates that a majority of the workforce in Türkiye is well-matched in terms of their skills to job requirements (58.94%), whereas 27.59% of the workforce are OS, and 13.47% are US. Furthermore, there are gender differences. A higher percentage of men are well-matched and overskilled, while a lower percentage is underskilled compared to women. 60.22% of employed men and 55.27% of employed women are well-matched. On the other hand, a higher percentage of women (19.37%) are underskilled, compared to 11.41% of men. Additionally, men have a higher percentage of being overskilled (28.37%) compared to women (25.36%).

Table 16. Comparison of Skill and Education Mismatches (%)

		Skill Mismatch		
		Overskilled	**Well-matched**	**Underskilled**
Education Mismatch (SA Method)	**Overeducated**	39.8	52.5	7.7
	Well-matched	25.1	60.8	14.1
	Undereducated	26.0	56.7	17.3
		Overskilled	**Well-matched**	**Underskilled**
Education Mismatch (RM Method)	**Overeducated**	37.9	54.7	7.4
	Well-matched	24.4	59.5	16.0
	Undereducated	16.1	67.1	16.8

2.7.2.1. Correlates of Skill Mismatch

Table 16 presents the distribution of skill mismatch categories across different levels of education mismatch as identified by SA and RM methodologies. Across all categories of education mismatch, a significant portion of individuals are found to be well-matched in terms of their skills, regardless of the method used. Among those who

are overeducated for their positions, a majority are either well-matched in skills or overskilled, according to both methodologies. More than half of overeducated individuals are considered well-matched in skills (52.5% in SA and 54.7% in RM), and a high percent are overskilled (39.8% in SA and 37.9% in RM), with only a small fraction being underskilled (7.7% in SA and 7.4% in RM). For those who are undereducated, more than half are well-matched in skills (56.7% in SA and 67.15% in RM), suggesting that lacking formal education does not always imply a lack of necessary skills.

Table 17 presents the results of the multinomial probit analysis of the correlates of skill mismatch. While the multinomial probit model allows us to understand the overall relationship between various predictors and the categorical outcomes (such as being well-matched, overskilled, or underskilled), it does not directly quantify the changes in probability associated with a one-unit change in the predictor variables. By looking at the marginal effects, we can see the changes in the likelihood of being overskilled or underskilled due to shifts in individual and job characteristics. Table 18 provides the marginal effects of the determinants on skill mismatch.

Being female increases the likelihood of being underskilled (ME=10.1 percentage point increase) but does not significantly affect the likelihood of being overskilled. The significance of the female coefficient indicates that women are more likely than men to have jobs that require higher levels of skills than they possess. It should be noted that the distribution of educational levels in our sample indicates that a higher proportion of women than men have attained tertiary education (See Appendix). Despite these higher levels of educational attainment, the results show that 24.22% of well-matched individuals, 23.73% of those overskilled, and 37.16% of those underskilled are female. This indicates that women are overrepresented in the underskilled category, given that this category has a higher percentage of females compared to the other two.

Moreover, when examining the distribution of numeracy skill scores among women, it is observed that only women in the underskilled category have significantly lower scores. Figure 12 provides minimum and maximum numeracy scores for different skill mismatch categories based on gender. This shows that underskilled women have a

wide range of scores, where women (62.49) score lower than men (104.03). The lower numeracy scores observed among women in the underskilled category might reflect their potentially lower participation in education. This could suggest that women at lower skill levels have had fewer opportunities or less access to enhance their numeracy skills through formal education, contributing to the differences seen in the scores. Alternatively, this might be the case if the education system or the specific programs that women are more likely to choose are not as quantitative. In that case women might graduate with lower relative numeracy skills. Moreover, maternity leave can also affect women's skill levels and their likelihood of being underskilled. The combination of having less time to develop skills and the potential for faster skill atrophy during maternity leave can create a cumulative effect that can affect a woman's skills.

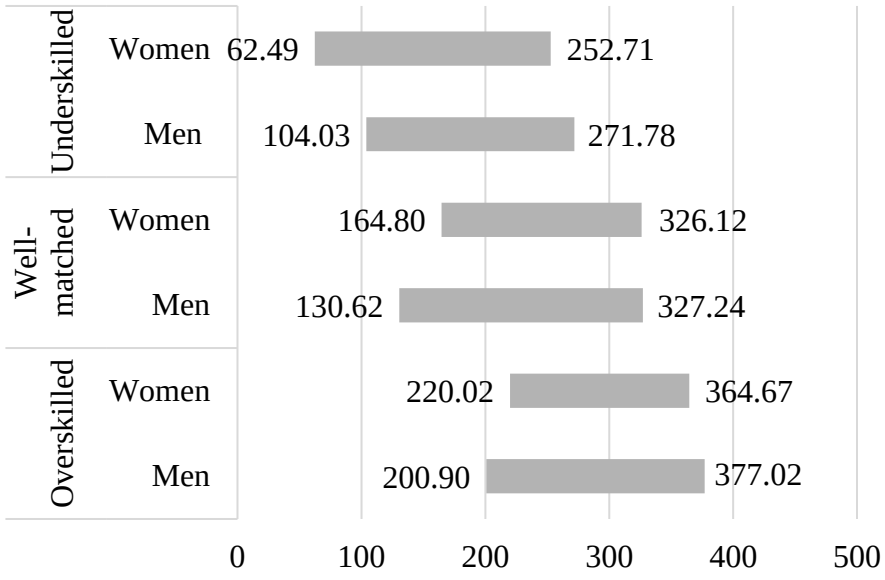


Figure 12. Numeracy Skill Scores by Gender and Skill Mismatch Category for Wage Earners in Türkiye (2015)

The results show that individuals in the entry age group (20-29) are less likely to be in jobs where they are OS and US. This might be because entry-level jobs align with the skills of recent graduates, reducing the likelihood of skill mismatch. The coefficients for individuals in the age group 45-54 are not significant for both OS and US, suggesting that being in this age range does not significantly affect the likelihood of experiencing either form of skill mismatch. The results for experience show that the

coefficient for experience and its square for both OS and US are not statistically significant. This suggests that additional years of work experience do not have a significant effect on reducing or increasing the likelihood of being either OS or US.

Table 17. Multinomial Probit Analysis of Skill Mismatch

Variable	**OS**	**US**
Female	-0.081	0.595***
	(0.145)	(0.167)
Entry age (20-29)	-0.367**	-0.463**
	(0.165)	(0.231)
Prime age 2 (45-54)	0.061	0.006
	(0.172)	(0.201)
Experience	-0.007	-0.043
	(0.028)	(0.030)
Experience squared (1/100)	-0.017	0.124
	(0.090)	(0.091)
Vocational education	0.293**	0.303*
	(0.144)	(0.171)
Dropout	0.174	0.046
	(0.207)	(0.256)
Readiness-to-learn	0.163***	-0.123
	(0.062)	(0.076)
Computer experience	-0.525***	0.654***
	(0.201)	(0.211)
Public sector	0.073	0.144
	(0.150)	(0.194)
Manual job	-0.043	0.241
	(0.135)	(0.178)
Constant	-0.256	-1.720***
	(0.377)	(0.449)
Obs.	1,355	1,355

In the analysis, vocational education is associated with a higher likelihood of OS and US. It should be reminded here that we are focusing on numeracy skill to measure skill mismatch. Vocational training programs may vary significantly in quality and content, leading to inconsistencies in the numeracy skills of graduates. While vocational training equips individuals with practical and technical skills relevant to their fields, it may not always align with the numeracy skill demands of the job market. The dual system of vocational education in Türkiye, designed to prepare students for specific careers, emphasizes practical skills alongside foundational skills like numeracy. This

result shows that there might be inefficiencies within this dual system if vocational graduates are more likely to experience skill mismatches.

Table 18. Marginal Effects of Individual and Job Characteristics on Skill Mismatch

	Overskilled			**Underskilled**		
Variable	**dy/dx**	**std. err.**	**Signif.**	**dy/dx**	**std. err.**	**Signif.**
Female	-0.051	0.032		0.101	0.025	***
Entry age (20-29)	-0.061	0.035		-0.054	0.032	
Prime age 2 (45-54)	0.015	0.040		-0.003	0.033	
Experience	0.001	0.006		-0.007	0.005	
Experience squared	-0.011	0.020		0.021	0.014	
Vocational education	0.053	0.031		0.034	0.026	
Dropout	0.038	0.046		-0.002	0.039	
Readiness-to-learn	0.045	0.014	**	-0.029	0.012	*
Computer experience	-0.159	0.044	***	0.135	0.032	***
Public sector	0.009	0.033		0.020	0.030	
Manual job	-0.023	0.030		0.042	0.027	

Readiness-to-learn and computer experience have significant effects on both OS and US. The marginal effects associated with readiness-to-learn indicate that individuals who are more inclined towards learning are 2.9 percentage points less likely to be underskilled and 4.5 percentage point more likely to be overskilled in their jobs. This finding suggests that while readiness to learn is a positive trait, it can also result in being overskilled. As Heckman and Kautz (2012) explains, the relationship between soft skills and outcomes is not always linear, especially in the context of measuring traits where too high levels can lead to negative outcomes. In this respect, an excess of a generally positive trait can become counterproductive, embodying the idea that "too much of a good thing can be bad" (Heckman and Kautz, 2012). In addition, the finding that readiness-to-learn significantly increases the likelihood of being overskilled can be explained through the concept of dynamic complementarity in skill formation (Cunha and Heckman, 2007). This theory posits that skills acquired at one

stage increase the productivity of subsequent skill investments. In this context, an individual's readiness-to-learn could lead to continuous skill acquisition (the “skill begets skill” view), making them more likely to surpass the skill requirements of their current job.

Computer experience significantly reduces the likelihood of being overskilled and significantly increases the likelihood of being overskilled. ME results show that individuals with computer experience are 15.9 percentage points less likely to be overskilled and 13.5 percentage points more likely to be underskilled for their jobs. The significant negative coefficient for OS suggests that individuals with computer experience are less likely to be overskilled in their jobs. This could be because individuals with computer experience are likely to find jobs that make better use of their skills, reducing the likelihood of being in positions where they are OS. This may result from the widespread need for computer skills across various jobs, where such skills are increasingly seen as essential. On the other hand, the positive coefficient for US suggests that individuals with computer experience are more likely to be in jobs that demand higher levels of skills than they currently have. The presence of any computer experience might signal to employers an assumed proficiency in numeracy, given the often-quantitative nature of computer-related tasks. However, having computer experience does not automatically translate to higher numeracy skills. Given that we are using numeracy skill scores to measure skill mismatch, workers who are otherwise skilled in general computer use might still fall into the underskilled category if their jobs require advanced numeracy skills. This scenario could lead to the observed positive correlation, reflecting that while these individuals can use computers, their numeracy skills do not meet the job requirements.

2.8. Consequences of Market Mismatch

2.8.1. Descriptive Statistics About the Outcomes

How does the distribution of hourly earnings across different deciles compare between genders? Figure 13 presents a gender-wise distribution of individuals across hourly earnings deciles. For males, the lowest decile includes 5.21% of individuals. The proportion increases through the middle deciles, with the 5th decile having the highest percentage at 13.65%. The highest earnings decile comprises 7.29% of the male

population. In the case of females, the distribution appears to be more skewed towards the lower income deciles. The lowest decile accounts for 9.45%, which is higher than their male counterparts. The second decile stands out with the highest percentage of 13.11%. However, the percentage of females in the highest earnings decile is slightly higher than that of males, at 7.93%.

How does the distribution of hourly earnings across different deciles vary with tertiary education? Figure 14 presents the distribution of hourly earnings deciles by tertiary education status. For those without tertiary education, there is a more even spread across the mid-range deciles, with the 5th and 6th deciles containing the highest percentages, at 13.21% and 13.81% respectively. The lowest decile has a smaller proportion of individuals at 8.16%, and the highest decile includes 5.40% of this group. On the other hand, for those with tertiary education, there is a skew towards the higher income deciles. The percentages in the lowest decile is lower at 2.86%, whereas the second and third highest deciles have the largest percentages, at 25.05% and 23.74% respectively. The highest earnings decile is also at 11.21%.

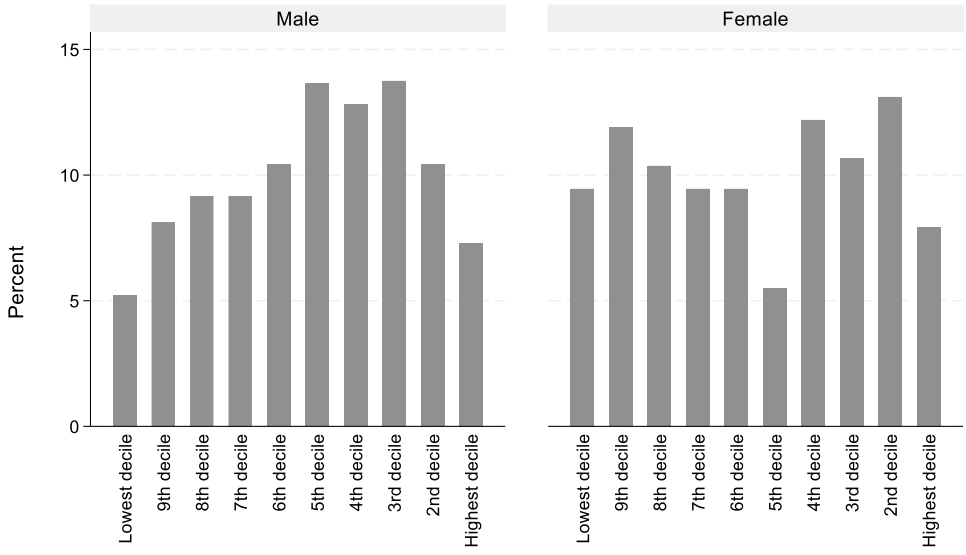


Figure 13. Distribution of individuals across hourly earnings deciles by gender

How does job satisfaction relate to earnings distribution across different hourly wage deciles? Figure 15 provides the distribution of hourly earnings in deciles, segmented by job satisfaction status. Individuals who are satisfied with their jobs tend to be more

evenly distributed across the higher earnings deciles, suggesting a positive correlation between higher wages and job satisfaction. Typically, it is believed that higher wages should logically lead to higher job satisfaction, assuming all other factors related to the individual and their job remain constant. This comes from the assumption that more income improves an individual's ability to satisfy their needs.

However, the empirical evidence regarding the relationship between wages and job satisfaction is complex especially when we examine the influence of education and skill mismatches. While some studies find a positive relationship, others do not observe a significant effect of wages on job satisfaction (Groot and van den Brink, 2000). For example, Verhaest and Omey (2006) analyzes the impact of overeducation on job satisfaction and finds that overeducated individuals may not necessarily achieve higher job satisfaction with higher wages, pointing to the importance of the alignment between job and education. On the other hand, Green and Zhu (2010) introduces a distinction between "real" and "formal" overeducation in the labor market, which focuses on whether overeducation is accompanied by skills mismatch. Overeducated workers who also report skill mismatch have lower job satisfaction, but those who have formal overeducation do not experience as severe decreases as job satisfaction as those in the “real” overeducation category.

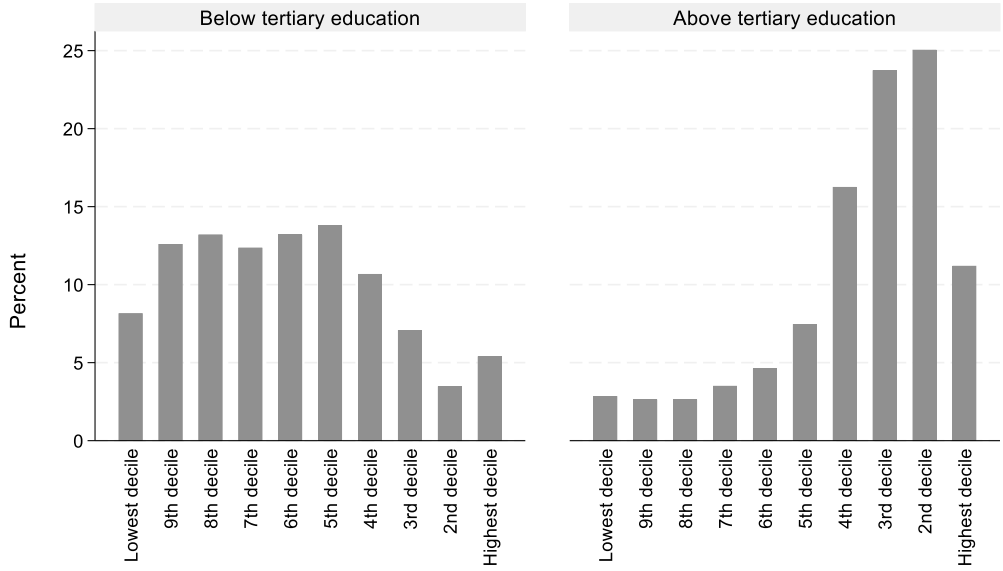


Figure 14. Distribution of individuals across hourly earnings deciles by education

status

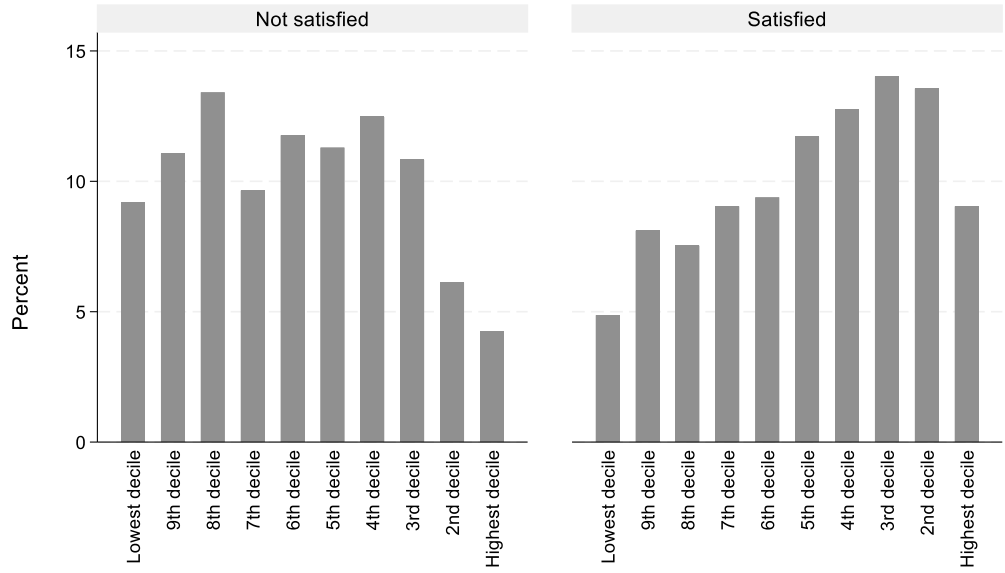


Figure 15. Distribution of individuals across hourly earnings deciles by job satisfaction status

2.8.2. What is the Impact of Labor Market Mismatch on Wages?

2.8.2.1.ORU Model Results

Table 19 presents the results of eight OLS regression models (Model 1 through Model 8) using two different models (the ORU model and the dummy variable model) and two methods (SA and RM methods). First two models (Model 1 and Model 2) use the self-assessment method and presents coefficients for the ORU model specifications whereas the following two models (Model 3 and Model 4) use the realized match method for the ORU model specifications. In the context of the ORU specification, the relationship between actual education (AE), required education (RE), overeducation (OE) and undereducation (UE) can be expressed as:

$$AE = RE + OE - UE$$

This equation means that an individual's actual education level is the sum of the education level required for their job and any excess education they have, minus any shortfall in their education relative to what is required. Here, the RE coefficient

measures the return to each year of required education for a job. A positive and significant coefficient for RE suggests that jobs requiring more education tend to pay higher wages.

The models that use self-assessment method (Model 1 and Model 2) show a positive and highly significant effect of required education on wages (0.352 and 0.348, respectively[18]), suggesting that higher educational requirements for a job are associated with higher wages. Similarly, the models that use the realized matches method (Method 3 and Method 4) shows a positive and significant effect on wages in both models (0.324 and 0.317, respectively), also indicating that higher required education levels are associated with higher earnings deciles, a consistent finding. Overall, a one-year increase in required education is associated with an increase by about 31.7% to 32.4% of a wage decile.

The overeducation and undereducation variables in the ORU model measure the effect of having more or less education than what is required by one's job on wages respectively, quantified in terms of additional years of education. For the first two models that use the SA method (Models 1 and 2), the negative and significant coefficients for undereducation indicate that each year of education less than what is required for the job is associated with lower wages. The significance of these coefficients suggests a wage penalty for undereducation. Overall, each year of undereducation is associated with a decrease in wages by about 19.0% to 19.2% of a wage decile. On the other hand, the coefficients of self-assessed overeducation are small and not statistically significant.

On the other hand, for the latter two models that use the RM method (Model 3 and Model 4), overeducation is significantly positive in both models (0.222 and 0.224, respectively), suggesting that additional years of education beyond what a job requires are associated with higher wages, reflecting a return on overeducation. The finding that overeducation is significant in RM models but not so in SA models shows that the

[18] Multiply the coefficient by 10 to reflect the change in percentage across the full range of wage deciles. For example, a coefficient of 0.332 implies a 3.32 decile change, which equates to moving up 33.2% within the wage decile scale.

Table 19. The OLS results for the impact of education and skill mismatch on wages (in deciles) in Türkiye, 2015

Panel 1	**ORU Model**			
	Self-Assessment Method		**Realized Match Method**	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Required education	0.352***	0.348***	0.324***	0.317***
	(0.029)	(0.029)	(0.028)	(0.029)
Overeducation	0.038	0.044	0.222***	0.224***
	(0.052)	(0.052)	(0.043)	(0.043)
Undereducation	-0.192***	-0.190***	-0.238***	-0.242***
	(0.052)	(0.053)	(0.068)	(0.067)
Overskilled		-0.382**		-0.404**
		(0.191)		(0.188)
Underskilled		-0.019		0.065
		(0.266)		(0.269)
Female	-0.652***	-0.659***	-0.624***	-0.633***
	(0.150)	(0.152)	(0.153)	(0.154)
Entry age (20-29)	-0.082	-0.111	-0.032	-0.058
	(0.189)	(0.188)	(0.189)	(0.189)
Prime age 2 (40-54)	-0.061	-0.041	-0.010	0.012
	(0.191)	(0.192)	(0.192)	(0.192)
Experience	0.181***	0.180***	0.190***	0.189***
	(0.029)	(0.029)	(0.029)	(0.029)
Experience squared (1/100)	-0.433***	-0.432***	-0.451***	-0.452***
	(0.091)	(0.090)	(0.092)	(0.091)
Average numeracy score	0.007***	0.009***	0.007***	0.010***
	(0.002)	(0.003)	(0.002)	(0.002)
Vocational education	-0.266*	-0.258*	-0.306*	-0.307*
	(0.151)	(0.152)	(0.162)	(0.163)
Readiness to learn	-0.003	-0.003	0.023	0.022
	(0.083)	(0.083)	(0.083)	(0.083)
Public sector	1.555***	1.543***	1.625***	1.618***
	(0.160)	(0.161)	(0.169)	(0.169)
Medium-sized enterprise	0.104	0.126	0.149	0.173

Panel 2	**Dummy Variable Approach**			
	Self Assessment Method		**Realized Match Method**	
Variables	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Actual education	0.293***	0.288***	0.281***	0.273***
	(0.028)	(0.029)	(0.029)	(0.029)
Overeducation	-0.848***	-0.820***	-0.395**	-0.354**
	(0.194)	(0.195)	(0.174)	(0.174)
Undereducation	0.446**	0.433**	0.139	0.095
	(0.206)	(0.207)	(0.266)	(0.263)
Overskilled		-0.425**		-0.432**
		(0.196)		(0.194)
Underskilled		0.096		0.124
		(0.268)		(0.269)
Female	-0.547***	-0.564***	-0.543***	-0.558***
	(0.156)	(0.158)	(0.158)	(0.159)
Entry age (20-29)	-0.264	-0.287	-0.217	-0.238
	(0.195)	(0.195)	(0.194)	(0.194)
Prime age 2 (40-54)	-0.019	0.004	0.033	0.054
	(0.195)	(0.195)	(0.194)	(0.194)
Experience	0.170***	0.169***	0.177***	0.176***
	(0.028)	(0.028)	(0.028)	(0.028)
Experience squared (1/100)	-0.408***	-0.410***	-0.420***	-0.423***
	(0.089)	(0.087)	(0.089)	(0.088)
Average numeracy score	0.008***	0.011***	0.008***	0.011***
	(0.002)	(0.003)	(0.002)	(0.002)
Vocational education	-0.315**	-0.306*	-0.316*	-0.315*
	(0.156)	(0.157)	(0.172)	(0.173)
Readiness to learn	0.026	0.026	0.045	0.044
	(0.085)	(0.086)	(0.085)	(0.085)
Public sector	1.836***	1.815***	1.855***	1.840***
	(0.160)	(0.160)	(0.165)	(0.165)
Medium-sized enterprise	0.077	0.107	0.100	0.128
	(0.170)	(0.172)	(0.172)	(0.175)

*Notes: Robust standard errors in parentheses. Experience squared divided by 100. *** p<0.01, ** p<0.05, * p<0.1*

labor market does value education beyond the requirements, but this is more clearly observed and quantified when overeducation is measured against standardized benchmarks rather than personal perceptions. On the other hand, undereducation remains significantly negative (-0.238 and -0.242), indicating that lacking years of required education for a job result in lower wages.

Models 2 and 4 includes the "Overskilled" and "Underskilled" dummy variables, which are not present in Models 1 and 3. The introduction of skill mismatch variables appears to have a minimal effect on the significance and estimated coefficients of other variables. While being overskilled did show a significant negative impact (-0.382) on wages in Model 2, indicating a penalty for being overskilled, this did not significantly change how other variables relate with wages. Like in Model 2, overskilled variable in Model 4 shows a negative but marginally significant effect on wages (-0.404). On the other hand, underskilled coefficient is not significant, suggesting no clear penalty or premium for being underskilled.

In all four models, the coefficient for the female variable is negative and statistically significant at the 1% level, suggesting that being female is associated with a wage penalty compared to being male. Female workers earn about 62.4% to 65.9% of a wage decile less than their male counterparts. The consistency of these findings across different model specifications shows a wage gap between male and female workers. This may be due to occupational segregation, if occupations that mostly employ women pay less than those that employ mainly men, even when skill levels or educational requirements are comparable. For example, in sectors like teaching, jobs often require high levels of education but traditionally pay relatively low wages compared to other professions that require similar levels of academic preparation. Moreover, women are likely to have interruptions in their careers, often due to caregiving responsibilities, which result in lower wages over time. In addition, this might also be due to discrimination in the labor market which can be in different forms, including biases in hiring, promotion, and wage determination.

The analysis of age variables, specifically focusing on early-career (20-29) and end-career (45-54) ages across all four models provides insights into how age impacts wages. The lack of statistical significance in all ORU models indicates that the data

does not provide strong evidence to say that age significantly impacts wage outcomes once other factors are controlled for. Of course, the inclusion of both experience and its squared term in the models helps control for the effect of labor market experience on wages, which in turn can affect how age variables are interpreted.

In fact, the positive coefficients for experience in all models show that additional work experience increases position in wage deciles. However, the negative coefficients for experience squared in all models show that the effect of experience on wages decreases at higher levels of experience. This implies that less experienced workers may see wage growth as they gain experience, but as they become more experienced, the rate of wage increase slows.

The variables for numeracy scores in the models provide insight into how foundational skills influence wages. The analysis across all models suggests that numeracy skills have statistically significant positive impact on wages, indicating that individuals with higher scores tend to earn higher wages. This suggests that higher numeracy skills are correlated with higher wages. But more importantly, numeracy skills can also be seen as a proxy for general cognitive abilities.

This is important as it implies that this variable acts as a control for unobserved ability. This means that including numeracy scores improves the model by adding a control that accounts for individual differences in ability. This makes the findings about other variables, like education and mismatch variables, more reliable since the observed effects for these variables are less likely to be biased by variations in cognitive skills that are not captured in other datasets.

The variables for public sector and firm size relate to job characteristics, specifically the type and size of the employer. The positive and statistically significant coefficients for the public sector variable across all models indicate a clear wage premium for public sector employment. Working in the public sector is associated with an increase in wages by about 154.3% to 162.5% of a wage decile compared to the private sector. For medium-sized enterprises, the coefficients across all models are positive but not statistically significant. On the other hand, the coefficients for large-sized enterprises are significantly positive in all models, indicating that working for a large firm is associated with a wage premium compared to working for smaller firms.

2.8.2.2.Dummy Variable Approach Results

The subsequent models (Model 5 through Model 8) transition from the ORU model specifications the dummy variable approach. In the dummy variable approach, the focus shifts towards understanding the effects of being overeducated or undereducated on wages, using dummy variables to represent these conditions.

In the dummy variable specification, the coefficient for actual education indicates the percentage change in wages associated with a one-unit increase in actual education. The consistently positive and statistically significant coefficients for actual education across Models 5 to 8 show that higher levels of actual education are associated with higher wages. Similarly, the statistically significant negative coefficients for overeducation in all models indicate that overeducated individuals earn less than their counterparts with similar education levels who are adequately matched to their jobs. This finding highlights a wage penalty for overeducation. On the other hand, undereducation shows a mixed effect. The coefficient is statistically significant in Models 5 and 6 (SA Method), but not in Models 7 and 8 (RM method), suggesting that undereducation's effect might vary depending on the assessment method.

In the ORU model that measures returns to years of undereducation, significant negative coefficients suggest that each additional year of undereducation relative to job requirements leads to lower wages. However, when we use the dummy variable approach, comparing undereducated workers to those who are educationally well-matched but at the same educational level, the coefficient is significant only in the SA model results. The lack of significance of undereducated variable in the RM results might be because minimum wages may be masking the effects. In other words, both undereducated and well-matched workers might be earning around the same minimum wage, which could dilute the observable effect of undereducation on wages when we use a dummy variable.

The Inflation Report 2021-I, published by the Central Bank of the Republic of Türkiye, there is a section (Box 2.6) which discusses wage distribution in Türkiye, focusing on the minimum wage. Using microdata from the Household Labor Force Survey (HLFS), the report categorizes individuals whose wages are within a 10% range above or below the minimum wage as "minimum wage earners." The proportion of workers

earning at or below the minimum wage for the average of years 2017-2019 is found to be 42.8% in non-agricultural sectors and 50% in the industrial sector. For a comparison of minimum wage earners, we can use the Eurostat data from 2018, which shows the proportion of employees earning less than 105% of the minimum wage in European countries. The average proportion for these 21 countries is approximately 7.03%, with Slovenia being the highest at 15.2%.

Data from Türkiye and Eurostat for a similar period (average of 2017-2019 and 2018, respectively) shows that a higher proportion of employees earn close to the minimum wage in Türkiye. This implies that Türkiye's labor market might be affected by minimum wage settings significantly. The presence of a minimum wage could compress the wage distribution at the lower end, reducing the variance in wages among low-educated or undereducated workers. This compression makes it harder to detect significant differences between undereducated workers and their equally educated well-matched counterparts with the dummy variable method, especially if many fall around the minimum wage threshold.

The coefficient for female variable across all models (Models 5 through 8) are consistently negative and statistically significant. This indicates that female workers, on average, earn less than their male counterparts in the similar jobs, highlighting a gender wage gap. The significance of these coefficients across different models suggests that this wage disparity is a robust finding, not sensitive to the specific model specifications or the skill mismatch. This finding is consistent with the literature on gender wage gap, which has identified various factors contributing to wage differences between men and women.

The age coefficients are not statistically significant in all four models. On the other hand, the coefficients for experience are positive and significant across all models (0.169 to 0.177). This indicates a positive relationship between the amount of work experience and wages. The coefficients for experience squared are negative and statistically significant (-0.408 to -0.423) across all models. The negative coefficient on the squared term suggests diminishing returns to experience.

The coefficients for the numeracy score are positive and statistically significant. This shows the robust importance of numeracy skills across various models. On the other

hand, the consistently non-significant coefficients for the readiness-to-learn variable across all models suggest that this soft skill, while potentially valued by employers, does not directly translate into higher wages. This does not imply that this soft skill is not valued. Instead, it might be rewarded in non-wage forms, such as greater job satisfaction, or more engaging work. The coefficients for working in the public sector have positive and significant coefficients which indicate that, holding other factors constant, jobs in the public sector are associated with higher wages compared to jobs in the private sector. The coefficients for working in a medium-sized enterprise are not statistically significant across most models whereas the coefficients for working in a large-sized enterprise range are positive and statistically significant in all models.

Models 6 and 8 incorporate the skill mismatch dummy variables, which are absent in Models 5 and 7. The results show that being overskilled is associated with a significant negative effect on wages, signaling a wage penalty for individuals whose skills exceed job requirements. However, the introduction of these variables does not change the significance or sign of the coefficients for other variables. On the other hand, the underskilled variables lack statistical significance in this specification as well, suggesting that the labor market does not penalize or reward individuals for being underskilled.

2.8.3. What is the Effect of Labor Market Mismatch on Job Satisfaction?

Wages are the most direct and quantifiable benefit provided by employment. It enables individuals to meet their basic needs and it is often the primary motivator for employment. However, while wages are an important component of utility from a job, it interacts with other job aspects such as work environment, job security and career advancement opportunities to influence overall job satisfaction (Groot and van den Brink, 2000). Hence, labor market mismatches can have significant implications for job satisfaction.

The results from Table 20 present the impact of labor market mismatch and other factors on job satisfaction, using both the RM and SA methods. The earnings variable explains how moving from one decile to another affects job satisfaction. The findings for earnings variable are consistent in all models. In both Model 1 and Model 3 (RM method), the significant positive coefficient for hourly earnings indicates that

individuals in higher wage deciles have higher job satisfaction. The consistent positive relationship shows that higher placement within the wage distribution increases job satisfaction.

The results from Models 1 to 4 show that the effect of actual education on job satisfaction is not significant, indicating that the level of education alone does not strongly determine job satisfaction. Furthermore, the insignificant effects of overeducation and overskilling on job satisfaction shows that these categories of mismatches does not affect how satisfied employees feel in their jobs. On the other hand, the significant positive effects of undereducation on job satisfaction in Models 3 and 4 (SA method) suggest that being undereducated for one's job increase job satisfaction. However, it does not have a statistically significant effect on job satisfaction in Models 1 and 2 (RM method). The significant positive effect of undereducation on job satisfaction in the self-assessment models suggests that undereducated individuals might nonetheless feel satisfied with their work.

Similarly, being underskilled has a significantly positive effect on job satisfaction in all models. The significance of this positive effect, even after controlling for wages, indicates that the effect of being underskilled or undereducated on job satisfaction is independent of wage levels. If underskilled and undereducated individuals who have jobs that require higher skills and education perceive themselves as having surpassed expectations or having achieved upward mobility, this can lead to increased job satisfaction due to a sense of achievement. Additionally, jobs that require higher skills and education levels often come with better benefits, contributing to satisfaction.

In all four models, the coefficients for the female variable are negative, indicating that female workers report lower job satisfaction compared to their male counterparts. The consistency of the negative effect on job satisfaction for females, even after controlling for wages, shows that there are gender differences that affect job satisfaction beyond just financial compensation. On the other hand, in Model 5, where education and skill mismatch variables are excluded but wages are controlled for, the coefficient for the female variable is not statistically significant. This outcome suggests that when the analysis is focused on wages without the influence of education and skill mismatches, the effect of gender on job satisfaction is not statistically significant.

Table 20. The Impact of Education and Skill Mismatch on Job Satisfaction (Categorical)

Variables	**RM Method**		**SA Method**		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Earnings	**0.054*** **		**0.047*** **		**0.056*** **
	(0.017)		**(0.017)**		**(0.017)**
Actual education	-0.018	-0.003	0.001	0.014	-0.011
	(0.015)	(0.014)	(0.015)	(0.014)	(0.013)
Overeducated	0.059	0.034	-0.128	-0.169	
	(0.091)	(0.090)	(0.107)	(0.105)	
Undereducated	0.149	0.153	**0.393*** **	**0.411*** **	
	(0.128)	(0.127)	**(0.111)**	**(0.110)**	
Overskilled	-0.113	-0.137	-0.109	-0.130	
	(0.094)	(0.094)	(0.096)	(0.095)	
Underskilled	**0.301** **	**0.306** **	**0.270** **	0.274**	
	(0.131)	**(0.130)**	**(0.129)**	(0.128)	
Female	-0.155*	-0.185**	-0.182**	**-0.208** **	-0.134
	(0.090)	(0.089)	(0.089)	**(0.089)**	(0.089)
Entry age (20-29)	**-0.267*** **	**-0.279*** **	**-0.311*** **	**-0.324*** **	**-0.273*** **
	(0.095)	**(0.094)**	**(0.094)**	**(0.094)**	**(0.096)**
Prime age 2 (40-54)	-0.045	-0.041	-0.071	-0.070	-0.044
	(0.104)	(0.104)	(0.102)	(0.102)	(0.103)
Experience	-0.025*	-0.015	-0.030**	-0.022	-0.027*
	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)
Experience sq.(1/100)	0.058	0.035	0.066	0.047	0.066
	(0.041)	(0.040)	(0.041)	(0.040)	(0.042)
Numeracy score	0.000	0.001	-0.000	0.001	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Readiness to learn	**0.098*** **	**0.099*** **	**0.088** **	**0.089** **	**0.100*** **
	(0.037)	**(0.037)**	**(0.037)**	**(0.037)**	**(0.037)**
Public sector	**0.323*** **	**0.423*** **	**0.321*** **	**0.406*** **	**0.337*** **
	(0.106)	**(0.100)**	**(0.107)**	**(0.101)**	**(0.108)**
Medium-sized firm	0.056	0.064	0.048	0.053	0.025
	(0.091)	(0.092)	(0.092)	(0.093)	(0.091)
Large-sized firm	0.001	0.036	-0.008	0.019	-0.016

Note: Bold coefficients indicate statistically significant marginal effects. Experience squared divided by 100.

The coefficients for Entry Age 1 (20-29) are consistently negative and statistically significant across all models. The significance of these findings suggests that individuals in their early careers report less satisfaction with their jobs. On the other hand, the coefficients for Prime Age 2 (45-54) are positive but not statistically significant. The coefficients for experience are negative in all models but only occasionally reach statistical significance. When the realized matches method is used for measuring education mismatch (Model 1), experience shows a statistically significant negative coefficient, indicating that, when wages are controlled for, additional years of experience are associated with a decrease in job satisfaction. In model 2 without the wages, experience does not show a statistically significant coefficient, suggesting that when wages are not included as a control variable, the direct relationship between experience and job satisfaction is not strong enough to be statistically significant. The significance of experience in affecting job satisfaction when wages are included might indicate that wages act as a mediating factor between experience and job satisfaction.

The results indicate that numeracy skills do not have a significant impact on job satisfaction when education and skill mismatch are controlled for in Models 1-4. On the other hand, the positive and significant relationship between readiness-to-learn and job satisfaction in all models suggests that individuals who are more willing to learn tend to be more satisfied with their jobs.

The variables related to the workplace, such as employment in the public sector and firm size, explain how the characteristics of the job impact job satisfaction. The positive and significant coefficients for public sector employment across all models suggest that individuals working in the public sector report higher job satisfaction compared to private sector employees. On the other hand, the coefficients for medium-sized and large-sized enterprises are not statistically significant in all models.

Overall, wages stand out as a primary motivator and important factor of job satisfaction, showing the direct quantifiable benefit employment provides. The analysis confirms that higher wages, indicated by placement in higher deciles, are related with increased job satisfaction across different models. A distinctive aspect of this analysis is its consideration of labor market mismatch alongside other traditional

factors affecting job satisfaction. While overeducation does not significantly affect job satisfaction, undereducation shows a positive effect in some models. This suggests that being undereducated may not lower, and may even increase, job satisfaction, possibly due to a sense of achievement or the benefits associated with jobs requiring higher skill levels. The inclusion of both education and skill mismatches in the analysis indicates that job satisfaction is influenced not only by worker qualifications and job requirements but also by the alignment between them.

2.9. Conclusion

Enhancing the overall educational attainment of a population is a fundamental component of economic development, and the expansion of higher education is a positive development as long as it increases accessibility to higher educational levels and equality in opportunity. However, if not planned strategically, it can also lead to an oversupply of highly educated workers, potentially causing labor market mismatches if the supply of graduates exceeds market demand.

The findings of this chapter indicate that education mismatch is highly prevalent in the Turkish labor market. When we measure education mismatch by using worker self-assessments, we see that 29% of workers are mismatched in terms of education level, with 16% being overeducated and 13% undereducated. Moreover, objective methods reveal a higher incidence of overeducation compared to self-assessments, which aligns with the literature. The objective approach indicates a higher mismatch rate of 42%, with 31% of workers overeducated and 11% undereducated.

In the context of Türkiye, our findings are largely consistent with those presented in existing literature. According to studies on Türkiye that employ objective methodologies, the incidence of overeducation (OE) varies between 22% and 34%, while undereducation (UE) ranges from 6% to 24% across different research (Filiztekin, 2011; Acar, 2016; Mercan et al., 2015; Eriş Dereli, 2017; Duman, 2018). These variations in OE and UE percentages can be attributed to differences in methodologies and sample compositions used in each study. Regarding subjective assessments, we can compare our findings with those from the OECD. By using the same PIAAC data as our study, the OECD (2016) reported an overeducation rate of 12% and an undereducation rate of 13% in Türkiye for the year 2015. The differences

in our findings compared to those reported by the OECD can be attributed to variations in the samples analyzed. While both studies use the same PIAAC data, our research specifically focuses on full-time wage earners in Türkiye. This subgroup might exhibit different patterns of educational mismatch compared to the broader population covered in the OECD report, which includes part-time workers and self-employed.

Furthermore, to put our findings in context with existing international literature, we can compare them with the average incidence of overeducation reported by McGuinness (2006). In his review of 33 studies on education mismatch, he found that the mean incidence of overeducation, based on objective measures, is 22%. In contrast, our analysis indicates that the incidence of overeducation in Türkiye, according to objective measures, is 31% which is higher than the average found in McGuinness (2006).

Regarding the incidence of skill mismatch, our findings indicate that there is also a high incidence of skill mismatch (41%) in Türkiye, where 28% of workers are overskilled and 13% are underskilled. To the best of our knowledge, there has been no previous study that has analyzed skill mismatch for Türkiye, therefore, direct comparisons with other findings are not possible. However, Perry et al. (2014), in their analysis using PIAAC, examine skill mismatch in Germany, Austria, and the USA. The findings indicate that in Germany, 13.02% of workers are overskilled and 2.88% are underskilled. In Austria, the percentages are 11.57% for overskilled and 1.80% for underskilled workers. Meanwhile, in the USA, 8.95% are overskilled of workers and 4.54% are underskilled. Comparing these results with our findings for Türkiye reveals a much higher incidence of skill mismatch in Türkiye.

Furthermore, our results show that many overeducated individuals (approximately 38% by both RM and SA) are also overskilled, indicating a dual mismatch in the labor market. This suggests that not only is their education level is above what is required for their jobs, but their skills are also underutilized, reflecting inefficiencies in the ability of the labor market to match workers' qualifications with job requirements. Additionally, more than half of overeducated individuals are well-matched in terms of skills (around 53% by both RM and SA), suggesting an issue with the quality of the education provided. While the education system produces highly educated individuals,

it may not be equipping them with the skills that the labor market requires.

Moreover, the incidence of workers experiencing some form of education or skill mismatch is 66% under the objective (RM) method and 57% under the subjective assessment (SA) method. This high prevalence of mismatch implies significant inefficiencies in the labor market, where a large portion of the workforce is not optimally utilized. Such mismatches can lead to reduced productivity, lower job satisfaction, and economic inefficiencies. These findings show the necessity of aligning educational outcomes with labor market needs in Türkiye to ensure that individuals' qualifications and skills are well-matched with job requirements. This alignment is necessary not only for maximizing the returns on investments in higher education but also for ensuring that the expansion of higher education translates into benefits for the economy.

Regarding the consequences of labor market mismatch, this study offers a comprehensive view of the effect of labor market mismatch on wages and job satisfaction, using two different model specifications and two methods. These analyses yield important findings:

1. In all models, both required and actual education have a positive and significant effect on wages, as expected. This effect remains robust across different modeling approaches, indicating a premium on higher education levels.

2. Our findings on the effects of overeducation align with the broader literature, confirming that **overeducated workers experience positive wage returns** (except in the self-assessment method of the ORU model), **but these returns are lower than those received by workers whose education levels match their job requirements.**

This is a common observation the literature. Both Human Capital Theory and Assignment Theory are used to explain these observations, but they emphasize different aspects. In terms of human capital theory, the compensation hypothesis posits that overeducation may reflect compensatory factors for unobserved worker heterogeneity (Korpi and Tahlin, 2007). Workers might be overeducated because they compensate for a lack of ability with higher formal education to achieve a similar wage

level. A key aspect of our analysis is the inclusion of controls for unobserved ability (i.e. numeracy skills measured objectively). By controlling for unobserved ability, we find that the effect of educational mismatch on wages does not support the human capital compensation theory.

Assignment theory, on the other hand, provides a framework by considering both the worker characteristics and the job requirements. It focuses on the optimal matching of workers to jobs based on their skills and the job requirements. In the context of Assignment Theory, wages are not just compensations for specific skills or educational levels. They have an allocative role. If available jobs are scarce, workers may end up in jobs that do not fully use their educational qualifications. Higher wages can incentivize workers to select into occupations that make the best use of their overeducation, even if the job does not require such education. This perspective allows us to understand overeducation not just as an inefficiency but as a potential outcome of rational choices within the given labor market structure.

The expansion of higher education in Türkiye could be a factor relating to this. A higher education expansion often leads to an increased supply of highly educated individuals. As more individuals access higher education, the average level of education within the labor force rises but these workers may not find jobs that match their level of education. While overeducated individuals may still receive a wage premium compared to less educated workers, they might face wage penalties relative to their educational investment, leading to a lower return on educational expenditure.

3. The ORU model reveals that **each additional year of undereducation relative to job requirements results in lower wages. However, this effect is not significant when employing a dummy variable approach**, particularly under the RM model.

This is likely due to the influence of minimum wage policies. More than half of the workers in Türkiye earn at or below the minimum wage, which contrasts with lower average observed for EU countries. The high prevalence of minimum wage in Türkiye suggests a compressed wage distribution, particularly at the lower end, which likely conceals the wage penalties typically associated with undereducation when a dummy variable is used.

4. **Being overskilled consistently results in a wage penalty in all models whereas being underskilled does not have a significant effect.**

This means that workers who possess higher skills than what their job requires tend to earn less compared to those whose skills are well-matched to their job requirements This suggests that the labor market penalizes workers whose skills are above job requirements but does not reward or penalize those whose skills are below such requirements. This is also likely due to the effect of minimum wages, which set a floor on earnings and might compress wage differences. For underskilled workers, the minimum wage ensures a base level of income, preventing their wages from falling too low regardless of their skill deficits.

5. **The analysis of wage outcomes shows that there are factors other than education and skill mismatch that significantly affect wage outcomes.**

Firstly, gender emerges as an important factor, with female workers experiencing a consistent wage penalty in all models. This shows the need to address gender related barriers in education and the labor market. Enhancing opportunities for skill enhancement for women, as well as providing support to mitigate the impacts of maternity leave, could help reduce the problems faced by female workers and promote greater equity.

Secondly, our findings show that there are serious challenges associated with vocational education in Türkiye. Individuals with vocational training are more likely to experience mismatches both in terms of skills and education relative to job requirements. These findings imply that vocational education in its current form may not be effectively preparing individuals for the labor market, leading to education mismatch. Moreover, individuals with vocational education consistently earn less than those with general education, even when labor market mismatches are controlled for. The wage penalties associated with vocational education indicate that these qualifications may not be valued as highly as general education by employers. This suggests that vocational training programs need to be better aligned with the actual demands of the labor market.

Lastly, the results regarding computer experience and labor market mismatch are

revealing. For education mismatch, computer experience significantly reduces the likelihood of being overeducated or undereducated, suggesting that computer skills are highly valued and can enhance the alignment between educational qualifications and job requirements. This alignment might be due to the broad applicability of computer skills, which can be transferred between jobs, making it easier for individuals to find suitable employment that matches their educational level. On the other hand, the relationship between computer experience and skill mismatch is mixed. While computer experience helps decrease the likelihood of overskilling, it correlates positively with underskilling. This suggests that, in some cases, computer experience might become more important than numeracy skills, allowing individuals to secure jobs based on their digital proficiency even if they lack the necessary numerical skills.

Overall, this study has revealed a high prevalence of both skill and education mismatches within the Turkish labor market, pointing to a significant misalignment as Türkiye endeavors to elevate its economic and industrial capacity to global standards. This misalignment has not only caused economic inefficiency but has also led to wage penalties for workers, indicating that the labor market is not optimally allocating the educational qualifications of its workforce.

These findings suggest substantial room for policy intervention and educational reforms to better synchronize educational outputs with labor market demands, thereby improving the overall efficacy of Türkiye's efforts. By taking necessary steps, Türkiye can significantly improve the alignment between educational outputs and labor market demands and drive economic growth by maximizing the potential of the workforce.

CHAPTER 3

FIELD-OF-STUDY MISMATCH AMONG HIGHER EDUCATED IN TÜRKİYE

3.1. Introduction

Qualification mismatch refers to the misalignment between the educational qualifications an individual has, and the qualifications required for their job. It includes both vertical (educational) mismatch and horizontal (field-of-study) mismatch. Vertical mismatch focuses on the difference between the level of education demanded by a job and the level of education possessed by a worker, whereas horizontal mismatch focuses on the field or type of education relative to the job. When mismatch is measured only by education level, it is assumed that all workers with the same years of education are identical and can be easily replaced with one another (Halaby, 1994). However, a mismatch may occur when the level of education matches, but the type or field of education does not match the requirements of the job (Sloane, 2003).

In Türkiye, several factors may have contributed to misalignments between the higher education system and labor market needs. As economic policies changed through different periods, this led to disconnections between the education system and labor market demands. Since the 1960s, Türkiye has seen a significant transformation in its economy, transitioning from one dominated by agriculture to one largely based on the industrial and services sectors (Pamuk, 2007). During the 1960s and 1970s, economic policies aimed to reduce dependence on volatile agricultural exports and foreign exchange through Import Substitution Industrialization (ISI), encouraging the development of industries in urban areas. The movement of people from rural to urban areas not only supplied the necessary labor force for these new industries but also increased economic activity and modernization. As cities grew rapidly, the demand for industrial goods increased. In other words, the accelerated migration from rural to

urban areas in the 1970s was both a cause and a consequence of industrial growth. As industries grew, they attracted workers from rural areas, leading to rapid urbanization (Şenses and Taymaz, 2003).

This transition has caused changes in labor demand. Industrialization requires a workforce with different skills compared to agriculture, including basic and technical skills. However, despite these policy changes, the transition of the labor force from agriculture to other sectors was not as successful as anticipated (İlkkaracan and Tunalı, 2010; Günçavdı et al., 2013). As Türkiye developed industrially, there was a growing need for workers who were not only literate but also had specific skills that could support industrial activities. However, the economy struggled to absorb the surplus labor from agriculture, resulting in continued high employment in the agricultural sector. (Şenses and Taymaz, 2003; Günçavdı et al., 2013).

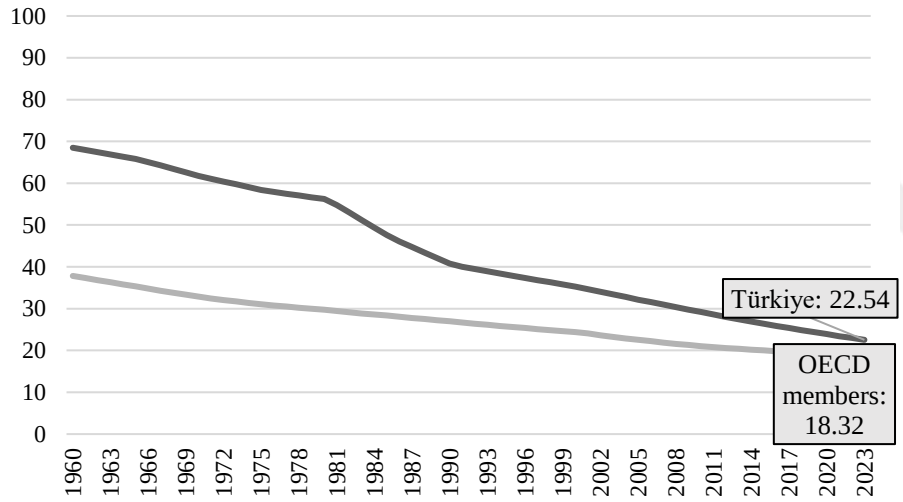


Figure 16. Rural population as a percentage of total population in Türkiye and OECD Members, 1960-2022.

Source: World Bank database

Starting in the 1980s, Türkiye transitioned towards more liberal economic policies under the influence of the IMF and the World Bank. This shift involved moving away from the ISI model to a framework that prioritized export-led growth, as part of structural adjustment programs. This transformation affected the country's production, employment, and growth dynamics. The agricultural sector, which employed over half of the total labor force in 1980 but only produced 25% of total output, was affected by

these reforms (Günçavdı et al., 2013). As the economy opened up, many in the rural workforce migrated to urban areas in search of better job opportunities in the growing industrial and service sectors. By 1980, the urban population was 44% of the total population. In the early 1980s, the urban population surpassed the rural population (See Figure 16). This trend continued in the 1990s (See Figure 17) with an increasing portion of the population moving to urban areas. On the other hand, the rural population, affected by the unfavorable economic conditions of the 1980s and 1990s, remained heavily reliant on government support through extensive income support systems (Aydin, 2013; Günçavdı et al., 2013).

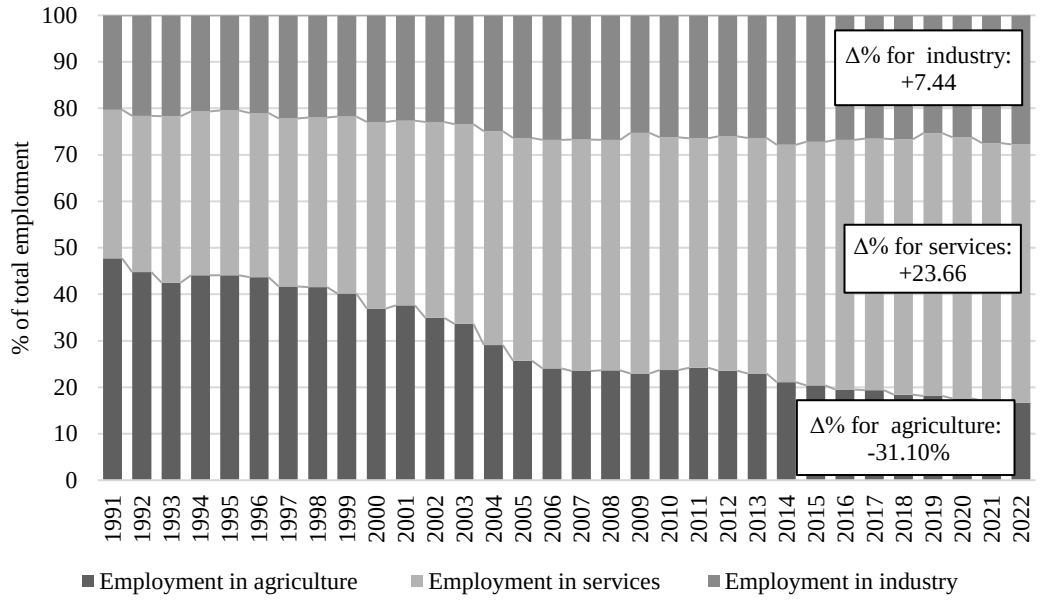


Figure 17. Employment rates in Türkiye for agriculture, industry, and services sectors, 1991-2022.

Source: World Bank database

The transformation of Türkiye's economy necessitated a shift toward a labor market with sophisticated skills. In response to these economic needs, Turkish governments implemented policies to expand higher education. Since the 1990s, Türkiye has gone through a transformation in its higher education system, characterized by a rapid increase in the number of universities (See Figure 18). The aim was to create a more skilled workforce by increasing the availability of higher education institutions to meet the new demands of the labor market. The policy included the opening of new

universities and programs, particularly in regions where higher education was limited. The first significant wave of expansion occurred in the early 1990s, and a second wave of expansion happened in the mid-2000s, and continued in the 2000s and 2010s, with a rapid increase in the establishment of private institutions.

Figure 3 and Figure 4 show the extent of this expansion. The number of universities increased from 75 in 2001 to 157 in 2012 and further to 208 in 2023, with the number of available quotas increased by 28% between 2012 and 2023. Furthermore, there has been a significant inflation in the number of faculties established in Türkiye over the decades, especially from the 1990s onwards (See Table 21). This rapid increase in the number of universities has raised concerns about the adequacy of quality and planning. The initial wave of higher education expansion in early 1990s attracted criticism for deviating from the plans. According to Öztürk and Dayıoğlu (2024), the original plan was to establish 9 public universities in 9 provinces by the 1998-1999 academic year. However, due to political pressures, the actual execution led to the establishment of 22 new public universities across 21 provinces in 1992, significantly exceeding the numbers outlined in the government's development plan. The second wave of higher education expansion in the mid-2000s also faced criticisms, mainly regarding the quality and equity of education. According to Caner et al. (2002), the rapid expansion of higher education in mid-2000s took place over a short period of time, during which resources (such as infrastructure) were limited. This likely led to a decrease in the quality of education and the productivity of new graduates.

Caner et al. (2022) also claim that the effectiveness of the university entrance exam in selecting students based on ability diminished during the expansion in mid-2000s. The authors claim that this decrease might have resulted in a lower average ability level among new college graduates, contributing to the decline in the college wage premium[19]. Furthermore, according to Polat (2017), the expansion of higher education

[19] There were significant changes made in the university admission system and the expansion of university quotas in Türkiye over the past decade as well. Between 2015 and 2021, the minimum achievement ranks required for admission into various programs were introduced (See Table A2 in Appendix). For example, the fields of engineering and teaching saw increases in minimum rank requirements. Additionally, the minimum score requirements remained stable from 2015 to 2020 but changed in 2021 (See Table A3 in Appendix) and were eventually removed in 2022-2023. The steady rise in the total quotas indicates efforts to expand access. However, the implementation of higher

in Türkiye, while aimed at increasing accessibility, faces challenges regarding equitable access. As shown by Caner and Okten (2013), students who enroll in private universities in Türkiye in this period come from higher income families. This suggests that private institutions may be attracting well-off students who can afford the tuition, leaving public universities more accessible to students from lower-income families. However, Caner and Okten (2013) further find that, of those who enter public universities, students from higher-income and more educated families are more likely to attend highly funded public universities.

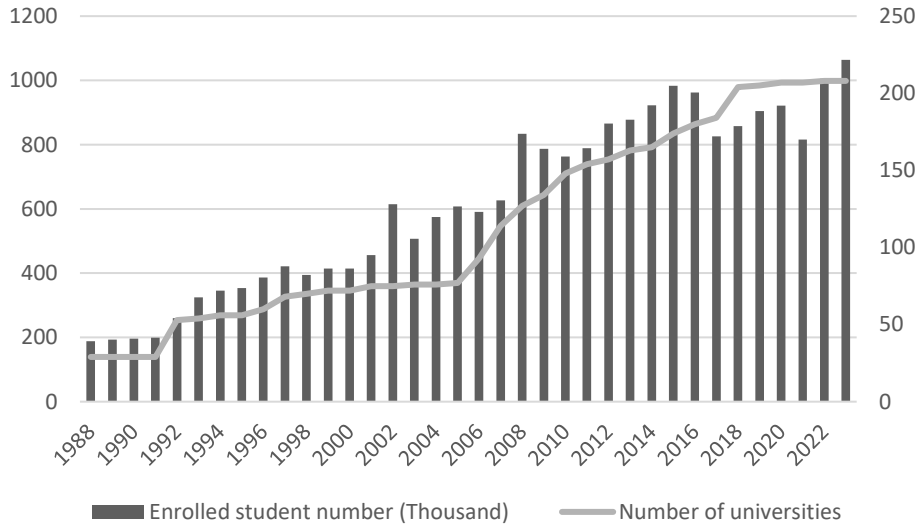


Figure 18. Number of Tertiary Education Institutions and Student Enrollments in Türkiye, 1988-2023

Source: CoHE[20]

minimum rank requirements has been accompanied by fluctuating percentages of unfilled quotas, with notable peaks in 2017 and 2021 (See Figure 19).

[20] The decree (no. 29779) published in the Official Gazette on July 23, 2016, mandated the closure of several universities in Türkiye. The universities listed in the decree are Altın Koza (İpek) University (Ankara), Bursa Orhangazi University (Bursa), Canik Başarı University (Samsun), Selahaddin Eyyubi University (Diyarbakır), Fatih University (Istanbul), Melikşah University (Kayseri), Mevlana University (Konya), Şifa University (Izmir), Turgut Özal University (Ankara), Zirve University (Gaziantep), Kanuni University (Adana), İzmir University (Izmir), Murat Hüdavendigar University (Istanbul), Gediz University (Izmir), and Süleyman Şah University (Istanbul). Students from these closed private universities were transferred to other state or private universities to continue their education without interruption. Additionally, Istanbul Şehir University was closed in 2020.

Given this backdrop, the third chapter of the thesis analyzed education and skill mismatches in the Turkish labor market. By focusing on the tertiary-educated wage earner individuals, the third chapter examines the alignment between higher education and labor market demands in Türkiye in terms of fields of study and aims to understand the extent to which specialized skills and knowledge are effectively used in the labor market. We expect to find a high incidence of field-of-study mismatch among tertiary-educated individuals in Türkiye, which leads to significant negative outcomes, including lower wages, even when controlling for other types of mismatches.

Table 21. Number of Faculties Established by Decade in Türkiye

	Social Sciences	Medicine and Dentistry	Engineering and Architecture	Teaching
Until 1990	24	31	26	19
1990-2000	43	41	33	29
2000-2010	48	55	48	25
2010-2020	76	210	143	24
2020 – 2024*	14	58	41	3
Total	205	395	291	100

*Source: CoHE, own calculations[21]. This does not include associate degree programs and covers only institutions in Türkiye and the Turkish Republic of Northern Cyprus. *As of June, 2024.*

To this end, we analyze the incidence, correlates, and outcomes of field-of-study mismatch for the higher-educated wage earners using PIAAC data set for 2015. To the best of our knowledge, no other study has simultaneously examined field-of-study mismatch, education mismatch and skill mismatch in the Turkish context by controlling foundational skills. By dissecting the individual effects of these three types of mismatches, the study shows how each type affects labor market outcomes, such as

[21] To classify faculties into different categories, the following keywords were used: For Social Sciences faculties, the keywords "iktisadi," "iktisat," "sosyal bilim," and "işletme" were identified. Engineering faculties were recognized using the keywords “mimar,” and "mühendis." For Medicine and Dentistry faculties, the keywords "tıp," "diş," and "sağlık" were employed. Lastly, for Teaching faculties, the keywords "eğitim" and "öğret" were used.

wages and job satisfaction. This analysis provides a more detailed and differentiated understanding of labor market mismatches, which is helpful for informing policy decisions aimed at improving the alignment between higher education outputs and labor market needs.

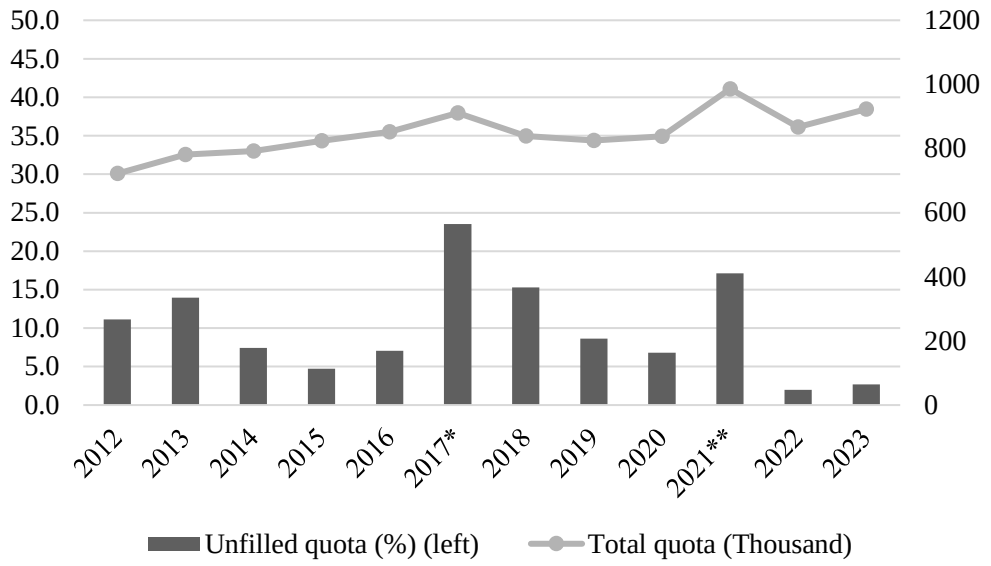


Figure 19. Tertiary Education Quotas in Türkiye (Total Quotas and Unfilled Percentages), 2012-2023

Source: SSPC (Student Selection and Placement Center)
* SSPC discontinued the transfer without exams for 2-year associate degree programs as of 2017.
** Before the first and second additional placements conducted in 2021.

The findings reveal a significant incidence of field-of-study mismatch, with 34% of full-time wage earners among higher educated working in jobs unrelated to their fields of study. This mismatch often coincides with overeducation, as 45% of those experiencing field-of-study mismatch are also overeducated. This dual mismatch indicates that nearly one in every six tertiary-educated worker is not only employed in jobs that are unrelated with their field of study but also exceeds the educational requirements of their jobs. Additionally, among those well-matched in terms of education level, 25% are still working in jobs that do not align with their field of study. These findings suggest a serious misalignment between the education system and labor market needs, where educational attainment does not necessarily guarantee job relevance. In fact, our results show that a significant majority of higher education graduates (78%) experience some form of mismatch.

The findings also show that field-of-study mismatch significantly affects wages of tertiary-educated workers, alongside other types of labor market mismatches. When education mismatch is measured using objective methods, the negative effect of field mismatch on wages is statistically significant. Individuals experiencing field-of-study mismatch face a significant wage penalty, earning less than their well-matched counterparts do. This finding remains consistent even when controlling for other forms of mismatches, such as overeducation and overskilling. However, when the subjective (self-assessed) method is used to measure education mismatch, the effect of field-of-study mismatch variable on wage is not statistically significant, suggesting that individuals struggle to accurately identify the requirements of their jobs in terms of education level and given the self-assessed education mismatch condition, field-of-study mismatch has no impact on earnings.

Importantly, when the analysis takes into account all three types of labor market mismatches, i.e. field-of-study mismatch, education mismatch and skill mismatch, and the required education level for the job is measured objectively, the wage effects of each type of mismatch are comparable in magnitude, meaning that each type of mismatch significantly reduces wages by a similar amount. The negative wage effect of field-of-study mismatch, even after controlling for education and skill mismatches, suggests that mismatches in the field of study are a source of wage penalties. This means that the labor market values not just the level of education and skills but also the relevance of the specific field of study to the job. In fact, the same magnitude of wage reduction suggests that the labor market penalizes field-of-study mismatch as severely as education and skill mismatches. This indicates that all three mismatches are equally detrimental to wage outcomes for tertiary-educated wage earners in Türkiye.

Finally, regarding job satisfaction, the analysis indicates that mismatches in field of study, education level, or skills do not significantly affect job satisfaction among tertiary-educated workers. This suggests that while mismatches affect earnings, they might not necessarily influence how satisfied individuals feel with their jobs. This might indicate that individuals are willing to trade off higher wages for other aspects of a job that contribute to their overall satisfaction. Factors such as earnings, public

sector employment, and firm size appear to have more significant effects in determining job satisfaction in Türkiye.

The structure of this chapter is as follows. The first section provides the theoretical and empirical literature on field-of-study mismatch. It begins with an overview of the theoretical frameworks used to explain field-of-study mismatch, followed by a review of empirical studies, including the wage effects of field-of-study mismatch, its impact on job satisfaction and previous studies focused on the Turkish context. The second section focuses on the data and methodology used in this study, explaining the approach for analyzing the correlates and outcomes of field-of-study mismatch using the Programme for the International Assessment of Adult Competencies (PIAAC) data by the OECD. The third section presents descriptive statistics for field-of-study mismatch among the highly educated in Türkiye. The following two sections examines the incidence, correlates and outcomes of field-of-study mismatch. Finally, the conclusion summarizes the key findings of the study and discusses their implications for the Turkish case.

3.2. Theoretical and Empirical Literature on Field-of-Study Mismatch

3.2.1. Theoretical Literature

Field-of-study mismatch occurs when the field in which an individual has specialized through their education is not the field in which they are employed. In the literature, the theoretical frameworks that are used to explain education mismatch are also used to explain field-of-study mismatch. Here, we will discuss four key theoretical perspectives: human capital theory, job matching theory, signaling theory, and assignment theory, which are explained in the context of education and skill mismatches in detail in the previous chapter of this thesis.

Human capital theory, introduced by Becker (1964), posits that the skills and knowledge acquired through education increase an individual's productivity and, consequently, their earnings. When there is field-of-study mismatch, the specific human capital (i.e., knowledge and skills directly related to the field of study) is not fully used. This leads to lower productivity as the worker is not able to apply the field related human capital to the job. According to HCT, firms adjust their production

process to make use of the available human capital stock. This means that, according to HCT, any type of mismatch between an individual's skills and job requirements should be temporary. There are situations where frictional mismatches can occur, such as when individuals are working in jobs that are not related to their field of study while they are looking for a new job that is more relevant to their field. This can happen, for example, when a person graduates with a degree in a specific field but is unable to find a job in that field immediately.

Signaling theory, proposed by Spence (1973), argues that education serves as a signal to employers about a worker's abilities and potential productivity. Employers often have different perceptions of different fields of study, depending on the specific skills and knowledge associated with each field. Therefore, employers may believe that certain fields signal higher productivity, leading them to hire workers from those fields. Still, when there is a field-of-study mismatch, this reduces the effectiveness of educational credentials as signals of worker capability. The difference is that field-of-study mismatch weakens the signal sent by the type of education, whereas education mismatch affects the overall signal of educational attainment.

Job Competition Theory provides a similar perspective, focusing on how employers select workers based on educational credentials as a sorting mechanism, rather than directly on the relevance of the field of study to the job. In this theory, wages are determined by the job characteristics rather than the worker's field of study. Therefore, there cannot be a wage penalty or premium for mismatch. According to the job competition theory, employers may be willing to hire individuals from different fields than the one related to the occupation. This may occur due to several reasons. For example, if employers are not able to find enough workers who graduated from the related field, they will draw workers down from the hiring queue and they may end up employing those that come from other fields.

In the assignment theory, on the other hand, it is both the demand and supply factors that determine the allocation process. Workers maximize utility, so they choose some jobs or occupations over others. At the same time, there are certain jobs or occupations that are available for them. In this framework, graduates from certain fields might be more fitting for certain jobs, but these jobs might not be available for them. As a result,

they may end up working in unrelated jobs or occupations. However, the wages they earn are determined by their productivity in those assigned jobs.

3.2.2. Empirical Literature on Field-of-Study Mismatch

A growing body of empirical research aims to understand the incidence and effects of field-of-study mismatch on labor market outcomes. To assess the incidence, two types of measures are used, which are a subjective method and an objective method (Groot and Massen van den Brink, 2000). For the first method, which is the subjective method, workers are asked how they perceived the alignment between their educational background and their actual occupation. A pioneering study by Robst (2007) examined the field-of-study mismatch in the U.S. using a subjective method, where workers assessed the relatedness of their jobs to their highest degree field. The study showed that 55% of workers reported their job as closely related to their field of study, while 25% said it was somewhat related, and 20% found it not related at all. Robst found that workers experiencing a mismatch faced wage penalties.

According to Robst (2007), field-of-study mismatch can arise from either demand-related or supply-related factors. Supply-related factors include factors such as pay, promotion opportunities, career prospects, working conditions, and location. A demand-related field-of-study mismatch, on the other hand, is considered involuntary, as the individual intends to find a match but is unable to do so due to limited job opportunities or other factors. Robst (2007) finds that the wage effects differ between demand-related and supply-related reasons, indicating that the underlying factors are important in shaping the earnings outcomes.

For the objective method, individuals are asked about their field of study for their highest level of qualification. This method involves assigning individuals to different occupational groups based on their field of study and matching these fields to occupations using the ISCO-08 classification. If the field of study reported by a worker does not correspond to the field assigned to their occupation, the worker is classified as mismatched. Montt (2015) analyze the incidence and effect of field-of-study mismatch using data from the PIAAC. This study employs an objective method for measuring field-of-study mismatch. Montt (2015) finds that on average, across the 22 countries studied, 39% of workers are employed in fields different from their field of

study. This prevalence varies between countries, with mismatch rates ranging from 23% in Finland to over 45% in Australia, UK, Italy, Japan, Korea, and the United States. He further finds that field-of-study mismatch is associated with significant wage penalties.

The choice of field of study not only shapes an individual's skill set and knowledge, but also influences their career, earnings potential, and likelihood of experiencing a field-of-study mismatch. The level of difficulty in learning these skills could differ based on individual abilities. Arcidiacono (2004), for example, finds that individuals with high math ability have certain preferences when it comes to choosing their college majors. High ability individuals prefer majors that they have a strong liking for the subject of these majors. In fact, for high ability individuals, the preference for the field is found to be more important than the returns to abilities in different majors.

3.2.2.1. Wage Effects of Field-of-Study Mismatch

After the influential work by Robst (2007), studies of field-of-study mismatch have typically used a Mincer-type earnings equation to estimate the effect on wages:

$$w_i = \emptyset_1 F_i + \emptyset_2 M_i + X_i'\beta + \mu_i \qquad (4)$$

where w_i is the hourly earnings in deciles, F is the dummy variable for field-of-study and M[22] is the dummy variable for field-of-study mismatch, so that the coefficient $\emptyset_2$ represents the wage effect of field-of-study mismatch. X is a vector of other control variables that include experience and μ is the error term.

Studies show that workers who are mismatched with their field of study typically earn lower wages than well-matched workers (Robst, 2007; McGuinness and Sloane, 2011), even when accounting for skill heterogeneity (Persson et al., 2010) or education mismatch (Robst, 2008). This is because they are unable to use the field-specific knowledge on their current job. They may also lack field-related skills that matched workers have. This results in lower productivity and a lower wage level than the well-

[22] Robst (2007) differentiated between being partially mismatched or completely mismatched. The wage regression that is used to assess the presence of wage effects is: $\log w_i = \emptyset_1 F_i + \emptyset_2 PM_i + \emptyset_2 CM_i + X_i'\beta + \mu_i$ where PM stands for partial mismatch and CM stands for complete mismatch.

matched workers. On the other hand, there are cases where some individuals may choose to be mismatched if it leads to higher wages. For instance, if there are certain occupations that offer higher wages, an individual may apply to those jobs even if they are not related to their field of study. In such cases, it is the wage variability that encourages field-of-study mismatch (Montt, 2015).

3.2.2.2. Impact on Job satisfaction

In the literature, there have been different findings regarding the relationship between field-of-study mismatch and job satisfaction. Bender and Heywood (2006) assess the implications of field-of-study mismatch for individuals holding doctoral degrees in the field of science and find that being mismatched leads to a decline in job satisfaction. Furthermore, they find that even when mismatch leads to higher pay or increased opportunities for promotion, the overall job satisfaction decreases. On the other hand, Allen and Van der Velden (2001) find no significant effect of field-of-study mismatch on job satisfaction, but find that it is influenced mainly from skill mismatch.

Wolniak and Pascarella (2005) focus on the relationship between field-of-study mismatch and job satisfaction with a focus on the effects of earnings. They find that individuals who believed that their current job was relevant to their field-of-study reported significantly higher levels of job satisfaction. However, this higher job satisfaction is not only a result of the alignment between the field and the job, but is indirectly influenced by the income they earned. In fact, income has a significantly larger effect on job satisfaction compared to the match between the field of study and the job.

Wolniak and Pascarella (2005) further distinguish between perceived and actual field-of-study mismatch. Perceived mismatch is based on the individual's own assessment of how well their job corresponds to what they studied. Actual mismatch is determined by comparing the specific requirements of the job with the individual's field of study. They find that the actual mismatch had either no effect or a significant negative effect on job satisfaction. In analyzing the relationship between perceived mismatch and job satisfaction, the results showed that only perceived mismatch had a significant positive effect on income, which led to positive significant indirect effects on job satisfaction.

In other words, perceived mismatch positively influenced job satisfaction through the increase in income.

3.2.2.3. Studies Focusing on the Persistence of Field-of-Study Mismatch

The persistence of field-of-study mismatch refers to the situation where individuals continue to experience a mismatch between their field of study and the requirements of their job over an extended period of time. In other words, it describes cases where people remain employed in positions that do not use the knowledge and skills they acquired through their formal education. Although the persistence of field-of-study mismatch is beyond the scope of this paper, it is explained briefly due to its importance for the dynamics of the labor market.

In the literature, two hypotheses have been used to explain the persistence of labor market mismatch: the stepping stone hypothesis and the trap hypothesis. According to the stepping stone hypothesis, accepting a mismatched job can be viewed as a means to gain work experience. Workers with field-of-study mismatch may compensate for their initial skill deficiencies by acquiring additional skills while on the job. Nordin et al. (2010) find that the return on experience for field mismatched workers is notably higher than for well-matched workers, suggesting that mismatched employees can mitigate their initial wage penalty by gaining relevant experience during their employment. Similarly, Malamud (2010) found that although being mismatched after graduation leads to a wage loss, these mismatched workers do not significantly earn lower wages six years after graduation when compared to graduates who are well-matched in their jobs at job entry. This implies that field-of-study mismatch tends to be a temporary phenomenon, as the wage gap diminishes over time as these employees acquire skills and experience.

The trap hypothesis suggests that once individuals accept a job that does not fully match their education, they may face challenges in transitioning to better-matched positions. Albert et al. (2023) find that although both education mismatch and field-of-study mismatch are quite persistent, field-of-study mismatch tends to persist more. Individuals that are mismatched horizontally remain in their jobs as they do not have enough incentives to look for a job that better matches their field of study, partly due to other compensating job features (Albert et al.,2023).

3.2.2.4. Empirical Literature on Türkiye

Field of study mismatch has not been extensively studied in the context of Türkiye, but there has been an increase in studies examining the incidence and determinants of these mismatches in recent years. The OECD (2016), by using the PIAAC data, provides findings on the incidence of field of study mismatch in a number of countries including Türkiye, for both upper secondary and tertiary levels. The results show that Türkiye has a higher percentage of field of study mismatch (43.76%) compared to the OECD average (39.64%).

Suna et al. (2020) address the field-of-study mismatch in vocational education in Türkiye. Their study, based on interviews and questionnaires, suggests that graduates of vocational education and training programs often find employment outside their field-of-study. This study focuses only on secondary level vocational education graduates. They find a high incidence of field-of-study mismatch among Vocational and Technical Anatolian High School (VTAH) graduates, with many graduates working in jobs that do not match their vocational training.

Orbay and Aydede (2021) use Labour Force Surveys from 2014 to 2016 to examine the incidence and effects of skill mismatch on wages in the Turkish labor market. The study employs two indices to measure the degree of relatedness between workers' education and their occupations for the classification of workers into matched or mismatched categories. The study finds that almost 40% of university graduates are employed in jobs unrelated to their field of study. They further find that for overeducated university graduates, field of study mismatch does not have any significant effect on wages. This suggests that most jobs for university graduates do not require specialization in any specific field of study in Türkiye.

In his doctoral thesis, Ege (2020) analyzed education and field-of-study mismatches among full-time employees in Türkiye in four categories, using the Labor Force Survey. These are education mismatch, field of study mismatch, full-mismatch (simultaneous education and field-of-study mismatch) and no mismatch. They found that the incidence of field-of-study mismatch in Türkiye is 30.3% in 2016. The incidence is significantly higher among graduates from vocational and technical high schools (VTHS) compared to those from higher education institutions, with VTHS

showing a mismatch incidence of 44.9%, while for higher education graduates it is 24.0% in 2016.

The findings further show that (i) women are less likely than men to experience any form of mismatch; (ii) younger employees (age 20-29) are less likely to be only overeducated or to have a mere field of study mismatch compared to older employees, but they are more likely to experience a full mismatch. In terms of job-specific characteristics (i) the likelihood of mismatch increases with firm size; (ii) those working in the public sector are less likely to be mismatched by field of study compared to private sector employees; (iii) temporary job holders and those not registered in the social security system (i.e. informal workers) are more likely to be fully mismatched and overeducated.

More recently, Ege and Erdil (2023) analyze the wage effects of field-of-study mismatch and education mismatch in Türkiye for 2016. The study finds that field-of-study mismatch has mixed effects on wages for higher education graduates. At lower quantiles of the wage distribution, field-of-study mismatch results in wage penalties, but at higher quantiles, field mismatched workers earn more than well-matched workers. This suggests that highly skilled employees who are mismatched by field can earn higher wages. However, for VTAH graduates, they find wage penalties in all quantiles.

Aytun and Meçik (2023) analyze the income effects of horizontal mismatch for Turkish higher education graduates using the Labor Force Survey from 2019. The results indicate that a matching between field of study and occupation leads to higher wages and a one-point decrease in the matching index leads to a 21.9% wage penalty. Furthermore, the analysis shows significant variation in the wage returns to matching across different fields of study and income quantiles. For example, business and administration graduates experience higher wage returns at lower income levels, while engineering graduates benefit more at higher income levels.

Overall, studies on field-of-study mismatch in Türkiye consistently find a high incidence of mismatch, but mixed wage effects. While the literature is narrower compared to other types of labor market mismatch, these studies show the importance of addressing field of study mismatch to understand the alignment between education

and employment in Türkiye in a more complete way. Our contribution to this literature involves examining all types of labor market mismatch simultaneously with a special dataset that allows for controlling other types of mismatches and individual skills. By doing so, we aim to provide a more comprehensive understanding of these mismatches in the context of Türkiye.

3.3. Data and Methodology

This study uses data from the Programme for the International Assessment of Adult Competencies (PIAAC), which is an international survey conducted by the Organization for Economic Co-operation and Development (OECD). PIAAC aims to assess and compare the basic skills and competencies of adults in around 40 countries, including OECD member countries and partner countries. The survey assesses both foundational skills (literacy and numeracy) and problem-solving skills in technology-rich environments. Since the survey methodology and content of PIAAC were described in detail in Chapter 2 of this thesis, further analysis will build on this information to avoid repetitions.

PIAAC collects detailed information on respondents' highest educational qualifications and areas of study. Participants also provide detailed job titles, which are classified using the International Standard Classification of Occupations (ISCO) codes. Hence, PIAAC is suitable for studying field-of-study mismatch due to this collection of information, as it allows mapping of jobs to fields of study and enables identification of mismatches. Additionally, although PIAAC is cross-sectional, it helps us understand field-of-study mismatch in conjunction with other types of labor market mismatches, such as education and skill mismatches. This makes PIAAC useful in understanding the causes and outcomes of labor market mismatch.

In the literature, the ISCO codes are employed to link occupational codes with specific fields of study (as seen in Wolbers, 2003). The assignment maps each occupation to one or more of the nine educational fields. If a respondent reports an educational field that does not align with the field(s) associated with their occupation, they are considered to have a field of study mismatch. PIAAC survey categorizes fields of study into nine groups, which corresponds to the Fields of Education and Training (FoET) categories:

- General Programmes
- Teacher Training and Education Science
- Humanities, Languages and Arts
- Social Sciences, Business and Law
- Science, Mathematics and Computing
- Engineering, Manufacturing and Construction
- Agriculture and Veterinary
- Health and Welfare
- Services

This study focuses only on full-time wage earners in Türkiye with tertiary education. This focus is due to the higher economic returns associated with tertiary education compared to lower levels in Türkiye. Moreover, focusing on tertiary education may provide information about the gender wage gap. Women who attain tertiary education in Türkiye represent a more selective group with different characteristics compared to the broader population. Lastly, differentiating fields at the upper secondary level is challenging with the data. To give more detail, in analyses focusing on field-of-study mismatch among secondary or upper secondary graduates with PIAAC, the variable "Area of Study" (B_Q01b) should be used to differentiate between general and vocational programs (level 4 in the ISCED classification). In that case, programs in “general education”, along with “humanities, languages, and arts”, would be classified as general education programs, where the remaining programs would be classified as vocational programs. However, general programs cannot be linked with specific fields or mapped to occupations to find mismatches. Therefore, focusing on tertiary education not only addresses this limitation but also aligns with the study's objective of examining the effects of higher education on labor market outcomes in Türkiye.

This chapter only uses data from Türkiye, in line with the focus of this thesis, which aims to analyze the field-of-study mismatch in the Turkish labor market. Furthermore, individuals younger than 20 and older than 54 are excluded to avoid including those who are likely still in education and not fully active in the labor market. Including individuals older than 54 might distort the analysis because the social security system leads to an increase in retirement rates beyond this age. Finally, certain categories of workers and occupational groups have been excluded from the analysis. This includes

self-employed individuals, as well as those who majored in "general programmes." Furthermore, occupations in the armed forces categorized under ISCO major group 0, legislators, and senior officials classified under ISCO 111, in addition to refuse workers and other elementary occupations within the ISCO 961-962 group, have been excluded from the analysis.

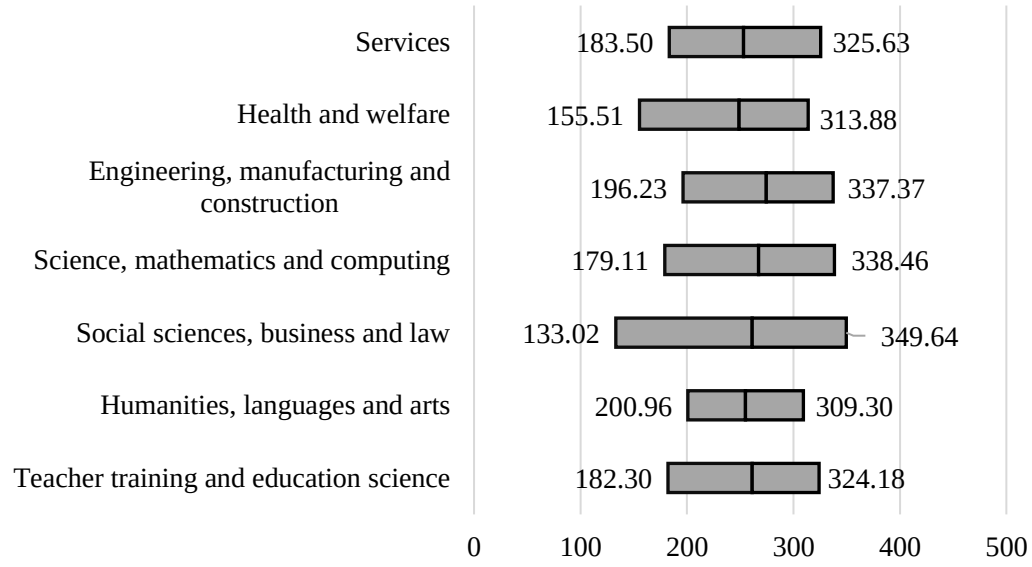


Figure 20. Distribution of Average of PIAAC Foundational (Numeracy and Literacy) Skill Scores Among All Tertiary Education Graduates in Türkiye (2015) (Employed, Unemployed, and OLF)

Note: Own calculations. The bars represent the minimum, maximum, and mean scores for each field.

The results from the PIAAC survey, which provide cross-sectional data, show that there are differences in numeracy and literacy skills across different fields of study (See Figure 20). Since PIAAC is not panel data, it does not allow us to analyze the effect of the recent expansion of higher education on this variability. However, it can show if further expansion of higher education could be risky in terms of labor market mismatch. Moreover, PIAAC is instrumental for examining the state of skill heterogeneity in the labor market. One significant advantage of the PIAAC data is its ability to directly measure foundational skills, which helps us control the unobserved abilities of individuals that are often not captured in other datasets. Information on qualification mismatch (i.e. both education mismatch and field-of-study mismatch) often leads to the assumption that individuals with the same levels of education or

fields of study have similar abilities. In reality, the education system does not produce homogeneous employees. This direct measurement of skills helps us better understand qualification mismatch, making numeracy skills serve as important controls.

Figure 3.1 presents the range and mean skill scores for graduates of different fields of study. The skill scores are derived from the PIAAC survey, which measures numeracy and literacy. It shows that the graduates from fields like "Engineering, Manufacturing and Construction", and "Science, Mathematics and Computing" have the highest mean scores. This suggests that these fields not only attract individuals with strong quantitative and analytical skills but also enhance those skills. On the other hand, graduates from fields such as "Health and Welfare" show a larger range of scores with relatively lower averages. This might indicate that these fields include a wide range of programs with different emphases on numeracy and literacy skills. For instance, the Health and Welfare field includes both highly technical healthcare programs and more general welfare studies, leading to a wider dispersion in skill levels among graduates. The field of "Social Sciences, Business and Law" also has a wide range of skill scores. This shows the nature of programs under this category. There are both more quantitative studies in this field, such as economics, and also more qualitative studies, such as sociology and law.

3.3.1. Analysis of the Correlates of Field-of- Study Mismatch

To analyze the correlates of field-of-study mismatch, we employ probit models considering various worker and job characteristics. We define the probit equation as follows:

$$y_i^{F*} = X_i^F \beta + \epsilon_i^F$$

where y_i^{F*} is the latent outcome variable for field-of-study mismatch which have categories matched and mismatched. I$[y^* > 0]$ is an indicator function that takes the value 1 if the mismatch is present and 0 otherwise. X_i represents control variables for factors that might influence the presence of a mismatch (See Table 22). $\in_i$ is the error term assumed to have a standard normal distribution. While acknowledging potential specification issues, the normality assumption of the error term remains standard (Wooldridge, 2003). This approach simplifies the estimation and interpretation,

focusing mainly on the influence of explanatory variables on the likelihood of being mismatched in terms of field of study, rather than the precise magnitudes of mismatch. This is because the magnitude of the coefficients β_j does not provide information by themselves without considering their effect on the mismatch probability.

This model is aimed at identifying factors that contribute to whether an individual's field of study is appropriately matched to their job requirements. As in the general labor market mismatch models, the focus here is not directly on the latent variable y_i^{F*} since it is not directly observable and lacks a practical unit of measurement. Instead, we concentrate on the impact of the variables X_i on the probability $P(y = 1|x)$, which is the probability that an individual is mismatched based on their field of study, given their characteristics captured by X_i.

Table 22. Control Variables for Probit Model Analyzing Field-of-Study Mismatch

Variable	**Type**	**Categories**
Overeducated	Dummy	1 if overeducated, 0 otherwise
Overskilled	Dummy	1 if overskilled, 0 otherwise
Gender of individual	Dummy	1 if female, 0 if male
Years of qualifications	Continuous	Total years of highest level of education
Numeracy score	Continuous	Numeracy score in PIAAC
Experience	Continuous	Measured in years
Squared experience	Continuous	Experience squared divided by 100
Employment sector	Dummy	1 if public sector, 0 if private sector
Age group	Categorical	Age groups (20-29, 30-44, 45-54)
Size of the firm	Categorical	Small, Medium, Large
Field of study	Categorical	Specific fields

3.3.2. Analysis of the Outcomes of Field-of-Study Mismatch

3.3.2.1.Wages

PIAAC provides wage data for Türkiye in deciles only. Rather than an ordered probit model, this thesis uses linear regression estimated by OLS since the wage data for Türkiye is divided into ten deciles. The use of OLS for the analysis was supported by the consistency of the results from the ordered probit and OLS models that were initially used. This approach simplifies the interpretation of results while maintaining the robustness of the findings. We integrate different worker and job characteristics to examine the effects of field-of-study mismatch on earnings. The model can be expressed as:

$$Y_i^* = \alpha + \beta_1 F_i + \beta_2 FMM_i + \delta_1 AE_i + \delta_2 OD_i + +\delta_3 OS_i + + \gamma' \mathrm{X}_i + \varepsilon_i$$

where Y_i^* is the wage outcome for individual i. F_i is a categorical variable represents the field of study, showing the specific academic field of the individual. FMM_i is a dummy variable for field of study mismatch, indicating whether an individual's job aligns with their field of study. AE_i is the actual number of years of schooling that individual i has completed. Overeducation (OD_i) and overskilling (OS_i) are included as dummy variables for individual i. δ_2 and δ_3 are the average wage differential associated with being overeducated or overskilled, respectively. X_i represents other control variables (see Table 2) included in the model, and ε_i is the error term.

3.3.2.2. Job Satisfaction

To analyze the outcomes of labor market mismatch on job satisfaction, we use ordinal probit models that incorporate both worker and job characteristics. The ordinal probit model is used when analyzing dependent variables that are categorical with a clear ordering but where the distances between categories are unknown or not equal. This model is useful for variables which are ranging across categories. Hence, ordinal probit models are suitable given the nature of the outcome variable job satisfaction, which is ordinal, ranging from 1 to 5. The objective is to assess how field-of-study mismatch can affect the likelihood that an individual will report each specific level of job satisfaction. The variable representing job satisfaction is captured using a five-point

Likert scale, which has responses from "Extremely dissatisfied" to "Extremely satisfied," with intermediate levels. The model can be expressed as:

$$S_i^* = \alpha + \beta_1 F_i + \beta_2 FMM_i + \delta_1 OD_i + \delta_2 OS_i + \gamma' \mathrm{X}_i + \varepsilon_i$$

where F_i is field of study, capturing the academic discipline of individual i. FMM_i is a dummy variable for field-of-study mismatch, indicating whether the individual's job aligns with their field of study. AE_i is the actual education in years of individual i, OD_i is the overeducation dummy, taking a value of 1 if individual i is overeducated, 0 otherwise. Similarly, OS_i is the overskilled dummy. X_i includes other control variables including the level of education, and ϵ_i is the error term.

Table 23. Control Variables used in the Analysis of Outcomes of Field-of-Study Mismatch

Variables	**Description**
Actual education	In years (Continuous)
Overeducation	1 if overeducated, 0 ow
Overskilled	1 if overskilled, 0 otherwise
Female	1 if female, 0 if male
Experience	Years of paid work experience (Continuous)
Experience squared	Experience squared divided by 100
Numeracy score	Score of numeracy skills (Continuous)
Public sector	1 if employed in the public sector, 0 if in the private sector
Medium-sized enterprise	1 if employed in a medium-sized enterprise, 0 otherwise
Large-sized enterprise	1 if employed in a large-sized enterprise, 0 otherwise

Table 23 presents the independent variables used to examine the effects of field of study mismatch on wage levels and job satisfaction. In the literature, the sign for the overeducation dummy variable is typically expected to be negative. This is because the overeducation dummy variable compares overeducated individuals to those who have a similar level of education but whose jobs are well-matched to their qualifications. Similarly, based on the literature and our previous findings in Part 1 of this thesis, the expected sign of the coefficient for the overskilled dummy variable is likely to be negative. Furthermore, empirical studies often find that overskilled workers tend to earn less than their well-matched counterparts because their higher skill levels are not fully utilized in their jobs. This can lead to lower job satisfaction, reduced productivity, and lower wages.

The coefficient for the actual education variable, which represents the actual number of years of schooling that an individual has completed, is expected to be positive. Additional years of education are associated with higher earnings due to both the direct benefits of increased knowledge and skills, and the signaling effect, where higher education levels signal higher ability and productivity to employers. Moreover, higher levels of education can lead to more job satisfaction due to better job opportunities, higher wages, and better working conditions. However, educated individuals may have different preferences that influence their job satisfaction, such as challenging work, which can affect their overall satisfaction levels. Similarly, higher numeracy skills are generally expected to have a positive impact on wages, and they can positively impact job satisfaction if individuals with high numeracy skills find themselves in jobs that can fully use their skills.

The expected sign of the female coefficient for tertiary-educated women is likely to be negative for wages, reflecting the gender wage gap, and could be either positive or negative for job satisfaction, depending on various job-related and personal factors. The coefficient for work experience is generally expected to be positive for wages, whereas the coefficient for the squared term of work experience is usually expected to be negative. This reflects the diminishing returns to experience. Initially, wages increase rapidly with experience, but the growth rate diminishes over time. The relationship between experience and job satisfaction can also be non-linear and might follow a similar pattern.

The impact of working in the public sector on wages is expected to be positive. Furthermore, public sector jobs often come with greater job security, and more predictable career progression, which can contribute to higher job satisfaction. Finally, a negative relationship between firm size and job satisfaction is generally expected due to several factors such as decreased autonomy, more bureaucratic layers and communication challenges (Garcia-Serrano, 2008), which is also the case for Türkiye (Tansel and Gazioğlu, 2014).

3.4. Descriptive Statistics for Field-of-Study Mismatch

Table 24 provides an overview of the demographic and employment characteristics of tertiary-educated individuals in full-time wage employment in Türkiye as of 2015, based on PIAAC dataset. The data indicates that 65.7% of the sample are males, while females make up 34.3%. In terms of educational attainment, the most common qualification among these workers is a bachelor's degree, making up 67.1% of individuals. Associate degrees are held by 23.7%, whereas 9.2%, hold master's or research degrees. For education mismatch, 49.8% of individuals are well-matched according to the RM method, whereas 45.1% are overeducated, and 5.2% are undereducated. This suggests that nearly half of the tertiary-educated workers may be underutilizing their educational qualifications. On the other hand, for the SA method of education mismatch, 68.3% are well-matched, where 27.2% are overeducated and 4.5% undereducated according to their own assessments. In terms of skill mismatch, over half (52.8%) of the tertiary-educated full-time workers are well-matched to their job demands, whereas 40.9% are overskilled, and 6.3% are underskilled. Given the relatively low representation of undereducated and underskilled individuals within full-time wage earners with tertiary education group, we include only overeducation and overskilling in our analysis of correlates and outcomes[23].

[23] In the analysis, undereducated and underskilled groups were not included due to their relatively small sample sizes. Instead, the probit results for these groups are provided in the appendix Table A1 to illustrate that the results are robust to the alternative specification where we include these groups, ensuring the main analysis remains focused and robust.

Table 24. Descriptive Statistics for Field of Study Mismatch Analysis, Tertiary-educated individuals engaged in full-time wage employment in Türkiye (2015)

Variable	Category	Freq.	%
Gender	Male (0)	280	65.7
	Female (1)	146	34.3
Education Level	Associate degree	101	23.7
	Bachelor's degree	286	67.1
	Master/research degree	39	9.2
Education Mismatch (RM)	Well-matched	212	49.8
	Over-educated	192	45.1
	Under-educated	22	5.2
Education Mismatch (SA)	Well-matched	291	68.3
	Over-educated	116	27.2
	Under-educated	19	4.5
Skills Mismatch	Well-matched	225	52.8
	Over-skilled	174	40.9
	Under-skilled	27	6.3
Employment Sector	Private sector (0)	223	52.4
	Public sector (1)	203	47.7
Firm Size	Micro/small-sized enterprises (w<50)	235	55.2
	Medium-sized enterprises (49<w<250)	109	25.6
	Large-sized enterprises (w>249)	82	19.3

Regarding the employment sector, there is an even distribution between the private (52.4%) and public (47.7%) sectors, suggesting balanced employment in these sectors for tertiary-educated individuals[24]. Firm size distribution shows that 55.2% are

[24] For comparison, Ege's (2020) study uses the 2016 Labor Force Survey, a large dataset consisting of 29,637 individuals in the group of higher-education (including associate degrees) wage-earners. Women represent 38.72%, the public sector represents 54.26%, and small and micro-sized enterprises represent 49.01% of that large dataset. This rough comparison indicates that although our sample size is small for the analysis of field-of-study mismatch, its general characteristics are quite well-matched with large population samples for similar periods.

employed in micro or small-sized enterprises. Medium-sized enterprises constitute 25.6%, and large-sized enterprises account for 19.3% of employment.

Table 25. Distribution of Tertiary Education Fields Among Full-Time Wage Earners in Türkiye (2015) [25]

Major	**Percent**
Teacher training and education science	21.9
Humanities, languages, and arts	4.5
Social sciences, business, and law	33.0
Science, mathematics, and computing	12.9
Engineering, manufacturing, and construction	14.9
Agriculture and veterinary	2.0
Health and welfare	7.0
Services	3.6
Obs.	442

Note: Own calculations from the PIAAC dataset.

Table 25 presents the distribution of tertiary-educated, full-time wage earners in Türkiye across various fields of study. The results show that, the most popular field of study among the sample is Social Sciences, Business, and Law (33.0%). Teacher Training and Education Science field attracts the second highest proportion of individuals (21.9%). Moreover, a significant portion is trained in Engineering, Manufacturing, and Construction (14.9%) and Science, Mathematics and Computing (12.9%) fields. These fields are components of the STEM category, but they also include other non-STEM areas. On the other hand, the smallest groups are those educated in Services (3.6%) and Agriculture and Veterinary (2.0%)[26]. In comparison,

[25] In comparison, Ege (2020) finds with the Labor Force Survey (total 29,637 observations) in 2016 that the distribution of students in higher education across various fields in Turkey was as follows: 18.45% in Teacher Training and Education Science, 8.42% in Humanities, Languages, and Arts, 38.06% in Social Sciences, Business, and Law, 6.54% in Science, Mathematics, and Computing, 16.25% in Engineering, Manufacturing, and Construction, 3.36% in Agriculture and Veterinary, 8.06% in Health and Welfare, and 4.87% in Service.

[26] The "Agriculture and Veterinary" category is excluded from probit analyses due to its small sample size (n=9). After this exclusion, observation number falls to 426.

Ege (2020) uses the Labor Force Survey (total 29,637 observations) in 2016 to analyze the field-of-study mismatch in Türkiye. Our sample, although smaller, shows a similar distribution. Given Ege's significantly larger sample size, we use his descriptive statistics as a benchmark and find that our sample is reasonably comparable. While we acknowledge there are differences, the overall characteristics suggest that our sample is suitable for analysis.

Figure 21 presents the percentage of graduates from various fields who are considered overeducated. The results indicate that the Services sector exhibits the highest level of overeducation with 86.7% of its graduates overeducated for their jobs, suggesting a disparity between education and job requirements. However, observation numbers are low for this field. The seemingly high percentage of overeducation in the Services sector could be influenced by the types of degrees typically provided by universities. Many service-related jobs, such as those in tourism, hospitality, and retail, might not require formal university degrees, or the degrees offered may not directly correspond to the specific skills demanded by these industries. This sector is followed by "Social Sciences, Business, and Law", "Science, Mathematics, and Computing", and "Humanities, Languages and Arts" with overeducation rates over 50%. This indicates a potential oversupply of highly educated professionals or a lack of adequate jobs that match their qualifications. On the other hand, fields such as "Engineering, Manufacturing, and Construction" and "Health and Welfare" show a much lower overeducation rate.

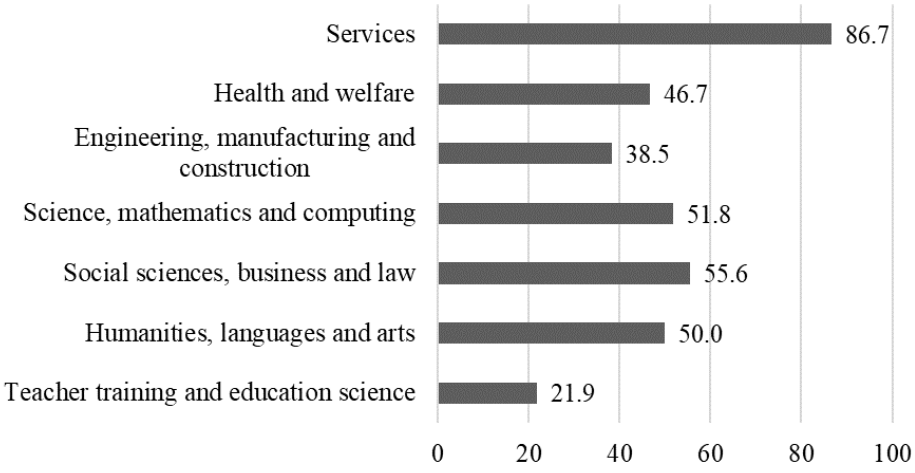


Figure 21. Percentage of Overeducation (RM) Among Graduates by Field of Study

3.5. The Incidence and Correlates of Field-of-Study Mismatch Among the Highly Educated in Türkiye

The analysis of field-of-study mismatch among full-time wage earners with tertiary education show that 66.20% of individuals are working in jobs that align with their field of study, while 33.80% are field-of-study mismatched. This rate is lower than the 43.76% reported by the OECD (2016) for Türkiye using the same data, but the OECD study includes both upper secondary and tertiary levels as well as vocational high schools. The higher mismatch rate in the OECD study is likely due to this broader sample, since vocational high school graduates might be experiencing higher incidences of mismatch, contributing to the overall higher rate observed by the OECD. Our finding is more comparable with Ege (2020), who reported a 24.0% incidence of field-of-study mismatch among full-time employees with higher education in 2016.

Table 26. The incidence of field-of-study mismatch in Türkiye, full-time employed workers (%), 2015

	Male	**Female**	**All**
Associate Degree	49.3	42.2	47.2
Bachelor's Degree	36.8	19.3	30.6
Master/Research Degree	26.9	28.6	27.5
TOTAL	39.3	23.3	33.8

Table 26 presents data on the incidence of field-of-study mismatch among full-time employed workers in Türkiye, differentiated by gender and level of educational attainment. When breaking down by gender, it is observed that a larger percentage of men, 39.29%, experience a field-of-study mismatch compared to 23.29% of women. These findings suggest that women with tertiary education in Türkiye are more likely to find employment in jobs that correspond to their field of study. For men, the higher rate of mismatch might indicate either a broader range of job opportunities outside

their field of study or challenges in finding jobs that directly correspond to their educational background.

Overall, 47.2% of associate degree holders ("önlisans" in Turkish) are mismatched, indicating nearly half of individuals in this category find themselves in jobs not aligned with their field of study. Ege (2020) also finds such high incidence of field-of-study mismatch, 44.9% of the sample, among those associate degree holders. The incidence of field-of-study mismatch decreases with higher levels of education. Among those with a bachelor's degree, the overall incidence of mismatch is 30.6%, suggesting a better alignment between education and employment at this level. For workers with a master's or research degree, the rate of mismatch further decreases to 27.5%. This pattern suggests that higher education may offer better alignment between individuals' fields of study and their jobs, due to the specialized nature of higher-level degrees.

Table 27. Education Mismatch by Field-of-Study (FoS) Mismatch Status for Tertiary Educated Full-Time Wage Earners in Türkiye, 2015

		No FoS Mismatch	**FoS Mismatched**
Education Mismatch (RM)	**Overeducated**	40.07	54.86
	Well-matched	56.03	37.50
	Undereducated	3.90	7.64

The data indicates gender disparities in field-of-study mismatch across different levels of education. In associate and bachelor's degrees, men tend to experience a higher incidence of mismatch than women. At the associate degree level, the mismatch incidence for women is 42.4%, which, while lower than their male counterparts (49.3%), still indicates a significant portion of women in jobs not aligned with their field of study. At the bachelor's degree level, the incidence of mismatch among men is 36.8%, which is higher than that of their female counterparts (19.3%). At the

master's or research degree level, the rate of mismatch among women is 28.6%. For men with master's or research degrees, the mismatch rate decreases to 26.9%.

The finding that women have a lower incidence of field-of-study mismatch compared to men can be attributed to two factors. First, women might be selecting fields of study that have a lower field-of-study mismatch incidence. Figure A2 in the appendix shows the percentage distribution of fields of study by gender for full-time wage earners in Türkiye with tertiary education. Further analysis in Figure 5.2, together with the distribution shown in Figure A1, indicates that fields where a higher proportion of women are enrolled, such as 'Health and welfare' and 'Teacher training and education science', generally have lower mismatch rates. For example, women often enroll in health-related fields, which have well-defined career paths closely related to their fields.

Similarly, education and teaching fields, favored by women, tend to have a lower mismatch rate because these fields typically offer clear career trajectories. As a result, field-of-study mismatch rates are likely lower for women because they tend to choose fields where their education is more likely to align with their field of study. Secondly, there is a possibility that when women face difficulties in securing employment within their fields, they may choose to withdraw from the workforce altogether, which might lower the observed rates of field-of-study mismatch among women.

How does vertical mismatch relate to horizontal mismatch? When we analyze the relationship between educational mismatch (RM) and field-of-study mismatch among full-time workers, the results show that (See table 27) among those without field-of-study mismatch, a majority (56.03%) are well-matched in terms of their education level to their job requirements, while 40.07% are overeducated, and a smaller portion (3.90%) are undereducated.

On the other hand, among individuals with a field-of-study mismatch, there is a higher proportion of overeducated individuals (54.86%) compared to those well-matched (37.50%), and a slightly higher percentage of undereducated individuals (7.64%) compared to the group without field-of-study mismatch. These findings suggest that overeducation is more prevalent among workers experiencing a field-of-study mismatch.

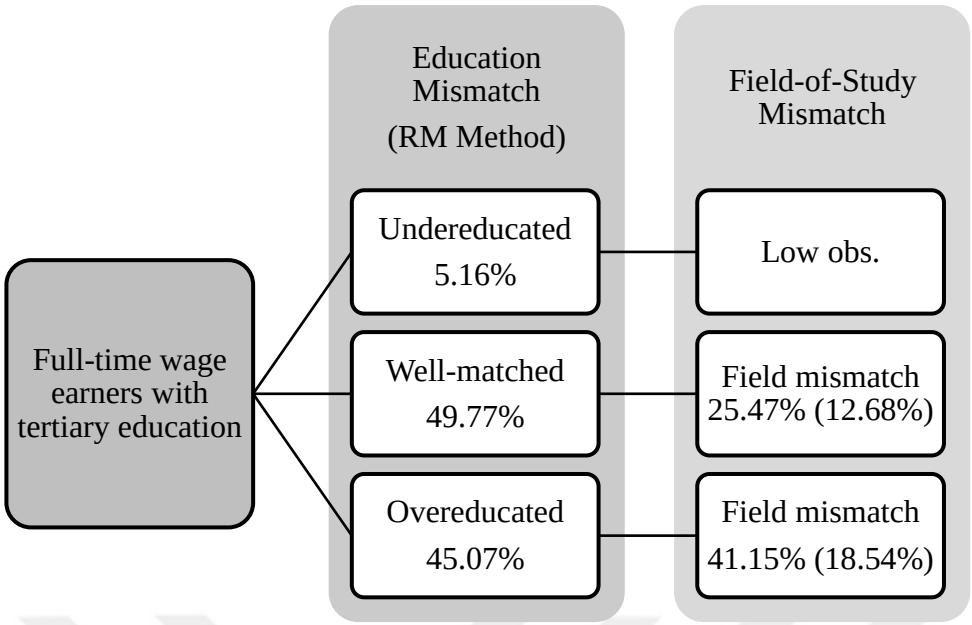


Figure 22. Field-of-Study Mismatch by Education (RM) Mismatch Categories Among Tertiary-Educated Full-Time Wage-Earners in Türkiye, 2015

Note: The percentages in parentheses show the proportion of tertiary-educated full-time wage earners within each education mismatch category who also experience a field-of-study mismatch.

Figure 22 presents the incidence of field of study mismatch by the categories of education mismatches for full-time wage earners who have completed tertiary education. The results show that 41.15% of overeducated individuals work in fields unrelated to their education. This means that 18.54% are both overeducated and working in fields unrelated to their studies. Moreover, of those who are well-matched in terms of education, 25.47% are still working in jobs that do not align with their field of study. These results are somewhat expected in an economy where the job market may not have expanded sufficiently to absorb the growing number of higher-educated individuals, or where the types of available jobs do not always match the specialized fields of study completed by graduates.

Figure 23 presents the percentage of full-time wage earners with tertiary education in Türkiye who experience field-of-study mismatch by field. The findings show that "Humanities, Languages, and Arts" graduates experience the highest mismatch rate at 70.0%, followed by graduates in "Science, Mathematics, and Computing" at 66.1%. On the other hand, "Teacher Training and Education Science" and "Social Sciences,

Business, and Law" graduates have lower mismatch rates of 22.9% and 21.5%, respectively.

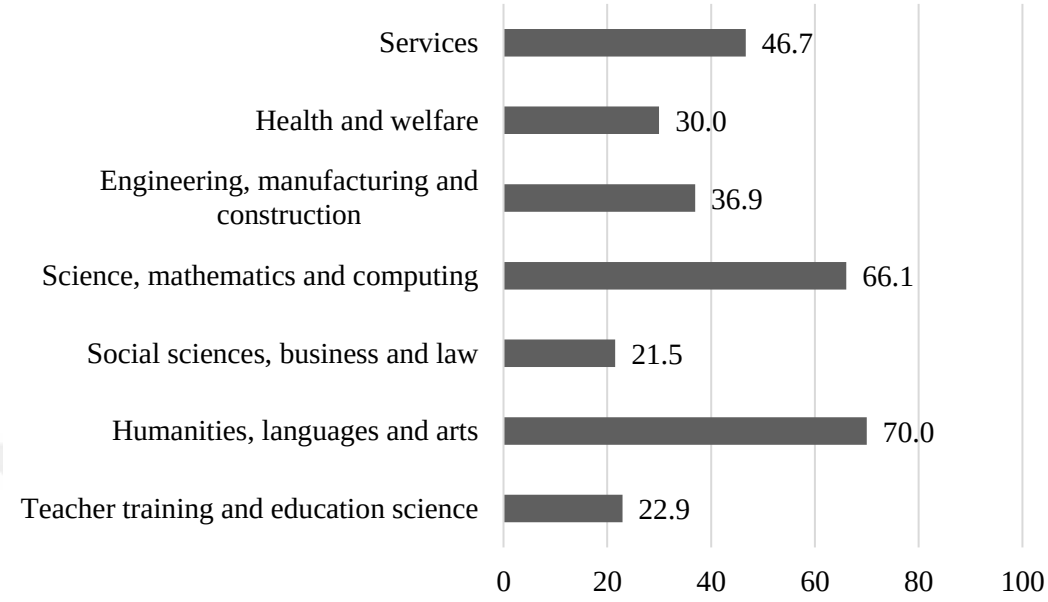


Figure 23. Percentage of Field-of-Study Mismatch Among Full-Time Wage Earner Tertiary Education Graduates in Türkiye by Field (2015)

When examining overeducation (Figure 21) and field-of-study mismatch (Figure 23) together, we see some interesting results that show the challenges faced by some graduates. Firstly, the field of "Humanities, Languages, and Arts" has a field-of-study mismatch rate of 70.0%, the highest among all fields, meaning that a significant proportion of graduates are working in jobs unrelated to their field of study. Additionally, the overeducation rate is 50.0%, indicating that even when graduates find related jobs, these jobs often do not require their level of education. Similarly, graduates in "Science, Mathematics, and Computing" also face challenges, with a field-of-study mismatch rate of 66.1% and an overeducation rate of 51.8%. These high rates suggest that many graduates are not working in their field of study, and even when they do find relevant work, it often does not match their level of education.

The field of "Social Sciences, Business, and Law" has a relatively low field-of-study mismatch rate of 21.5%. It appears that many graduates find employment within their field of study. However, the high overeducation rate of 55.6% shows that a significant number of these graduates are employed in positions that do not require their level of

education. This suggests that while graduates are finding jobs related to their field, these jobs often do not require their educational qualifications, leading to inefficiencies in the labor market. On the other hand, the field of "Teacher Training and Education Science" has a relatively better alignment with labor market needs. The field-of-study mismatch rate is 22.9%, one of the lowest, and the overeducation rate is 21.9%, the lowest among all fields. These low rates suggest that graduates in this field generally find jobs that are well-matched to their education and skill levels, indicating a better alignment between educational programs and labor market requirements.

It is possible to compare the findings for field-of-study mismatch percentages between this study and those of Ege (2020) due to the similarities in context and year. In "Teacher Training and Education Science" and "Engineering, Manufacturing, and Construction", both results show similar mismatch rates (22.9% vs. 21.1%, and 36.9% vs. 35.5%, respectively), suggesting consistent findings. The "Social Sciences, Business, and Law" field also shows comparable results, with our findings indicating a slightly higher mismatch rate (21.5% vs. 17.9%). However, larger differences are observed in "Humanities, Languages, and Arts" (70.0% vs. 32.5%), "Science, Mathematics, and Computing" (66.1% vs. 41.0%), "Health and Welfare" (30.0% vs. 9.6%), and "Services" (46.7% vs. 17.9%) fields. These differences indicate that our results suggest a more severe mismatch in these fields.

3.5.1. Correlates of Field-of-Study Mismatch

Table 28 presents an analysis of the correlates of field-of-study mismatch among full-time workers in Türkiye, using two different methods to measure educational mismatch: the RM method and the SA method. Moreover, Table 29 shows the marginal effects of individual and job characteristics on field-of-study mismatch using the RM and SA methods for measuring overeducation in these models. The significant positive coefficients for overeducation variables in these models indicate that being overeducated increases the likelihood of experiencing a field-of-study mismatch. Similarly, being overskilled is significantly associated with field-of-study mismatch in both models.

For the overeducation variable, the regression results indicate a significant increase in the likelihood of experiencing a field-of-study mismatch in both models, where being

overeducated increases the probability of field-of-study mismatch by 12.6 percentage points in the RM model and by 34.4 percentage points in SA model. For the overskilled variable, both methods show a significant positive effect on the likelihood of field-of-study mismatch. The RM method indicates that being overskilled increases the probability of mismatch by 14.5 percentage points. Similarly, the SA method shows a 13.7 percentage point increase in mismatch likelihood.

The negative coefficients for attained education under both methods suggest that each additional year of education reduces the likelihood of experiencing a field-of-study mismatch. Under the higher education system in Türkiye, there are three main groups of programs. These are associate degrees ("önlisans" in Turkish), bachelor's degrees, and master's/research degrees. Associate degree programs typically last two years and are designed to provide vocational education [27]. These are offered by vocational schools ("meslek yüksekokulları" in Turkish) affiliated with universities and other higher education institutions. Bachelor's degree programs typically last four years and are offered by universities and higher education institutions. These programs provide a more comprehensive education in a wide range of academic and professional fields. Master's programs typically last two years, while PhD programs can take several additional years beyond a master's degree. These programs are also offered by universities and research institutions [28].

Given this structure, the negative coefficient for attained education suggests that as we move from vocational training (2-year degrees) to bachelor's, master's, or research degrees, there is a decreasing probability of being field-of-study mismatched. Normally, it would be expected that the vocational focus of associate degrees would result in a lower field-of-study mismatch because these programs are closely aligned with specific job requirements. However, our results show that despite the vocational focus of associate degrees, higher levels of education (bachelor's and above) are associated with a reduced likelihood of field-of-study mismatch. This may be due to

[27] Graduates can pursue further education through "dikey geçiş" (vertical transfer) to 4-year bachelor's programs.

[28] Further details about the education system in Türkiye can be found in Chapter 2 of this thesis.

problems within the associate degree programs, such as outdated curricula, or lack of alignment with the industry needs.

In Türkiye, significant reforms in Vocational Education and Training (VET) have been implemented to better align education with labor market needs and to enhance the overall quality of vocational education. However, despite the efforts, studies indicate that Turkish VET curricula often lag behind modern industry standards and technologies. This gap reduces the employability of graduates as they lack the up-to-date skills needed by employers. In response, there have been calls for continuous updates and integration of current industry practices and technological advancements into VET programs (Özsoy, 2015; Özer, 2020). For example, the OECD (2013) highlighted that many VET programs have not been updated regularly, leading to a mismatch between the skills taught and those required by employers.

Women are less likely to experience field-of-study mismatch compared to men in our sample. Moreover, the regression results for female variable have significant negative effect on the likelihood of field-of-study mismatch in both methods, where women are around 11-11.5 percentage points less likely to experience mismatch. This could be due to gender differences in career choices, where women may choose fields of study that align more closely with available job opportunities.

Moreover, women might be working in a more narrow set of jobs, which might be expected to increase mismatch due to limited employment options within these fields. However, the relatively lower rate of labor force participation among women might counteract this, as those who do enter the workforce might find jobs that align more closely with their qualifications.

Finally, the results show that the entry age category (20-29) does not significantly affect field-of-study mismatch. However, the prime age group (45-54) is significantly less likely to have field mismatch. This could be because older individuals have had more time to adjust their careers to better fit their educational backgrounds or have gained experience that leads to a better match. The regression results for RM method shows that workers aged 45-54 are 29.3 percentage points less likely to have a mismatch. Similarly, the SA method indicates a 28.3 percentage point reduction in mismatch likelihood.

Table 28. Correlates of field-of-study mismatch in Türkiye, 2015

	Field-of-Study Mismatch Coefficient estimates (standard errors)	
Edu. mismatch method	**RM Method**	**SA Method**
Overeducated	0.389**	0.786***
	(0.153)	(0.169)
Overskilled	0.447**	0.443**
	(0.187)	(0.191)
Female	-0.343**	-0.371**
	(0.161)	(0.160)
Attained education	-0.160**	-0.195***
	(0.069)	(0.070)
Entry age (20-29)	0.287	0.313
	(0.200)	(0.203)
Prime age 2 (45-54)	-1.266**	-1.262**
	(0.510)	(0.520)
Experience	-0.018	-0.023
	(0.048)	(0.047)
Experience squared (1/100)	0.146	0.170
	(0.183)	(0.183)
Numeracy skill	-0.001	-0.001
	(0.002)	(0.003)
Ready to learn	0.088	0.148*
	(0.085)	(0.085)
Public	-0.111	-0.035
	(0.165)	(0.164)
Manual	-0.163	-0.231
	(0.152)	(0.158)
Constant	1.679*	1.957*
	(0.985)	(1.057)
Observations	425	425

*Note: Robust standard errors in parentheses. Experience squared divided by 100. *** p<0.01, ** p<0.05, * p<0.1.*

Table 29. Marginal Effects of Individual and Job Characteristics on Field-of-Study Mismatch

	Realized Match Method		
Variable	**Coefficient**	**Std. Err.**	**Significance**
Overeducated	0.126	0.048	*
Overskilled	0.145	0.059	*
Female	-0.111	0.051	*
Attained education	-0.052	0.022	*
Entry age (20-29)	0.101	0.070	
Prime age 2 (45-54)	-0.293	0.072	***
Experience	-0.006	0.015	
Experience squared	0.047	0.059	
Numeracy skill	0.000	0.001	
Ready to learn	0.029	0.027	
Public sector	-0.036	0.053	
Manual	-0.053	0.049	
	Self-Assessment Method		
Variable	**Coefficient**	**Std. Err.**	**Significance**
Overeducated	0.244	0.048	***
Overskilled	0.137	0.059	*
Female	-0.115	0.049	*
Attained education	-0.060	0.021	**
Entry age (20-29)	0.105	0.069	
Prime age 2 (45-54)	-0.283	0.073	***
Experience	-0.007	0.015	
Experience squared	0.053	0.056	
Numeracy skill	0.000	0.001	
Ready to learn	0.046	0.026	
Public sector	-0.011	0.051	
Manual	-0.072	0.049	

*Note: * p<0.05, ** p<0.01, *** p<0.001.*

gained experience that leads to a better match. The regression results for RM method shows that workers aged 45-54 are 29.3 percentage points less likely to have a mismatch. Similarly, the SA method indicates a 28.3 percentage point reduction in mismatch likelihood.

3.6. The Outcomes of Field-of-Study Mismatch

Table 30 presents findings from five models analyzing the outcomes of field-of-study mismatch. Each model progressively includes additional controls related to education and skill mismatches to evaluate the segregated effects of different types of mismatches on earnings. Model 1 focuses on the wage effect of field-of-study mismatch to see how field mismatches on its own might influence wages. Following this, Models 2 (SA) and 3 (RM) include controls for overeducation, allowing us to assess how wages are affected when both the mismatch in the field and the level of education are considered. This helps us to see the wage effect of being field mismatch together with the influence of being in the wrong level of education. Models 4 (SA) and 5 (RM) further expand the analysis by including the overskilling variable, examining how being overskilled effects the wage penalties associated with educational mismatches. Note that in all these models, we control individual level skills with the numeracy skill score.

The analysis from Model 1 shows that individuals who work in jobs not aligned with their field of study move down the earnings decile by 0.453 points compared to those whose jobs match their field of study. This shows that there is a wage penalty faced by individuals whose fields of education does not align with their job demands. In Model 2 (SA), where education mismatch is self-assessed and included in the model, the field-of-study mismatch variable is not statistically significant. In Model 3 (RM), where education mismatched is measured using the realized matches method, the coefficient for field-of-study mismatch is negative and significant at the 10% level. The effect size is in Model 3 is only slightly lower than in Model 1. These results indicate that when education mismatches are assessed using objective methods, the negative effect on wages remains statistically significant and sizable.

The effect of overeducation is significant and negative in both models. The effects of overeducation are significant and negative in both models, indicating that

overeducated individuals earn less than their counterparts who are not overeducated, with the same level of education. This suggests a wage penalty for overeducation. Model 3 results show that the effects on wages are quite similar for two types of mismatches, with field-of-study mismatch reducing the position of the individual in the wage distribution by 0.410 points and overeducation reducing wages by 0.387 points. The close magnitude of these coefficients suggests that both types of mismatches have comparable effects on wage outcomes.

The insignificance of the field-of-study mismatch variable in the models using self-assessed overeducation (SA) suggests that individual perceptions about educational mismatch conditions may lead to different conclusions about the effects of different types of mismatches. Figure A2 in the appendix helps us understand these results by showing the box plots for hourly earning deciles of tertiary-educated wage earners, based on whether individuals are well-matched or overeducated, by two methods of assessing educational match. With the SA method, the overeducated individuals have a lower median and a wider interquartile range, indicating that self-assessed overeducated individuals generally report lower earnings and more variability in earnings than those assessed with the RM method. Therefore, in conjunction with the results of the econometric models, the effect of field-of-study mismatch is not found to be significant within the groups of self-assessed overeducated and well-matched individuals.

These results imply that, among tertiary educated, individuals who self-assess as overeducated tend to be in lower-paying jobs, whereas self-assessed well-matched individuals tend to be clustered in well-paying jobs. Thus, when both mismatches are included in the model (for SA case), the dominance of education mismatch on wages mask the less pronounced effects from field-of-study mismatch. It should also be noted that when the job requirements are self-assessed, fewer individuals consider themselves overeducated, and the distribution of those classified as overeducated covers most of the lower-paying jobs as well. Consequently, there is a tendency to associate low-paying jobs with overeducation in self-assessments. When the RM method is used, many of those who considered themselves well-matched in the SA are classified as overeducated and the distribution of both well-matched and overeducated

across wage deciles changes significantly, revealing that field-of-study mismatches within both groups have significantly different wages.

Table 30. Impact of Field of Study Mismatch on Earnings, Full-Time Employed Workers with Tertiary Education, 2015 (OLS Results)

	Coefficient estimates (standard errors)				
	Model 1	**Model 2 (SA)**	**Model 3 (RM)**	**Model 4 (SA)**	**Model 5 (RM)**
FoS mismatch dummy	-0.453**	-0.148	-0.410*	-0.088	-0.360*
	(0.211)	(0.209)	(0.212)	(0.210)	(0.217)
Overeducation dummy		-1.272***	-0.387**	-1.282***	-0.378**
		(0.242)	(0.180)	(0.239)	(0.178)
Overskilled dummy				-0.453**	-0.405*
				(0.211)	(0.218)
Years of education	0.284***	0.319***	0.292***	0.313***	0.286***
	(0.090)	(0.090)	(0.090)	(0.088)	(0.089)
Numeracy skill	0.012***	0.011***	0.011***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female	-0.109	-0.214	-0.195	-0.247	-0.221
	(0.200)	(0.197)	(0.201)	(0.196)	(0.199)
Experience	0.215***	0.207***	0.205***	0.215***	0.213***
	(0.050)	(0.050)	(0.051)	(0.050)	(0.051)
Experience sq. (1/100)	-0.535***	-0.526***	-0.505***	-0.550***	-0.527***
	(0.169)	(0.170)	(0.171)	(0.172)	(0.173)
Public sector	1.208***	1.041***	1.151***	1.021***	1.135***
	(0.191)	(0.187)	(0.194)	(0.184)	(0.191)
Medium-sized enterprise	0.367	0.316	0.395*	0.327	0.405*
	(0.239)	(0.236)	(0.239)	(0.235)	(0.239)
Large-sized enterprise	0.599**	0.600**	0.639**	0.626**	0.661***
	(0.252)	(0.250)	(0.252)	(0.246)	(0.250)
Constant	-1.180	-1.206	-1.048	-1.902	-1.672
	(1.260)	(1.318)	(1.258)	(1.315)	(1.263)
(Field-of-study)	Yes	Yes	Yes	Yes	Yes
Obs	401	401	401	401	401

*Note: SA stands for self-assessment method and RM stands for realized matches method. Robust standard errors in parentheses. Experience squared divided by 100. *** p<0.01, ** p<0.05, * p<0.1*

The last two models (Model 4 and Model 5) show how field-of-study mismatch, alongside other forms of labor market mismatch, affect earnings. In Model 4 (SA), the field-of-study mismatch does not show a statistically significant effect. On the other hand, in Model 5 (RM), field-of-study mismatch remains significantly negative. The persistence of this significance in Model 5, despite the inclusion of other mismatch variables, shows the robust effect that field-of-study mismatch has on earnings when RM method is used. The comparison within Model 5 shows that all types of mismatches are significantly associated with reduced wages. This indicates that mismatches in any form are detrimental, each resulting in a reduction in wages, with coefficients ranging between -0.360 and -0.405.

The outcomes for other variables in the analysis align with expectations typically observed in labor market studies. Years of education consistently show a positive effect across all models, suggesting that higher educational attainment is associated with higher wages, even among higher educated individuals, reflecting the effects of both masters/doctoral degrees and associate degrees. The positive association across different models confirms the robustness of the impact of the level of education on earnings, irrespective of how mismatches are measured or controlled. Numeracy skill also consistently demonstrates a positive impact on wages in all models, reflecting the value placed on quantitative skills in the labor market.

The coefficient for females is consistently negative across all models but not statistically significant. This might be because tertiary-educated women who are engaged in full-time work in Türkiye represent a more selective group. Women in this selective group may experience different labor market conditions compared to their less-educated peers. For example, they might work in sectors that traditionally offer less wage disparity or in environments that are more meritocratic due to their qualifications. The statistical insignificance of the gender wage gap might also suggest that the types of jobs held by tertiary-educated women might be similar enough to those of their male counterparts, reducing observed differences in wages.

Experience shows a positive linear relationship with wages, and the experience squared term is consistently negative, as typically expected. This suggests that while experience initially increases wages, the rate of wage increase slows down as

experience continues to accumulate. Working in the public sector is associated with higher wages compared to the private sector in all models. This finding may reflect the structured pay scales and job security typically associated with public sector jobs, which can offer higher baseline wages than those found in the private sector. Similarly, larger firms pay higher wages, which could be due to better financial capabilities, or economies of scale.

Table 31. Impact of Field of Study (FoS) Mismatch on Job Satisfaction, Full-Time Employed Workers with Tertiary Education, 2015 (Ordered probit model)

	Coefficient estimates (standard errors)			
	Model 1 (RM)	**Model 2 (RM)**	**Model 3 (SA)**	**Model 4 (SA)**
Earnings		**0.158*** **		**0.158*** **
		(0.046)		**(0.046)**
FoS mismatch	-0.002	0.073	0.043	0.073
	(0.137)	(0.135)	(0.140)	(0.137)
Overeducated	0.025	0.104	-0.168	0.043
	(0.126)	(0.129)	(0.147)	(0.152)
Overskilled	-0.202	-0.165	-0.207	-0.162
	(0.153)	(0.161)	(0.154)	(0.162)
Years of education	0.078*	0.032	0.083*	0.033
	(0.043)	(0.044)	(0.044)	(0.045)
Numeracy Skill	-0.002	**-0.005** **	-0.003	**-0.005** **
	(0.002)	**(0.002)**	(0.002)	**(0.002)**
Female	**-0.316** **	**-0.265***	**-0.334** **	**-0.284** **
	(0.140)	**(0.141)**	**(0.139)**	**(0.139)**
Public Sector	**0.448*** **	0.225*	**0.418*** **	0.215*
	(0.122)	(0.126)	**(0.126)**	(0.129)
Medium-sized ent.	-0.294*	**-0.383** **	-0.300**	**-0.373** **
	(0.151)	**(0.150)**	(0.151)	**(0.148)**
Large-sized enterprise	-0.203	-0.326*	-0.199	-0.317*
	(0.164)	(0.170)	(0.163)	(0.170)
(Field-of-study)	Yes	Yes	Yes	Yes
Obs	401	401	401	401

*Note: SA stands for self-assessment method and RM stands for realized matches method. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 31 presents the results from an ordered probit model analyzing job satisfaction among tertiary-educated full-time wage earners in Türkiye. Models 1 and 2 use the RM method to measure overeducation, whereas Models 3 and 4 use the SA method to measure overeducation. These models are used to analyze how various factors affect job satisfaction, with the main difference being whether earnings are included. Models 2 and 4 add earnings as an additional control variable. The field-of-study mismatch variable is not statistically significant in any of the models. This suggests that field mismatch does not have a significant effect on job satisfaction for tertiary-educated wage earners in Türkiye. However, it is important to note that the direction of the coefficient changes from positive (Model 1) to negative (Model 2), which could suggest that the inclusion of earnings changes the dynamics of how field of study mismatch interacts with job satisfaction, but not to a statistically significant degree. Similarly, the overeducated and overskilled variables are both insignificant in all four models, indicating that neither type of mismatch significantly affect job satisfaction. Overall, the findings imply that job satisfaction among tertiary-educated workers in Türkiye is not significantly affected by mismatches in the field of study, education level, or skill level.

The analysis identifies several variables that are significant in explaining job satisfaction. The positive and significant coefficient for earnings in Models 2 and 4 suggests that as individuals move to higher deciles of hourly earnings, their likelihood of reporting higher job satisfaction increases. This shows the importance of financial compensation in influencing how satisfied individuals are with their jobs. Higher earnings provide several benefits that contribute to overall job satisfaction, such as financial security and quality of life.

The variable for years of education is positive and significant in Models 1 and 3, indicating that more years of education are associated with higher job satisfaction. However, when earnings are added to the models (Models 2 and 4), the effect size of education decreases and it becomes statistically insignificant. The results suggest that education affects job satisfaction directly and indirectly through its effect on earnings. Furthermore, numeracy skill is negative and significant in Models 2 and 4, where

earnings are included, but not significant in Models 1 and 3. This change in significance indicates that the inclusion of earnings indicates a negative relationship between numeracy skills and job satisfaction.

Being female is consistently negative and significant across all models, indicating that women report lower job satisfaction compared to their male counterparts. When earnings are added to the models (Models 2 and 4), the negative coefficient remains significant, though slightly reduced in magnitude. This suggests that while earnings do play a role in job satisfaction, they do not fully account for the gender disparity in job satisfaction. Other factors, such as workplace discrimination, work-life balance issues, and differences in career advancements may contribute to the lower job satisfaction reported by women, even when earnings are considered.

Working in the public sector is positively associated with job satisfaction, with this variable being significant across all models. This indicates that public sector employment contributes to higher job satisfaction independently of earnings. The coefficient for working in a medium-sized enterprise is negative and significant in all models. On the other hand, the coefficient for working in a large-sized enterprise is negative and significant in Models 2 and 4 when earnings are included, but not significant in Models 1 and 3. This indicates that the negative effect on job satisfaction for employees in large firms becomes evident when earnings are taken into account. While large firms may offer higher earnings, this does not seem to fully compensate for other factors that contribute to lower job satisfaction, such as bureaucratic structures.

3.7. Conclusion

While both education mismatch and field-of-study mismatch indicate misalignments between qualifications and job requirements, field-of-study mismatch relates to the relevance of educational qualifications to the job. Working in a job unrelated to their field can affect an individual's productive capabilities and lead to the underutilization of their skills and knowledge. For the economy, field-of-study mismatch contributes to labor market inefficiencies, such as reduced productivity and a suboptimal allocation of human capital.

The findings from this chapter show that there is a high incidence of field-of-study mismatch among tertiary-educated wage earners in Türkiye, and individuals experiencing these mismatches face a significant wage penalty. The analysis of field-of-study mismatch among highly educated individuals in Türkiye reveals that 34% of full-time wage earners are working in jobs that do not align with their field of study. Furthermore, our findings show that 41% of overeducated individuals work in fields unrelated to their studies, with 19% being both overeducated and mismatched in their field of study. Even among well-matched individuals in terms of education level, 25% still work in jobs not aligned with their field of study. This indicates that mismatches extend beyond the level of education to include the type of education, affecting many workers. In fact, workers that are overeducated are found more likely to be field-mismatched. The likelihood of experiencing a field-of-study mismatch increases by 9.7 percentage points (RM method) and 23 percentage points (SA method) for overeducated individuals. This strong correlation indicates that overeducated workers are more likely to be in jobs that do not match their field of study, suggesting a compounded effect of qualification mismatch.

Moreover, the results indicate that individuals experiencing field-of-study mismatches face a wage penalty. Although the effect of field-of-study mismatch is not significant when using the SA method to measure overeducation, it consistently results in significant wage penalties when analyzed with the RM method. Overeducation also significantly reduces wages in all models. Furthermore, when we include all types of mismatches in the analysis, we find that field-of-study mismatch, overeducation, and overskilling each significantly reduce wages with comparable effects when required education level is objectively measured.

The same magnitude of wage reduction for field-of-study mismatch, when compared to education and skill mismatches, shows that all three types of mismatches are equally significant in determining wage outcomes. In other words, all three mismatches are equally detrimental to wage outcomes for tertiary educated wage earners in Türkiye. This indicates that the labor market and education system need to address these mismatches comprehensively and simultaneously to ensure that workers are well-matched to their jobs in terms of education level, skills, and field of study. The negative wage effect of field-of-study mismatch shows that it is necessary for educational

programs to be relevant with job market requirements. Moreover, the fact that skill mismatch significantly affects wages even when we control for other types of mismatches indicates that, apart from relevance, the quality of education is also very important.

The fact that field-of-study mismatch does not significantly affect wages in models using self-assessed overeducation suggests that personal perceptions of education mismatches might conceal the actual effects of field-of-study mismatch, leading to contradictory conclusions and potentially underestimate the importance of this issue. Fewer individuals consider themselves overeducated when they assess job requirements themselves, and those who are classified as overeducated typically fall into the lower end of the wage distribution. When the RM method is used, many individuals who considered themselves well-matched under SA are instead classified as overeducated. Thus, this redistribution of individuals, according to the RM method, results in significant wage differences for those having field of study mismatch given the status of education mismatch.

Other than earnings, the analysis also considers non-monetary job outcomes, which is measured by job satisfaction, to provide a comprehensive analysis of how field-of-study mismatch affect overall job quality. The analysis of job satisfaction among tertiary-educated full-time wage earners in Türkiye shows that labor market mismatch variables do not significantly affect job satisfaction. On the other hand, earnings have a positive and significant effect, indicating that higher pay leads to higher job satisfaction. Overall, the findings suggest that job satisfaction among this demographic is more influenced by financial compensation, gender, and workplace conditions than by labor market mismatches.

For Türkiye, addressing labor market mismatches, and field-of-study mismatch in particular, will require comprehensive reforms in both the education system and the labor market. This includes aligning educational programs more closely with labor market needs and ensuring that requirements of the labor market match the qualifications and skills of graduates. The education system might also need to open up more interdisciplinary programs that are applicable to wider range of jobs. Additionally, reviewing and updating the quotas for different fields of study to better

align with labor market demand could help reduce field-of-study mismatches. More importantly, there is a need for career guidance that helps students choose fields of study that would be in demand in the labor market.

CHAPTER 4

CAPITAL-SKILL COMPLEMENTARITY, TECHNOLOGY USE AND EDUCATION IN TÜRKİYE

4.1. Introduction

Labor economics literature has long been trying to explain the relationship between education and technological advancements, focusing on how these factors influence economic outcomes like wage inequality and employment. The relationship between education and technology is described by the "race" metaphor, referring to the competition between the increasing educational attainment of the workforce and the increasing skill demands due to rapid technological advancements (Tinbergen, 1974; Goldin and Katz, 2008). This implies that there is a constant need for the educational system to keep up with technological advancements. If technological advancements outpace educational developments, there tends to be a shortage of workers that can work with new technologies. This results in higher wages for those who have the required skills, thereby increasing wage inequality between more and less educated workers.

This race implies that as technological advancements accelerate, there is a corresponding increase in the demand for more educated workers who can use these new technologies. This often leads to more people seeking tertiary education. However, if the expansion in tertiary education exceeds the demand for skilled jobs or the quality of tertiary education is not well-aligned with the new advances, it can lead to mismatches in the labor market that lead to wage penalties.

In the first two chapters of this thesis, we conducted a comprehensive analysis of labor market mismatch in Türkiye, addressing education mismatch, skill mismatch, and field of study mismatch. These chapters examined mostly the supply side of the labor

market, focusing on how educational attainment and skills align with job requirements. In the third chapter of this thesis, we shift the focus to the demand side, to the effect of technology on wages. By examining the interaction between education and technology, we aim to find how different levels of ICT use affect earnings and how these effects vary with educational attainment. Furthermore, we incorporate an analysis of job tasks to understand their effect on wage outcomes. By constructing variables that measure routine, cognitive, and interactive task intensities, we aim to provide a detailed view of how different job characteristics influence earnings.

In sum, our analysis contributes to the literature by:

- **Analyzing the effects of different levels of ICT use on wages:**

By leveraging PIAAC data to control for unobserved cognitive abilities, this study examines the effects of different levels of ICT use on earning instead of using a binary variable for computer use. This approach allows for a more detailed understanding of how basic and more complex ICT skills influence wages and how these skills interact with the education level to influence wages

- **Examining the effects of routine, cognitive and interactive tasks on wages:**

By integrating job task characteristics into the wage determination models, the study offers a comprehensive analysis of how the nature of job tasks influences earnings, alongside education, technology use and unobserved cognitive abilities.

Existing literature has extensively documented a wage premium associated with higher education and advanced technological skills, often focusing on developed economies (Goldin and Katz, 2008; Card and DiNardo, 2002). However, there is a growing interest in understanding these dynamics in developing countries, where labor market structures and technological adoption rates may differ significantly. Previous studies about Türkiye have analyzed the general impacts of education and technology on earnings but have not fully addressed how the intensity of job tasks influences these outcomes. This thesis further aims to fill this gap by analyzing the effects of education, computer use, and the task content of jobs on hourly earnings among full-time wage earners in Türkiye. By incorporating routine, cognitive, and interactive tasks into the

analysis, we provide a comprehensive understanding of how different types of job tasks interact with education and technology to shape wage outcomes.

The third chapter of this thesis seeks to answer the following questions:

- How does computer use influence wages in Türkiye?
- How does the effect of computer use vary with educational attainment?
- How does the complexity of computer use effect positioning within wage deciles?
- How does routine, cognitive and interpersonal task intensities influence positioning within wage deciles?

The findings from the analysis align well with the implications of skill-biased technical change (SBTC) theory and its emphasis on capital-skill complementarity. First, the results consistently show that workers who use computers at work improve their positions in earning deciles compared to those who do not use computers in Türkiye. This is evident across all models, where straightforward and complex ICT uses are associated with significant increases in earnings deciles. This finding aligns with the SBTC literature, which posits that technological advancements benefit workers who are equipped to use these technologies effectively, thereby increasing their earnings.

Second, we find that the wage effect of computer use is higher for more educated workers, particularly for those with tertiary education using complex ICT. There is no significant interaction effect for straightforward ICT use and tertiary education, implying that basic ICT skills may not provide an additional wage effect when combined with higher education. Similarly, the lack of significant interaction terms for upper secondary education with ICT use suggests that the wage benefits of straightforward ICT use do not interact with this education level. This indicates that capital-skill complementarity is particularly effective in enhancing wages for workers with higher education and advanced technological skills in the Turkish labor market.

Furthermore, our findings from the analysis of job tasks in the labor market in Türkiye shows that routine task intensity is initially weakly associated with lower wages. There

is also a significant positive correlation between interactive task intensity and wages. However, the relationship between routine intensity and wages becomes less pronounced when controlling for cognitive abilities. This indicates that the lower wages in routine-intensive jobs may be partially due to the lower cognitive abilities (i.e. numeracy skills) of workers in these jobs. Workers with higher numeracy skills, when employed in routine-intensive jobs, may experience less of the wage depreciation associated with those jobs.

From a task-based approach and routine-biased technical change (RBTC) perspective, technological advancements tend to reduce the demand for routine tasks, thereby lowering wages for routine-intensive jobs. Our findings partially support that view. However, workers with higher cognitive abilities can mitigate this wage penalty because their skills enable them to adapt to the new technologies that augment routine work. This shows the importance of worker skills in complementing routine tasks and suggests that policies aimed at enhancing foundational skills among workers could mitigate the negative wage impacts of automation.

This chapter is structured as follows. The next section reviews theoretical literature on technological changes affecting labor market, which are Skill-Biased and Routine-Biased Technological Change. The third section reviews empirical literature on the computer wage premium and capital-skill complementarity. The fourth section discusses the potential effects of AI and advanced technologies on the labor market. This is followed by section five, where the data and methodology of the study is explained, including the construction of variables related to ICT requirements and task intensities. Section six provides descriptive statistics to give job and worker characteristics relevant to the analysis. Section seven shows the findings of empirical analyses of the effects of ICT use, task intensities, and education on wages. The last section concludes with a summary of findings and implications.

4.2. Theoretical Literature

4.2.1. Skill-Biased Technical Change

The concept of production technology in economic theory is formalized through a production function, which mathematically represents the relationship between input

factors and the output produced. This function captures not just the quantities of inputs used but also how efficiently these inputs are transformed into output, with a factor generally thought as representing technology. Technical change is formulated as a shifting this factor in the production function. This means that for the same amounts of inputs, the economy can produce more output or produce the same output more efficiently with increasing technology. Such a shift can result from improvements in knowledge, equipment, or organizational changes that enhance factor productivity. Solow (1957), who laid the foundation for the modern analysis of economic growth and the role of technology within it, differentiated between growth that could be attributed to increases in inputs and growth that could not be explained by input increases alone. This unexplained portion of growth, attributed to improvements in the efficiency with which inputs are used, is identified as total factor productivity (TFP) growth.

Traditional models provide a foundational framework but they encounter limitations in explaining the effects of recent technological developments on labor market, such as the changing relative prices (wages) of skilled and unskilled labor. Over the last several decades, there has been a noticeable change in how earnings are distributed to different levels of education and skills. Despite the growing number of college-educated individuals, the demand for their skills (and thus their wages) has also increased (Goldin and Katz, 1996). This implies that the demand for skilled labor has risen faster than its supply, which indicates a shift towards a skill-intensive economy where higher education becomes increasingly valuable.

Tinbergen (1975) made a seminal contribution to the literature by bridging the gap between two previously distinct strands of literature: demand-oriented educational planning and supply-oriented human capital research (Heckman, 2019). The former focuses on the demand for education and skills in the labor market. It looks at how economies require different levels of education and skills based on the jobs available and how educational policies should be tailored to meet these demands (Bowles, 1970; Dougherty, 1972). The latter examines how investments in human capital enhance worker productivity and affect economic outcomes and emphasizes on the benefits of increasing the education and skill levels of the workforce (Becker, 1964; Mincer, 1974). Tinbergen (1975) analyzed how technological advancements could lead to

increased demand for skilled labor, widening the income gap between the more and less educated workers unless the supply of skilled labor increased through higher educational attainment. His framework considered both the demand for and supply of education and skills, explaining how they interact in the labor market (Psacharopoulos, 1987; Heckman, 2019).

The foundational work by Tinbergen (1975) initiated the discussion on how the demand for skills is related with technological advancements and the concept of "*skill-biased technical change*" (SBTC). The main observation driving the SBTC literature is that the wage premium for skilled labor, such as that of college graduates compared to high school graduates, has been increasing over several decades in the US and other advanced economies (Acemoglu and Autor, 2011). This increase in the wage premium for skilled labor has occurred despite a significant increase in the number of workers with college degrees. In other words, even though the supply of skilled labor (college-educated workers) has gone up, the returns to having a college degree (higher wages compared to high school graduates) have also increased. According to Acemoglu (2000), the nature of technological change has been *skill-biased*, meaning that technological advancements have disproportionately benefited skilled over unskilled labor.

As a result of more public investment in education and a greater inclination among individuals and families to pursue higher education, there has been a significant increase in the supply of skilled labor over time. Despite this increase in supply of high-skilled workers, the demand has also risen. This dynamic is described as a "race" between the expansion of education (supply of skills) and technological advancements (demand for high skill labor). The race metaphor refers to the competition between the increasing availability of education which produces more high-skilled workers and technological progress, that in turn raises the demand for these types of workers more. The outcome of this race influences wage structures, the skill premium, and overall economic inequality.

In line with this research, in their book *"The Race between Education and Technology,"* Goldin and Katz (2008) explore the race in the context of U.S. economic history, examining how periods when education outpaced technology led to reduced

income inequality, and vice versa. Goldin and Katz (2008) expand Tinbergen's analysis by providing empirical evidence from the history of the U.S. and show how the race has played out over time, by explaining historical periods and shifts in technology and education policy that have influenced the outcome of the race. Goldin and Katz's analysis utilizes what Acemoglu and Autor (2010) calls the *canonical model*. A key aspect of this model is the relationship between technological advancement and human capital. As technology progresses, it creates a higher demand for skilled labor. If the supply of skilled labor (human capital) does not keep up with this demand, wage inequality increases because skilled workers become rarer and thus more valuable, which increases inequality.

4.2.1.1. The Canonical Model of SBTC

The canonical model provides a foundational framework for understanding the relationship between educational attainment and wage disparities within the labor market (Acemoglu and Autor, 2010; Autor, Goldin and Katz, 2020; Deming, 2023). The model simplifies the labor market into two primary groups based on skill level (e.g., high-skilled vs. low-skilled workers) and assumes these groups perform tasks in two distinct and not perfectly interchangeable occupations or produce two types of goods that are not perfectly substitutable. Technology, in this model, is considered as "*factor-augmenting*," enhancing the productivity of either the low-skilled or high-skilled workers.

The production function for the aggregate economy is:

$$Y = [(A_L L)^{\sigma} + (A_H H)^{\sigma}]^{\frac{1}{\sigma}} \quad (1)$$

where Y is the total output, and L and H are quantities of low-skilled and high-skilled labor, respectively. A_L and A_H are the factor-augmenting technology terms for low-skilled and high-skilled labor, showing how technological advancements enhance the productivity of each labor type differently. σ relates to the elasticity of substitution between low-skilled and high-skilled labor. The *CES* production function here allows for a more flexible substitution between low-skilled and high skilled labor than the Cobb-Douglas function, characterized by this substitution parameter.

In a competitive labor market, the wage of a worker is equal to the marginal product of labor. To find the marginal product of low-skilled labor (MP_L), we differentiate the production function Y with respect to L, which, in a simplified form and applying the chain rule, yields:

$$MP_L = \frac{\partial Y}{\partial L} = [(A_L L)^{\sigma} + (A_H H)^{\sigma}]^{\frac{1}{\sigma}-1}.(A_L L)^{\sigma-1}.A_L \quad (2)$$

The marginal product of high-skilled labor (MP_H) can easily be written in a similar fashion. The marginal product depends on the factor-augmenting technology term A_L, the quantity of low-skilled labor L, the elasticity of substitution σ, and, indirectly, on the quantity of high-skilled labor H and its factor-augmenting technology term A_H, through the overall level of output in the production function. The marginal rate of technical substitution (MRTS) between low-skilled and high-skilled workers is the rate at which one can substitute H for L without changing the output level, Y. Mathematically, it is given by the ratio of the MP_L to the MP_H, which we can represent as:

$$MRTS = \frac{MP_L}{MP_H} = \frac{\partial Y/\partial L}{\partial Y/\partial H} = \left(\frac{A_L}{A_H}\right)^{\sigma}.\left(\frac{H}{L}\right)^{1-\sigma} \quad (3)$$

After taking the logarithm of the marginal rate of technical substitution to simplify, we get:

$$\ln(MRTS) = \sigma.\ln\left(\frac{A_L}{A_H}\right) + (1-\sigma).\ln\left(\frac{H}{L}\right) \quad (4)$$

In the context of the *CES* production function and assuming competitive labor markets, what happens when the relative supply of skills increases, i.e., H/L increases? In a competitive labor market, the wage of low-skilled labor (w_L) would be set equal to its (value of) marginal product ($w_L = MP_L$)[29]. If the fraction of high-skilled to low-skilled labor (H/L) increases, the effect on w_L depends on the elasticity of substitution (σ) between high-skilled and low-skilled labor. If high-skilled and low-skilled labor are substitutes, an increase in H/L might lead to a decrease in w_L as firms could prefer the now more abundant high-skilled labor over low-skilled labor, reducing the demand

[29] In this model, the price of output is normalized to 1 for simplicity.

for the latter. If high-skilled and low-skilled labor are complements, an increase in H/L could lead to an increase in w_L because more high-skilled labor would increase the productivity of low-skilled labor, raising its marginal product and, consequently, its wage.

The ratio A_L/A_H compares the productivity of low-skilled labor to that of high-skilled labor. A change in this ratio signifies a shift in the relative productivity of low-skilled versus high-skilled labor. If the ratio decreases, it means that the productivity of high-skilled labor has increased relative to low-skilled labor. This can be due to innovations or improvements in technology that particularly increase the output produced by high-skilled labor. In other words, under the assumption that $\sigma > 1$, a decrease in the ratio A_L/A_H is indicative of skill-biased technical change. Here, the substitution parameter σ indirectly captures how easily skilled and unskilled labor can be substituted in response to changes in their relative costs or productivity. A higher σ indicates easier substitution, which can moderate the increase in the skill premium by making it easier to substitute away from increasingly expensive skilled labor. However, if technology enhances the productivity of skilled labor and does not make substitution easy (often assumed under SBTC), the skill premium is expected to rise.

The skill premium is typically defined as the ratio of wages of high-skilled workers to the wages of low-skilled workers. The wage of each type of labor is proportional to their marginal products and the marginal product of labor for each type of labor is the derivative of the production function with respect to that type of labor. To solve for the skill premium using the production function in (1);

$$\omega = \frac{w_H}{w_L} = \frac{\partial Y/\partial H}{\partial Y/\partial L} = \left(\frac{A_H}{A_L}\right)^{\sigma} . \left(\frac{L}{H}\right)^{1-\sigma} \quad (5)$$

This expression represents how the skill premium is influenced by the relative productivity parameters (A_L and A_H) of low-skilled and high-skilled labor, respectively, as well as the quantities of each type of labor (L and H). Tinbergen's views are captured in two components of this expression. First, an increase in A_H/A_L implies that technology is evolving in a way that increasingly favors high-skilled workers over low-skilled workers. This is called as skill-biased technological change, suggesting that as technology advances, it disproportionately benefits those with

higher skills, making them more productive and, leading to higher wages for these workers relative to their less-skilled counterparts.

The second aspect is captured by the ratio H/L, which reflects the ratio of the supply of high-skilled workers to low-skilled workers in the labor market. Changes in this ratio can influence wage dynamics and the distribution of employment across different skill levels. For example, an increase in the supply of high-skilled workers relative to low-skilled workers (an increase in H/L) might be expected to lower the wage premium for high-skilled labor, assuming demand remains constant. Therefore, the skill premium increases with the relative productivity of high-skilled labor compared to low-skilled labor and the ratio of low-skilled to high-skilled labor quantities. This outcome is consistent with the economic intuition that higher relative productivity of high-skilled workers, as well as a greater supply of low-skilled workers relative to high-skilled workers, would both increase the skill premium.

How does the canonical model explain wage increases for both skilled and unskilled workers due to technological advancements? The model posits that technological advancements are a primary driver of economic growth. As technology improves, it enhances the efficiency and productivity of labor and capital. Many of these technological advancements are considered as skill-biased. Initially, these advancements directly raise the demand for skilled labor, pushing up their wages. However, the model suggests that the benefits of technological progress are not confined to skilled workers alone. As the economy grows due to increased productivity, it is creating more jobs and increasing the demand for labor across all skill levels. This increased demand, in turn, pushes up wages for both skilled and unskilled workers. A critical point here is the increasing supply of high-skill labor. If the supply of skilled workers keeps pace with or exceeds the demand generated by technological progress, the resulting economic growth can lead to higher wages without significantly widening wage disparities.

4.2.1.2. Capital-Skill Complementarity

The concept of capital-skill complementarity is central to the SBTC hypothesis. SBTC suggests that technological advancements tend to increase the productivity of skilled workers more than that of unskilled workers, thereby increasing the demand for skilled

labor relative to unskilled labor. This can lead to shifts in the labor market that favor skilled workers, contributing to a rise in the wage gap between skilled and unskilled workers, or the skill premium.

The idea that capital and skilled labor are complementary, and that technological progress might favor skilled workers, has been discussed by Zvi Griliches. In his work during the 1960s, he discussed how technological advancements interact with labor and capital in production, and how these interactions might lead to different outcomes for skilled and unskilled workers. Griliches (1969) discussed the idea that skill (or education) may be more complementary with physical capital than unskilled or raw labor in the production process. This idea is significant because it suggests that investments in physical capital could have different effects on the demand for skilled versus unskilled labor.

In his analysis, Griliches (1969) employs a three-input demand model, which includes raw labor, capital, and skill or schooling, to test the hypothesis of capital-skill complementarity. He uses cross-sectional data from the United States, focusing on the manufacturing industries and shows evidence supporting the hypothesis of capital-skill complementarity. Specifically, he finds that the elasticity of substitution between raw labor and capital is higher than between skilled labor and capital. In simpler terms, as firms invest more in physical capital, the demand for skilled labor increases more than the demand for unskilled labor, suggesting that skilled workers are more complementary to capital investments.

According to Violante (2008), capital-skill complementarity can be explained in three different ways within the context of economic theories. The first is based on Krusell et al. (2000), which present an argument that the significant reduction in the cost of equipment capital plays a key role in driving SBTC. An important development after WWII has been the significant reduction in the cost of equipment investment. This decline in equipment costs, especially in information technologies, has had important implications for the U.S. economy. It has made it financially easier for firms to adopt new technologies, which in turn has driven productivity growth and shifted labor demands, increasing the need for skilled labor that can effectively use these advanced technologies. This shows the economic shift towards skill-biased technological

change, where advancements in technology disproportionately benefit skilled over unskilled labor (Krusell et al., 2000; Violante, 2008).

The second explanation of the capital-skill complementarity hypothesis is influenced by Nelson and Phelps (1966), which emphasizes the role of education in facilitating the spread of new technologies. According to their hypothesis, the more educated a worker is, the faster they can integrate new technologies and production methods into their work. The reasoning behind this is that education provides a set of skills and a base of knowledge that makes it easier to comprehend and implement new techniques. Moreover, Nelson and Phelps (1966) suggest that education accelerates technological diffusion. This hypothesis is supported by empirical evidence in U.S. agriculture; farmers with higher levels of education were more prompt in adopting productive innovations than their less educated counterparts. The implied reason is that better-educated farmers can read and understand information on new products and processes more effectively.

According to Violante (2008), when a new technology is introduced, there is a high demand for skilled workers who can learn and adopt this technology quickly and these skilled workers earn higher wages. However, the increase in skill premium is only temporary. As the ability to work with the new technology spreads and more workers gain the necessary skills, the wage gap should narrow because the supply of skilled workers increases. This contrasts with the hypothesis by Krusell et al. (2000). According to Krusell et al. (2000), as technology becomes a bigger part of production, the demand for skilled labor continues to increase, suggesting a permanent effect on the skill premium due to capital deepening (Violante, 2008).

Finally, the third explanation for the capital-skill complementarity hypothesis is based on technological transformation accompanied by changes in organizational structure. This perspective shifts the focus from individual adaptation to technological change to organizational adaptation and the resultant change in the structure of firms. According to this, technological change often goes hand-in-hand with organizational change. When these two types of change occur together, their combined impact on a firm's performance is greater than the sum of their individual effects.

Piva et al. (2003) claim that the introduction of ICT has changed the way decisions are

made within firms, because these technologies can make traditional hierarchical structures less necessary as they enable more direct interaction among workers, which can lead to more collaborative and efficient decision-making processes. According to Violante (2008), as organizations become flatter, the roles of individual workers change. Instead of performing highly specialized and routine tasks, workers are expected to undertake a wider range of tasks. This shift requires workers to be more flexible and adaptable, having a broader skill set rather than highly specialized ones. This shift in organizational structure due to the adoption of information technologies is said to be skill-biased. It favors workers who are not just technically skilled but also versatile and capable of handling various tasks. These workers become more valuable in the new organizational setup, which may increase their demand and potentially their wages relative to those who lack such skills.

4.2.1.3. Criticisms of SBTC

The canonical model provides a theoretical basis to understand the rising inequality associated with technological advancements that disproportionately benefit skilled workers over less skilled ones. The model has shown considerable success in accounting for historical patterns of wage inequality. However, while the model offers a framework that explains the relation between technological advancements and the relative supply of skilled labor, it falls short in several areas.

The first challenge concerns the difference between observed and predicted wage inequality. While the model predicted a substantial rise in wage inequality, the actual increase was less than expected. Although the model predicts that technological advancements and increasing demand for skilled labor should continuously widen the wage gap, the data from the early 1990s onwards reveal a different picture, especially for the middle of the income distribution. According to Acemoglu and Autor (2012), in the 15 years following the early 1990s, the gap between the 10th percentile and the median wages began to narrow. This suggests that the wages at the bottom of the income distribution were increasing, or decreasing less steeply, relative to the median. On the other hand, during the same period, the gap between the 90th percentile and the median continued to expand rapidly, remaining consistent with the model predictions, indicating a continued increase in returns for the highest skill levels. This shows the

importance of distinguishing not just between high and low skill levels but recognizing a middle category (Autor, Katz and Kearney, 2008; Autor and Acemoglu, 2012).

Secondly, the canonical model suggests that as technological change favors skilled over unskilled workers, not only should the wage gap between these groups increase, but the real wages of all skill groups should also rise. Despite the widening skill premium, the model predicts that the real earnings of all skill groups, including both skilled and unskilled workers, will increase, based on the idea that technological advancements increase overall productivity and economic growth, creating higher wages for everyone, albeit at different rates. However, empirical data contradicts this prediction (Autor and Acemoglu, 2012). Katz and Murphy (1992) find that there is a decline in real wages for less educated workers, particularly males without a four-year college degree, between 1979 and 1992. Moreover, the growing wage premium for college-educated workers has mainly been driven by falling wages among the less educated, rather than increases among the more educated.

Thirdly, wage growth at both the highest and lowest ends of the wage distribution, which results in a U-shaped or *polarized growth of wages*, is difficult to explain with models that categorize the workforce into only two skill groups. Acemoglu and Autor (2012) provides a quantitative analysis of how wage levels have changed, focusing on the period from 1974 to 2008. The analysis divides the sample into two intervals, 1974-1988 and 1988-2008. During the initial period, the evidence shows a more uniform, monotonic pattern of wage changes. However, the subsequent period shows a polarized pattern of wage growth. This polarization is characterized by higher wage increases at both the upper and lower ends of the distribution than in the middle. This suggests that while high-skill, high-wage jobs have continued to see growth, there has also been a relative improvement or less steep decline in the lowest-wage jobs, contrary to the stagnation or decline in middle-wage, middle-skill jobs.

The fourth challenge is *occupational polarization*, which refers to the trend where employment simultaneously expands in both high-skill, high-wage occupations and low-skill, low-wage occupations, while there is a decline in the proportion of middle-skill jobs. Occupational polarization is thought to be driven by factors such as technological advancements, industrial policies and changes in demand for different

skill sets. While high-skill jobs grow due to technology and an increasing need for related skills, low-skill jobs expand, likely due to the non-automatable nature of many service tasks. Meanwhile, middle-skill jobs, often susceptible to automation and offshoring, decline. Acemoglu and Autor (2012) find that, between 1979 and 1989, there was a nearly monotonic growth pattern in U.S. labor market where high-skill occupations gained a larger share of employment, while lower-skill occupations declined. However, from 1990 to 2007, the growth pattern changed. Low-skill service jobs, which often do not require post-secondary education, have grown, contributing to the expansion of the lower end of the employment. This trend has been more pronounced in the 1990s and 2000s. On the other hand, the share of employment attributed to middle-skill jobs has decreased, from 58.9% in 1979 to 44.5% by 2010 (Acemoglu and Autor, 2012).

4.2.2. Routine-Biased Technological Change and The Task-Based Approach

The literature on routine-biased technological change (RBTC) provides a framework to understand how technological advancements, particularly in information and communication technologies (ICT), have affected jobs by automating tasks that are routine and codifiable. RBTC posits that technological progress has increasingly allowed machines and ICT to perform tasks that follow explicit, well-defined procedures (i.e. codifiable tasks). This has led to the displacement of workers performing such (routine) tasks, which are often found in middle-skill jobs, such as clerical work and certain types of manufacturing. On the other hand, it is claimed that non-routine tasks, which require problem-solving, and interpersonal skills, have been less susceptible to automation.

Autor, Levy and Murnane (2003) (ALM, henceforward) have significantly contributed to this literature through their seminal work, which explained how technological advancements have affected the labor market by automating routine tasks. In their analysis, ALM make three observations and assumptions to explain how technological advancements effect the labor market, regarding the substitution between routine and non-routine tasks and their implications for jobs and wages. Firstly, ALM assume that technology, or computer capital, is more easily substituted for human labor in performing routine tasks than it is for non-routine tasks. This is because routine tasks

are defined by their codifiability, making them easier to automate with recent technologies. The second assumption ALM make is that routine and non-routine tasks are imperfect substitutes. Finally, ALM assumes that automating routine tasks can actually increase the marginal productivity of non-routine tasks, because the automation of routine tasks can free up human capital to be used more on non-routine tasks, i.e. complementing the labor in non-routine tasks, thereby increasing overall productivity.

ALM (2003) introduced a simple production function framework, demonstrating how information technology could have these effects on labor: displacing it from routine tasks due to automation and complementing it in non-routine tasks by augmenting human capabilities. Then, the model outlines how a technical advancement (a fall in the price of computer capital) changes wages. ALM (2003) define the Cobb-Douglas production function as $q = R^{1-b}N^{b}$ where q represents the total output, R and N stand for the inputs of routine and non-routine tasks, respectively, and b is a parameter between 0 and 1, indicating the share of non-routine tasks in the production process. Labor supply is modeled following Roy (1951), positing that workers select occupations, categorized into routine and non-routine tasks, based on their comparative advantage. Each worker is endowed with a certain productivity in routine and non-routine tasks, expressed in efficiency units R_i and N_i . The relative efficiency of a worker in non-routine versus routine tasks is denoted as $\alpha_i = N_i/R_i$. Workers choose to supply either efficiency units of routine task input or efficiency units of non-routine task input to maximize their earnings.

Since ALM (2003) assume computer capital and human labor are perfect substitutes for performing routine tasks and technology is more easily used in routine tasks due to their codifiable nature, the wage per efficiency unit of routine labor (w_R) is directly linked to the price of computer capital (P), which is assumed to decrease exogenously over time due to technological advancements ($w_R = P$)[30]. ALM (2003) claim that a

[30] The model specifies that the marginal worker, who is indifferent between supplying labor to routine or non-routine tasks, does so when $\alpha^* = w_N/w_R$. Here, α^* is the relative efficiency threshold that makes a worker indifferent between routine and non-routine jobs.

fall in the cost of computer capital results in decreased wages for workers in routine tasks and leads to a decrease in employment in routine jobs. This shift towards a higher reliance on technology for routine tasks subsequently increases the marginal productivity of non-routine tasks, thereby increasing the wages for labor involved in non-routine tasks on a per efficiency unit basis. This supports the observed labor market dynamics, where technological advancements disproportionately displace routine task-based employment while increasing the demand and wages for non-routine employment.

The ALM model serves as a basis to explain the job polarization phenomenon, as observed by Goos and Manning (2007), and Autor and Dorn (2013). The literature suggests that as routine tasks get automated, jobs in the middle of the skill distribution (which involve a high proportion of routine tasks) decline; whereas there will be growth at the high and low ends of the skill distribution: high-skill jobs that involve non-routine analytic and interpersonal tasks (e.g., management, professional services) and low-skill jobs that involve non-routine manual tasks (e.g., care services, installation, and repair). This leads to a U-shaped employment growth pattern, with middle-skill jobs hollowing out. The RBTC literature also addresses the issue of rising wage inequality, attributing part of this phenomenon to the impact of technology on routine versus non-routine tasks. As demand for workers in high-skill, non-routine jobs increases, their wages rise. Meanwhile, the wages of workers displaced from routine tasks may stagnate or decline, even if they find new employment, often because the new jobs may not fully use their skills or may pay less.

4.2.2.1. Differences Between the Canonical Model and The Task-Based Model

ALM (2003) set forth a conceptual framework to explain the effect of computerization on the labor market. They propose that the susceptibility of jobs to automation depends not on the workers themselves but on the nature of the *tasks* that their jobs comprise, shifting the focus from the categories of skilled and unskilled labor to the specific tasks that workers perform. In the task framework, skills refer to the capabilities and competencies that workers have, which enable them to perform tasks. They are, therefore, a worker's stock of capabilities for performing a variety of tasks, accumulated through education, training, and experience, which are applied to tasks

in exchange for wages (Autor, 2013). In the task-based framework, skills do not directly produce output but are applied to tasks. Tasks, on the other hand, are defined as units of work activity that produce output.

On the other side, in the canonical model of SBTC, there is a one-to-one mapping between skills and tasks. In other words, it is implicitly assuming a direct match between workers' skills and the tasks they perform, so that one skill directly corresponds to one task. In the task-based approach, workers perform various job tasks requiring different skill sets, and these differences mean that workers have different comparative advantages in performing these tasks (Acemoglu and Autor, 2013). Workers allocate their skills to different tasks based on labor market prices, meaning they choose tasks where they have a comparative advantage and can earn higher wages.

In the canonical model of SBTC, the production function typically includes capital and labor either as complements or substitutes. Similarly, different types of labor (e.g., high-skilled vs. low-skilled) can also complement or substitute for each other. These are often seen as fixed or static. However, this view attracted criticisms. According to Autor (2013), the distinction between "labor tasks" and "capital tasks" is not rigid but subject to change, particularly with technological advancements. Technological progress can cause shifts in how tasks are allocated between labor and capital. For example, automation technology can take over tasks that were previously performed by labor (substituting for labor), while also creating new tasks where technology increases human productivity (complementing labor).

The task-assignment model, developed by Acemoglu and Autor (2011) and further improved by Autor (2013), introduces a framework for examining the relation between skill supplies, technological advancements, and their effect on labor demand, the allocation of factors to tasks, and the productivity and wages of each factor of production. In contrast to the canonical model of SBTC, the task-assignment model is built around the concept of job tasks as the core units of production.

The model uses the principle of comparative advantage to allocate factors to tasks. This means that in equilibrium, each task is assigned to the factor that can perform it

at the lowest cost. This dynamic allocation mechanism contrasts with the canonical model, where the roles of labor and capital are fixed.

4.2.2.2.The Task-Assignment Model [31]

The model is set in a static, closed economy without trade in tasks, focusing on the production of a unique final good. The final good is produced by aggregating a continuum of tasks (ranging from 0 to 1) using a constant elasticity of substitution (*CES*) function. Each task contributes to the final output based on its production level, with an elasticity of substitution parameter showing the ease of substituting one task's output for another. Consider that the production of the final good, Y, is given by:

$$Y = \left(\int_0^1 y(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}$$

where $y(i)$ represents the *"service"* or production level of task i and σ is the elasticity of substitution between tasks. There are three categories of labor based on skill level: high, medium, and low, supplying fixed amounts of labor denoted as H, M, and L, respectively. Each available task has a production function incorporating labor from any of the three skill types or capital. The productivity of labor in performing tasks varies across skill levels and tasks, influenced by factor-augmenting technology parameters and task-specific productivity schedules.

The production function for each task i is:

$$y(i) = A_L \alpha_L(i) l(i) + A_M \alpha_M(i) m(i) + A_H \alpha_H(i) h(i) + A_K \alpha_K(i) k(i) \qquad (6)$$

where A_L, A_M, A_H and A_K are factor-augmenting technology parameters for low, medium, high skill labor, and capital, respectively. $\alpha_L(i), \alpha_M(i), \alpha_H(i)$ and $\alpha_K(i)$ represent the productivity schedules of low, medium, high skill labor, and capital for task i. Finally, $l(i), m(i), h(i)$ and $k(i)$ denote the amount of low, medium, high skill labor, and capital allocated to task i. The production function implies that any task can be performed by workers of any skill level. However, due to differences in

[31] The equilibrium framework of this model is formulated in Acemoglu and Autor (2011).

comparative advantage (α terms), certain tasks are more suitably performed by workers of a particular skill level.

The task-based model is often referred to as a Ricardian model due to its foundation in the principle of comparative advantage. Originally, comparative advantage explained how countries could gain from trade by specializing in the production of goods for which they have a relative productivity advantage, even if they do not have an absolute advantage in producing any goods. In the context of the task-based model applied to the labor market, the "Ricardian" name emphasizes how different types of labor have a comparative advantage in performing specific tasks. The task-based model suggests that the labor market adjusts to technological changes by reallocating labor to tasks where they have comparative advantages. This reallocation is driven by differences in relative productivity across tasks, influenced by technological progress.

The equilibrium in the economy explains how tasks are distributed among workers of different skill levels, based on the concept of comparative advantage. The model posits that workers' productivity and hence their comparative advantage vary across tasks, with higher skill workers being more productive in more complex tasks. Therefore, there is a structure of comparative advantage such that $\alpha_L(i)/\alpha_M(i)$ and $\alpha_M(i)/\alpha_H(i)$ are strictly decreasing, indicating that as tasks become more complex (i.e. moving towards 1 on the [0,1] interval), high-skill workers become relatively more productive compared to medium-skill workers, and medium-skill workers more productive than low-skill workers.

The model identifies two cut-off points, I_L and I_H, which divide the tasks among low, medium, and high skill workers. Tasks indexed $i < I_L$ are most efficiently performed by low skill workers. These tasks are such that the comparative advantage of employing low skill workers over medium or high skill workers is the greatest. Tasks indexed $i > I_H$ are those for which high skill workers have the comparative advantage and are, therefore, most efficiently performed by them. The tasks that fall between these cut-off points ($I_L > i > I_H$) are those that medium skill workers are comparatively more efficient at performing. The tasks allocated to medium skill workers, falling in the intermediate range, are often characterized as *routine tasks.* These are typically repetitive and follow a set of pattern or rules, common in

production, clerical, and administrative support roles (Autor and Acemoglu, 2011).

A key aspect of the model is the *allocation of skills across tasks*. In the equilibrium described by the model, the range of tasks in the economy is divided into three distinct groups, each optimally assigned to workers of different skill levels. This division into sets is not arbitrary but is instead determined by the principles of comparative advantage. The cut-off points between these sets, I_L and I_H , are endogenously determined [32]. If technology enhances the productivity of low skill workers in certain tasks, some tasks previously performed by medium skill workers might shift to the low skill set. On the other hand, if the supply of high skill workers increases, reducing their wage relative to productivity gains, tasks near the boundary (I_H) might shift to be performed by high skill workers instead. Therefore, by allowing for the endogenous determination of task boundaries and the substitution of skills across tasks, tasks are performed by the group of workers who can do so most efficiently (given the current state of technology and labor supply).

In equilibrium, all tasks that employ low skill workers must offer the same wage (w_L), and the same applies to medium (w_M) and high (w_H) skill workers. This is due to the competitive nature of the market, which would otherwise cause labor to shift away from lower paying tasks. In equilibrium, for workers to be paid the same wage within each skill group, the value of marginal product of their labor must equalize across all tasks they perform. This implies:

$$\text{For low-skilled workers in tasks } i < I_L,\ w_L = p(i).A_L.\alpha_L(i)$$

$$\text{For medium-skilled workers in tasks } I_L > i > I_H,\ w_M = p(i).A_M.\alpha_M(i)$$

$$\text{For high-skilled workers in tasks } i > I_H,\ w_H = p(i).A_H.\alpha_H(i)$$

The difference in prices between any two tasks performed by the same type of worker must exactly compensate for the productivity difference of this worker type between these two tasks. This ensures that despite different tasks potentially having different

[32] For a task at the cut-off point (e.g., I_L), the cost of performing the task must be the same regardless of whether it is done by L or M workers, ensuring no arbitrage. The model finds unique cut-points due to this no-arbitrage condition.

levels of productivity for workers, the wages adjust to keep the labor supply consistent and workers indifferent between tasks of the same skill level. This wage determination mechanism ensures that the labor market reaches an equilibrium where workers are efficiently allocated to tasks based on their comparative advantage and skill level.

How does technological advancement effect the distribution of wages across different skill levels in the labor market according to the task-based model? In the task-based model, not all technology impacts all workers equally. Some technological advancements make high-skilled workers more productive without offering the same benefits to medium or low-skilled workers. This suggests that the impact of technology on jobs depends on how it affects the tasks that occupations comprise, rather than displacing workers based on their skill levels. In the canonical model of SBTC, technological advancements increase all workers' wages. On the other hand, within the task-based model, technological advancements favoring high-skilled workers (i.e. an increase in high skill biased technical change A_H) may actually lead to a decrease in wages for workers with medium skills.

An increase in A_H means high skilled workers become more efficient at performing tasks, potentially taking over tasks previously done by medium skilled workers. This does not affect I_L but affects I_H, pushing I_H to include more tasks under the domain of high skilled workers due to their increased efficiency. Hence, technological advancements diminish the comparative advantage the medium-skilled workers held, thereby displacing them from certain tasks they were previously competent in. As high-skilled workers take over more tasks, the demand for medium-skilled labor decreases in those areas, reducing w_M.

4.2.2.3. Task Displacement, Ripple Effects and Labor Market Mismatch

One of the most significant contributions of the task-based framework and the RBTC literature is its ability to analyze the consequences of capital taking over tasks that were traditionally performed by labor (Autor, 2013). Generally, it might be expected that tasks done by labor across all skill levels are at risk of being replaced by capital. However, drawing from the empirical evidence and the theoretical insights provided by ALM (2003), it is posited that tasks most vulnerable to this shift are those that are routine or can be easily codified.

According to Acemoglu and Autor (2011), technology that replaces tasks could decrease the wages of the affected skill group, whereas it increases overall production. This happens because such technological changes displace the workers who previously handled these tasks, resulting in an "excess supply" of labor. These workers are then forced to move to tasks where they are less competitive, which decrease their wages. At the same time, by lowering the costs and increasing the usage of the tasks that have been automated, this technological change actually complements the remaining tasks that are still performed by labor. These opposing effects indicate that the real wages of the group displaced by technology from their previous tasks may not necessarily fall in real terms. However, in practical terms, a decrease in real wages for this group is the likely outcome (Acemoglu and Autor, 2011; Autor, 2013).

More recently, Acemoglu and Restrepo (2022) develop a framework where tasks are allocated to labor and capital across industries, and automation is seen as expanding the set of tasks performed by capital, displacing workers from jobs where they had comparative advantage. This framework links the changes in the wages of a skill group to the task displacement caused by automation and implies that task displacement is a significant driver of changes in wage structures.

There are also indirect consequences that result from this initial displacement. According to Acemoglu and Restrepo (2022), there are indirect ways through which automation influences wages in a general equilibrium. One of these indirect effects is the ripple effect that occurs when workers displaced by automation. Acemoglu and Restrepo (2022) claim that when automation displaces workers, not only are the wages and employment of these workers directly affected, but there can also be indirect effects on other workers and industries. For example, when middle-skilled workers lose their jobs to automation, these workers may then seek employment in other areas. This causes an oversupply of labor in the new area. Thus, when workers from one sector are displaced by automation, they move to other sectors and compete for tasks there, lowering wages not just for themselves but also for the workers in those sectors.

Task displacement and the ripple effects are related with mismatches in the labor market. When certain tasks become automated, it is not just about replacing human work with machine work; it also affects the demand for workers performing these

tasks. This can be thought of as fewer non-automated jobs, where displaced workers may need to compete for a shrinking pool of jobs that have not been automated. The increase in labor supply can lead to increased competition for jobs, driving down wages and pushing some workers into jobs for which they are mismatched.

4.2.2.4. Criticisms of the Task-Based Model

While the task-based model offers a different approach compared to the canonical model, it is not without its criticisms (Mishel et al., 2013). Despite their differences, both the traditional and task-based models share a fundamental similarity. Specifically, each task is assumed to be done by only one kind of worker, whether absolutely, as seen in the canonical model, or depending on technological advancements and comparative advantage, as observed in task-based models (Sevinc, 2017).

Furthermore, it is claimed that there is a lack of consistent empirical evidence supporting the model's predictions about job polarization, where middle-skill jobs decline while both high-skill and low-skill jobs increase. Mishel et al. (2013) points out that empirical findings often show mixed results, which do not always align with the theoretical predictions of the task-based model. While some sectors and regions might show signs of job polarization, others do not show these signs as clearly or at all.

Finally, the task-based model has attracted criticism regarding its assumptions about how workers adapt to technological changes in the labor market. This model assumes that automation of certain tasks results in the displacement of workers who previously carried out these tasks, which is considered overly simplistic because it fails to adequately account for the potential of workers to adapt by developing new skills (Mishel et al., 2013).

4.3. Empirical Literature

Several theories and models are used to explain the relationship between education, technological advancements, and labor market outcomes. Starting with the mismatch literature, these theories explain the causes and consequences of the differences between the skills that educational institutions provide and those that employers need.

The labor market mismatch theories focus on the *supply side* of the labor market, particularly the qualifications and skills that workers possess. The aim is to find whether these qualifications and skills that workers have match with the requirements of available jobs (See Part 1). On the other hand, the SBTC hypothesis and the task-based approach shift focus to the *demand side* of the labor market. The SBTC theory suggests that technological progress is a key driver in shaping labor demand, suggesting that as technology advances, the types of jobs available and the skills required for these jobs change. Task-based approach also focuses on the demand side but on how technology affects the tasks within jobs, by examining which tasks are more likely to be automated by technology and how this changes the structure of jobs and the skills demanded.

A growing body of research, started by ALM (2003) and expanded by Acemoglu and Autor (2011), Autor and Handel (2013), Goos et al. (2014), and more recently by AR (2018), has focused on the changing structure of labor demand by employing a theoretical model based on the task-based approach, where production is done by assigning tasks to factors of production, and technological advancements causes changes in these assignments. The task-based approach offers a different perspective on the effect of technological advancements on the labor market from those presented by the SBTC hypothesis, which suggests that technological advancements tend to benefit skilled workers more than unskilled workers, leading to increased wage differences based on skill levels. Therefore, the canonical model of SBTC differentiates between skilled and unskilled workers, equating tasks directly with skills (Katz and Murphy, 1992). However, the task-based approach distinguishes between tasks and skills, emphasizing the importance of considering *occupations as the primary unit* for empirical analysis (Acemoglu and Autor, 2011; Firpo et al., 2011).

4.3.1. The Capital-Skill Complementarity

The computer wage premium refers to the premium earned by workers who use computer at work in comparison to those who do not use computers, even when other factors are similar. This concept is often discussed within the framework of SBTC, suggesting that technological advancements like computers disproportionately benefit workers who have the skills to utilize these technologies effectively. As a result, the

wage gap between skilled and unskilled workers widens because technology increases the productivity and the wages of skilled workers more than those of unskilled workers.

This rise in inequality is widely attributed to the capital-skill complementarity, mainly driven by the adoption of computers and information technology. The focus of earlier research, such as Krueger (1993) and Autor, Katz, and Krueger (1998), has been on capital-labor complementarities. In his pioneering study, Krueger (1993), focusing on the relationship between computer use at work and wages, shows that the use of computers in the workplace is associated with approximately a 10 to 15 percent higher wage for those workers who use them, compared to workers who do not use computers. This is attributed to the increased productivity that computer usage provides. Autor, Katz and Krueger (1998) analyze the impact of technological changes on the demand for workers with different education levels in the U.S. labor market from 1940 to 1995. They find that the relative demand for college-educated workers grew more rapidly in the last 25 years covered by the study (1970-95) compared to the earlier period (1940-70). Moreover, the spread of computer technology is estimated to explain as much as 30 to 50 percent of the increase in the relative demand for more skilled workers since 1970.

These results suggest a substantial impact of technology, specifically computer usage, on wages. However, other studies question these findings. DiNardo and Pischke (1997) analyze whether the wage differentials associated with using computers at work reflect productivity gains or if they might be attributed to unobserved heterogeneity. They find that not just computers, but also other office tools like calculators, telephones, and pens or pencils, are associated with significant wage differentials. Similar to computer wage premiums, using a pencil or pen at work is found to be associated with a wage premium almost as large as that for computer use. DiNardo and Pischke (1997) argue that if even simple tools like pens, which are unlikely to increase productivity, show similar wage effects as computers, this challenges the interpretation that computers are driving wage structure changes through SBTC. Instead, it might be that factors associated with the type of jobs that use these tools or the characteristics of the workers are causing these wage differences.

Borghans and ter Weel (2001) claim that while there is considerable evidence supporting the positive relation between computer use and higher wages for skilled workers, the use of computers in a job does not always correlate with high skill levels in the literature. This suggests that there may be some unobserved factors that could also influence wage differences that might favor skilled workers independently of their computer use, such as cognitive abilities, interpersonal skills, industry-specific knowledge, or non-cognitive skills. Furthermore, measuring whether or not someone uses a computer at work might not sufficiently capture the economic value of their computer use. In fact, Borghans and ter Weel (2001) suggest that 'sophisticated' computer tasks that involve programming or advanced software use require higher skills and are associated with higher wages. They find that higher computer skills correspond to higher wage premiums, particularly when computer use is more complex.

4.3.2. Task Substituting Computer Capital and Routine Task Intensity

The task-based view led to a new understanding of how technological changes affects abstract, routine, interactive and manual tasks differently, thereby changing the skill demands in the labor market (Sevinc, 2017). In their influential paper, ALM (2003) introduce a framework for classifying job tasks along two categories: one differentiating between routine and non-routine tasks, and the other between manual and cognitive tasks (See Table 32). Routine tasks are characterized by their codifiable nature, allowing for automation. These include both manual and cognitive tasks where the procedures can be precisely defined. On the other hand, non-routine tasks, which necessitate decision-making or interactive skills, are less suitable for automation. In the ALM (2003) framework, non-routine cognitive tasks include activities that demand high-level cognitive skills such as problem-solving, persuasion, and creativity. These tasks are typically found in professions that require significant education and analytical skills. Occupations that involve non-routine manual tasks include those in the service sector, like healthcare support, personal care, and customer service roles. These jobs often do not require high levels of formal education but demand adaptability and interpersonal skills (ALM, 2003).

Table 32. Impact of Computerization on Tasks

	Routine	**Non-Routine**
Cognitive	High substitution potential	High complementarity potential
Manual	Substitution possible but limited	Low potential for substitution/complementarity

Note: This table is based on ALM (2003).

ALM (2003) use U.S. DOT to categorize tasks into routine and non-routine categories, as well as into cognitive and manual, to analyze how technological advancements might displace routine tasks while complementing more complex cognitive tasks. Each category includes specific variables chosen for their relevance. These variables are then subjected to Principal Components Analysis (PCA) to create composite indicators that represent these task categories. Expanding on the foundational work of ALM (2003), subsequent studies have developed similar indices to analyze the routine content of occupations (See Table 33). More recently, Goos et al. (2010) and Autor and Dorn (2013) adapted this model. They consolidated the routine dimension and expanded the categorization to identify tasks as abstract, routine, or manual.

Spitz-Oener (2006) is one of the earlier studies to extend the task-based framework developed by ALM (2003), applying their method of categorizing job tasks into routine and non-routine as well as cognitive and manual. This study examines the effect of technological advancements on skill requirements in Germany from 1979 to 1999, with the aim to understand whether these changes have led to a rise in the demand for more complex skills and how this relates to educational requirements. In this study, the index of occupational skill requirements is constructed by pooling individual activities reported in a survey into five categories of tasks.

Each task category is measured by counting the activities an employee performs in that category and expressing it as a proportion of the total number of activities in that category across the dataset. The study finds that occupations that experienced greater

computerization saw a significant increase in the requirements for analytical and interactive skills, while the demand for routine manual and cognitive skills declined.

Table 33. Construction of Task Indices Across Studies

	Categories	**Tasks**	**Variables**
Autor et al. (2003, 2006)	• Non-routine vs Routine • Cognitive • Manual	R: Defined as repetitive and unchanging tasks. Analytic and cognitive tasks not defined, except NR cognitive which includes tasks needing flexibility, creativity, problem-solving, and complex communications.	• NR analytic: Quantitative reasoning. • NR interactive: Managerial and interpersonal tasks. • R cognitive: Adaptability within defined limits. • R manual: Finger dexterity. • NR manual: Coordination of eyes, hands, and feet.
Spitz-Oener (2006)	Same as ALM	R tasks (both manual and cognitive) are defined as easily programmable and executable by computers at economically feasible costs. NR tasks are undefined and currently non-programmable. Analytical involves problem-solving in the workplace; Interactive includes effective communication and teamwork.	• NR analytical: Research, analysis, evaluation, planning. • NR interactive: Negotiation, coordination, teaching, customer service. • R cognitive: Calculations, bookkeeping. • R manual: Machine operation. • NR manual: Repairing, renovating, serving.
Goos et al. (2010)	• Abstract • Routine • Service	Routine tasks are easily computerized, involve repetitive physical or non-complex cognitive skills. Abstract tasks involve complex problem-solving. Service tasks involve care and interaction.	• Routine: Monitoring, maintenance, quality control. • Abstract: Managerial and problem-solving tasks, interaction with computers. • Service: Assistance, care, sales, public interaction.

Autor and Handel (2013)	• Abstract • Routine • Manual	Abstract tasks include creative and organizational tasks. Routine tasks are codifiable and follow explicit procedures. Manual tasks require physical adaptability.	• Abstract: Document reading, math, problem-solving, supervision. • Routine: Repetitive tasks with no customer interaction. • Manual: Physical tasks.
Marcolin et al. (2018)	• High-RI • Medium-RI • Low-RI • Non-routine	The index includes variables like the ability to change the sequence of tasks and the flexibility of task content, with higher scores indicating more routine intensity.	Routine Intensity Index (RII) based on: • Sequence of tasks, • Flexibility, • Planning of own work, • Organization of own work time.
De La Rica et al. (2020)	• Abstract • Routine • Manual	Abstract tasks are related to NR cognitive abilities like problem-solving. R tasks involve repetitive cognitive and manual skills. Manual tasks are linked to non-routine physical activities.	• Abstract: problem-solving activities. • Routine: repetitive data entry, clerical work. • Manual: physical tasks such as handling machinery.
Lewandowski et al. (2020)	• NR Cognitive Analytical • NR Cognitive Interpersonal • R Cognitive • Manual	Non-routine tasks involve those that are not easily automated. Routine tasks are repetitive and predictable.	• NR Cognitive Analytical: problem solving, programming. • NR Cognitive Interpersonal: supervising, presentations. • R Cognitive: form filling, simple calculations. • Manual: physical tasks.

Source: Autor et al. (2003, 2006); Spitz-Oener (2006); Goos et al. (2010); Autor and Handel (2013); Fernandez-Macias and Hurley (2016); Marcolin et al. (2018); De La Rica et al. (2020); Lewandowski et al. (2020). NR stands for non-routine, R stands for routine, and RI stands for routine intensive.

Later research has used worker-level data, such as the OECD's PIAAC data, to conduct analyses of the relation between job tasks and technological changes. Marcolin et al. (2016, 2018) use data from the PIAAC to construct a Routine Intensity Indicator (RII), based on the degree to which workers can modify the sequence of their tasks and decide the type of tasks to be performed on the job, measuring the codifiability and flexibility of tasks. They find that there is a negative relation between the routine intensity of occupations and the skill levels required for those jobs. Occupations that are more routine-intensive require lower skill levels. Moreover, they find that the effect on wages depend on the routine content of occupations. Typically, jobs with higher routine content tend to be associated with lower wages, reflecting the lower skill requirements and higher potential for automation.

Lewandowski et al. (2019) also developed a Routine Task Intensity (RTI) index to quantify the level of routine tasks across various occupations. Similar to Marcolin et al. (2016, 2018), the study analyzes the tasks and their intensities across 42 countries to establish the task measures for each country. Manual tasks are excluded due to difficulties in differentiating between routine and non-routine manual tasks and lower comparability across countries. They find that the intensity of routine tasks within occupations tends to decrease with an increase in a country's GDP per capita, particularly for high-skill occupations (Lewandowski et al., 2019).

Marcolin et al. (2018) and Lewandowski et al. (2019) construct task indices by averaging items from PIAAC data, while Spitz-Oener (2006) calculated means of variables to determine whether a worker performs certain tasks. Recently, De La Rica et al. (2020) analyzed the relationship between job tasks and wages across a sample of 19 developed countries to see how differences in the types and intensities of job tasks are related to wage differences both within and across these countries. They use PIAAC data at the worker level to measure the task intensities. The results show that increases in abstract tasks are associated with wage premiums, while increases in routine tasks generally result in wage penalties. Moreover, the findings of the study suggest that the differences in task prices across countries are affected by development factors and labor market institutions such as union coverage and employment protection legislation.

It should be noted that as technology continues to advance, tasks that were once considered non-routine can become more susceptible to automation, leading to changes in task contents of the jobs. For instance, Marcolin et al. (2018) discusses how the interpretation of "finger dexterity" and "abstract reasoning" have changed in the context of identifying routine-intensive tasks over time. In earlier studies, such as ALM (2003), "finger dexterity" is used to identify manual, routine tasks in jobs that involve repetitive, precise manual skills. However, jobs requiring "finger dexterity" today are not strictly routine, but applies to more complex and higher-value manual tasks such as arts and crafts. Similarly, the “abstract reasoning” was previously associated with non-routine analytical tasks that require high-level mathematical skills. According to ALM (2003), tasks involving "abstract reasoning" were non-routine and mathematically demanding. However, Marcolin et al. (2018) claims that even jobs requiring significant mathematical and abstract reasoning skills, like data mining, can now be codified and outsourced. This suggests that the tasks traditionally considered as requiring high-level cognitive skills can sometimes be transformed into more routine tasks that can be automated.

4.3.3. Challenges to the Empirical Analyses Based on Task-Based Approach

There are three main challenges to empirical analyses that are based on task-based approach. The **first challenge** is the *measurement of tasks*. Traditional indicators of skill, like educational qualifications and work experience, are mostly obtained through surveys and are generally recognized as reliable indicators of an individual's human capital. In the canonical model, where one skill level corresponds to one task level, an individual's human capital is an adequate measure of their productivity and thus their wage. Therefore, in such a setting, asking about the tasks an individual performs given their human capital might seem redundant. Hence, unlike data on education and work experience, detailed information on the tasks performed by workers in their jobs is not commonly collected by large-scale, representative surveys.

The task approach distinguishes between skills and the tasks performed at work. A fundamental concept of the task-based approach is that while tasks are performed using skills, skills themselves are not equivalent to tasks (Autor, 2013). The gap in data collection makes it hard to accurately map out which skills are being applied to

which tasks across different jobs. According to Autor (2013), there are three methods used in the literature to overcome this issue. The first method involves using occupations as proxies for the tasks associated with those occupations. This method is appealing since occupational categories can be thought of as groupings of tasks. However, using these classifications directly as measures of tasks is impractical because they are broad categorizations and tasks that overlap across different jobs are not captured in standard occupational classifications. These hide the similarities in the tasks performed in different occupations. To identify similarities in tasks between these broad occupational categories, additional classifications must be made, which introduces a level of subjectivity that can make the analysis biased.

The second method to address measurement issues is to manually categorizing occupations into groups, which involves attaching standardized descriptions of job tasks to each occupation. These descriptions then may serve as a basis for creating specific measures of job tasks (Autor, 2013). In the United States, sources like the U.S. Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET), provide these standardized job descriptions. The main advantage of this technique is that it uses validated job content data from external sources, ensuring reliability in the measures used. However, this method tends to ignore the variety of tasks that can exist within the same job title, given that workers' skills and the tasks they actually perform can vary widely even within a single occupation. Moreover, assigning tasks to occupations in this way provides a static approach, which could lead to an underestimation of how tasks are reallocated within the labor market, especially since tasks within occupations are likely to change with technological change (Autor, 2013).

A third strategy for measuring job tasks is to collect information about job tasks from survey respondents, alongside other data like demographics, employment, and wages. This method has been used with the IAB/BIBB labor force data from Germany, the British Skills Survey, the U.S. based survey of Skills, Technology, and Management Practices (STAMP) and more recently internationally by the OECD PIAAC, which provide detailed self-reported data on workers' job tasks. One significant finding from these efforts is that measuring routine and codifiable tasks through surveys is not straightforward. Tasks that seem routine to humans may be hard to automate,

reflecting the difficulty for workers to assess the codifiability of their tasks for machine execution. Still, gathering data directly from employees about the tasks they perform allows for a higher level of detail that is not possible with broad occupational classifications (Autor, 2013).

The **second challenge** for incorporating task measures into wage analyses is related to both conceptual and empirical issues. According to the task framework, if the market value of tasks in which a certain skill group has comparative advantage begins to fall, then, assuming constant task efficiencies (α), the wages of that skill group should decline as well. This occurs even if the skill group shifts its labor to other tasks. The important point here is that the wages for specific tasks can differ from the wages paid to a specific skill group, given that skill assignment to tasks is endogenous. For instance, if technological advancements increase the productivity of high-skilled workers across all tasks, the range of tasks these workers undertake could expand. Consequently, tasks that middle-skilled workers used to perform might shift to high-skilled workers, raising the wages for those tasks due to the higher productivity of high-skilled workers. However, the wages for medium-skilled workers who previously performed these tasks could decrease.

A significant complication with this approach is that the wage associated with a particular task might decrease or increase independently from the wages of the skill group that typically performs it. Unlike education, which is considered a fixed attribute by the time an individual enters the labor market, the tasks a worker performs are determined by both their skills and the current market demands for those tasks, which makes it challenging to draw conclusions from regressions of wages on tasks.

4.3.4. Empirical Literature on Turkish Labor Market

The existing literature on the Turkish labor market, as explained below and summarized in Table 34, focuses on labor market polarization, the effect of technological advancements, and the effects of demographic changes. This thesis aims to explain the relationship between technological advancements and wages, focusing on task content and ICT requirements within the Turkish labor market. By examining how ICT use and task intensities correlate with wage levels, this research contributes to the ongoing discussion on job polarization by providing an analysis at the individual

level. Moreover, by comparing the effects of ICT use at different levels, this analysis distinguishes between the wage effects of merely using computers versus using computers for more complex digital tasks.

In her doctoral thesis, Das (2017) analyzes wage inequality in Türkiye to determine whether the labor market has experienced polarization in terms of employment and wages between 2004 and 2015. She employs a quantitative methodology utilizing the Household Budget Survey data. Das (2017) finds that despite a decrease in wage inequality after the year 2000, it increased again by 2011 and it remains high compared to many developed countries. She finds that the influence of education on wage inequality is pronounced, with the return to university education declining. Despite this, wage inequality among university graduates, particularly between the 90th and 50th percentiles, has increased.

The findings from Bakis and Polat (2013) provide a backdrop to these findings. Polat analyzes the wage inequality dynamics in Türkiye between 2002 and 2010, using data from the Household Labor Force Surveys (HLFS). The findings suggest that there is a stability in the relative supply of workers with higher education levels (high school graduates and above) compared to workers with lower education levels (primary school education or below) between 2002 and 2004, accompanied by a simultaneous decline in their relative wages that benefited the less-educated workers. This coincides with the increase in the real minimum wage in 2004. However, from 2004 onwards, the supply of more educated workers rises, and their wages either remain constant or increase, disproportionately benefiting this group.

A recent study by Bakis and Polat (2023) extends the analysis up to 2019 and uses decomposition analysis to understand the effect of minimum wage changes. The study confirms earlier findings, showing that the minimum wage hikes in 2004 and 2016 reduced wage inequality. These resulted in real wage gains for lower-wage earners and narrowed the wage gap not only at the lower percentiles but across the entire wage distribution. This suggests that minimum wage policies in Türkiye have been effective in adjusting wages, especially in the absence of strong labor market institutions and collective bargaining frameworks.

Given the findings from Bakis and Polat (2013, 2023), the results of Das (2017) can

be interpreted as showing a specific aspect of wage inequality. Polat finds that from 2004 to 2010, the supply of more educated workers increased, and their wages either remain constant or increased, suggesting that overall, higher education still commands a premium in the labor market. However, Das finds that within the group of university graduates, wage inequality increased, particularly between the highest earners (90th percentile) and mid-level earners (50th percentile). This suggests that while education does increase wages, the benefits are not uniformly distributed among the highly educated.

Moreover, Das (2017) claims that this could be attributed to technological advancements, which may lead to the elimination of certain tasks and decrease the relative demand for specific occupations. Another explanation might involve the changing quality of university graduates, suggesting that shifts in the supply side of the labor market could explain this phenomenon. Moreover, she finds that after 2004, there was an observed increase in the relative wage of female subgroups that had initial specialization in manual tasks. According to Das (2017), this suggests that manual tasks have possibly gained a comparative advantage relative to routine tasks during this period. This could indicate a form of job polarization, where non-routine low-skilled (manual) and high-skilled (abstract) jobs see wage growth or increased demand compared to middle-skilled, routine jobs.

Krieger-Boden and Sorgner (2018) analyze how digitalization impacts gender equality in labor markets. The study discusses the gender-specific risk of digitization of occupations using data from the OECD's PIAAC data and includes Türkiye in their analysis. Their findings suggest that in Türkiye, as in other countries, the average risk of digitization of women’s jobs is comparable or even less than that of men's jobs. However, the prospects for medium-skilled occupations and the high risk of automation for certain job categories may affect women differently in various countries, including Türkiye. The authors note that on average, women are less likely to have their jobs automated than men, primarily because of women's stronger social abilities, which are becoming more important in the digital era, particularly when combined with higher educational attainment and advanced digital skills.

Sumer (2018) aims to explain the changes in employment patterns in Türkiye due to

advancements in technology, specifically Industry 4.0. The data used comes from the TURKSTAT's Household Labor Force Surveys from 2001 to January 2017. She discusses the dual nature of technological advancement, claiming that while it might lead to job losses in certain sectors, it may create new employment opportunities in others. Sumer (2018) categorized jobs into four occupational groups based on their tasks being routine and non-routine. The main inference of this study is that any growth in jobs characterized by routine activities is likely to be replaced by new technologies, potentially leading to widespread job loss.

Akgunduz and Torun (2020) analyzes the economic impact of the inflow of approximately 2.5 million Syrian refugees on the Turkish labor market, focusing on how this sudden increase in low-skilled labor supply influenced the tasks performed by native workers and the capital intensity of firms in Türkiye. The study utilized both survey and administrative data to estimate these effects. To analyze the effects of the Syrian refugee influx on the tasks performed by Turkish workers, they matched occupation-level task scores calculated from PIAAC data with those from the Turkish Labor Force Survey (LFS) since the PIAAC data provided a complementary source of information on the nature of tasks associated with different occupations.

Akgunduz and Torun (2020) find that that the inflow of refugees led to an increase in the complexity of tasks performed by native workers, with a shift from manual tasks towards more abstract tasks. This shift was more pronounced among highly educated and young native workers. On the other hand, lower-educated natives did not experience significant changes in the nature of their tasks and were more likely to be negatively affected in terms of employment. Akgunduz and Torun (2020) suggest that lower-educated workers were less able to adapt to the labor market shifts induced by the refugee inflow, likely due to the inability of these workers to transition to jobs that complement the type of labor offered by Syrian refugees. Additionally, the administrative firm data revealed that manufacturing firms responded by reducing their capital intensity and investments, particularly among smaller-sized firms. The study concludes that the labor provided by Syrian refugees acted as a substitute for manual tasks and capital inputs, while complementing more complex tasks.

Demir Seker et al. (2020) analyzes the susceptibility of jobs across different sectors in

Türkiye to the COVID-19 crisis. The authors aim to determine the sectors most capable of transitioning to work-from-home arrangements by identifying those where the largest proportion of workers can perform their tasks remotely. They then develop an Employment Vulnerability Index (EVI) for Türkiye that combines this work-from-home amenability with other vulnerability factors, aiming to highlight sectors where jobs are most at risk. The paper incorporates an analysis of routine versus non-routine work as part of its assessment of employment vulnerability across different sectors, and it finds that routine tasks are a factor contributing to job vulnerability.

Demir Seker et al. (2020) measure routine tasks by referencing the definition and framework established by Acemoglu and Autor (2011). Accordingly, routine tasks are those that are sufficiently well-defined that they can be performed following a set of predetermined instructions, making them more susceptible to automation and replacement by machines or algorithms. In contrast, non-routine tasks involve problem-solving, creativity, and interpersonal communication, which are harder to automate and typically require human judgment and flexibility. The analysis claim that jobs involving routine tasks are at higher risk of being affected by the pandemic due to their potential for automation or the ease with which they can be replaced by other workers. Conversely, non-routine tasks, which typically require higher levels of cognitive skills, creativity, or interpersonal interaction, are deemed less vulnerable in the COVID-19 crisis.

More recently, Atasoy et al. (2021) analyzed the effect IT skills on labor market outcomes by distinguishing between basic and advanced IT skills, analyzing how each type influences employment and wage outcomes. The paper uses data from TURKSTAT's Household IT Use (HITU) survey, which details individual IT skills, and the Household Labor Force (HLF) survey between 2007 and 2015, which provides information on wages, occupations, and industries, to analyze the effect of IT skills on labor market outcomes.

In the context of the paper, basic IT skills are defined as skills necessary for performing elementary digital tasks. These include using word processors, managing files and folders, basic internet usage like browsing and emailing, and using spreadsheets at a fundamental level. On the other hand, advanced IT skills refer to more sophisticated

abilities. These include programming, advanced data analysis, software development, network management, and complex problem-solving using technology. Moreover, the study measures routine and non-routine tasks by using the U.S. Department of Labor's O*Net categories and the ISCO-88 classifications.

Atasoy et al. (2021) finds that basic IT skills significantly increase the likelihood of employment, particularly for traditionally disadvantaged groups like women and the elderly. This improvement comes through increased labor force participation and better transitions from unemployment to employment. Advanced IT skills, while not significantly increasing the likelihood of employment beyond basic skills, help workers secure higher-paid jobs and are beneficial for occupations involving non-routine tasks.

There are also studies on the Turkish labor market that focus on employment and wage polarization. Akcomak and Gurcihan (2013) analyzes the Turkish labor market over the last decade, highlighting three main developments observed in labor markets of industrialized countries that are also evident in Türkiye: (i) an increasing share of the services sector in employment, (ii) employment polarization with rising employment shares in both low- and high-skilled jobs, and (iii) wage polarization where average wages in both low- and high-skilled jobs have increased relative to other jobs. They use microdata from the TURKSTAT's Household Labor Force Survey between 2004 and 2010 to confirm that similar trends are present in the Turkish labor market.

Dagli and Kosekahyalioglu (2021) aim to test the hypothesis of job polarization within the Turkish labor market by using data from the ILOSTAT spanning from 1982 to 2019 for Türkiye. Their methodology involves a qualitative analysis supported by descriptive statistics. The findings suggest that Türkiye has experienced significant job polarization over the last two decades. Since 2000, there has been an increase in the share of both high-skilled and low-skilled occupations within total employment, coupled with a decrease in the share of medium-skilled occupations. This shift is attributed to technological advancements being complementary for high-skilled labor and the growth of the service sector creating new job opportunities for low-skilled labor.

Table 34. Literature on task content of jobs and wage and employment polarization in Turkish Labor Market

Author(s) (Year)	Summary
Das (2017)	• Analyzes whether the labor market has experienced polarization in terms of employment and wages between 2004 and 2015. • Finds that the influence of education on wage inequality is pronounced, but the return to university education declining. • Despite this, wage inequality among university graduates has increased, particularly between the 90th and 50th percentiles, • Claims that this could be attributed to technological advancements, which may lead to the elimination of certain tasks and decrease the relative demand for specific occupations.
Sumer (2018)	• Analyzes potential changes in employment patterns in Turkey due to advancements in technology (2001-2017) • Categorized jobs into four occupational groups based on their tasks being routine and non-routine • Mentions dual nature of technological advancement, claiming that while it might lead to job losses in certain sectors, it may create new employment opportunities in others
Krieger-Boden and Sorgner (2018)	• Analyzed the impact of digitalization on gender equality in labor markets, including Turkey, • Women have a lower risk of job automation, partly because of women's stronger social abilities, • They emphasized the importance of social skills and digital literacy for women in the digital age.
Akgunduz and Torun (2020)	• Studied the economic impact of Syrian refugees on the Turkish labor market • An increase in the complexity of tasks performed by native workers, with a shift from manual tasks towards more abstract tasks. • Lower-educated workers were less able to adapt to the labor market shifts induced by the refugee inflow, likely due to the inability of these workers to transition to jobs that complement the type of labor offered by Syrian refugees.
Demir Seker, Ozen, and Acar Erdogan (2020)	• Assessed job vulnerability across different sectors in Turkey due to COVID-19, • Non-routine tasks, which typically require higher levels of cognitive skills, creativity, or interpersonal interaction, are less vulnerable in the COVID-19 crisis.

Building on the existing body of research, this study addresses a gap in the literature by analyzing an aspect of the Turkish labor market that has not been directly examined

in previous studies. While prior research has provided valuable information about wage inequality, job polarization, and the impact of technological advancements, this thesis focuses on the relation between education, technology use, and wage outcomes in Türkiye. Importantly, it also integrates unobserved abilities, utilizing numeracy scores from the PIAAC data as a proxy. This inclusion offers explanations for the factors that influence wage differences, such as innate cognitive abilities that may affect the productive use of technology in the workplace.

4.4. Potential Effects of AI and Advanced Technologies on the Labor Market

From a theoretical perspective, recent technological advancements, particularly in areas like AI and advanced robotics, have a dual effect. These technologies have the capacity to handle tasks that were traditionally performed by humans. This includes both routine tasks and increasingly, more non-routine tasks. At the same time, technology also complements labor by increasing productivity and enabling workers to focus on more complex tasks. In other words, it may replace labor, leading to a displacement effect, but it might also increase labor demand in areas not affected by AI due to increased productivity, known as the productivity effect, and through the creation of new jobs, known as the reinstatement effect. Therefore, the impact of advanced technology on overall labor demand is uncertain (OECD, 2023).

Organizations such as the IMF and the OECD conduct studies on the effect on the labor market to understand how AI can drive economic growth, improve productivity, and potentially exacerbate or mitigate inequality. IMF published a report in 2024, discussing how AI could affect global labor markets. The study finds that advanced economies are likely to experience the effect of AI earlier and more intensely due to their employment structure focusing more on cognitive-intensive tasks. These economies have a higher exposure to AI, with about 60% of jobs potentially affected. Moreover, the report finds variation in AI exposure across different demographic groups. For instance, women and college-educated individuals are generally more exposed to AI but also more likely to benefit more from it due to higher potential for AI complementarity in their jobs (IMF, 2024).

Recent progress in AI and advanced automation has made it possible to automate different tasks that were once thought to be difficult for technology to replicate. In jobs

where cognitive skills were traditionally valued, AI systems can now augment or replace human efforts. For instance, AI applications now assist medical professionals with diagnostic processes (OECD, 2023).

Moreover, AI technologies have seen significant advancements in their ability to understand and produce both spoken and written language. A 2017 OECD report examining how computers compare to humans in various skills revealed that, at the time, computers were not as proficient as humans in answering literacy questions, even those considered simplest for humans (Elliott, 2017). Fast forward to a more recent OECD study from 2023, AI can correctly respond to approximately 80% of the literacy questions presented to adults in the PIAAC. In fact, according to the OECD, AI might be able to complete the full PIAAC literacy test by 2026.

This rapid closing gap between AI and human performance on literacy tasks is attributed to the evolution of network architectures (Littman et al., 2021). Recently, Natural Language Processing (NLP) models have gained attention for their capabilities. NLPs are statistical models that capture the likelihoods associated with various sequences of words in a language. The main function of a NLP is to estimate the probability distribution of natural language, which involves predicting the likelihood of occurrence of a sentence or a sequence of words. This involves calculating how likely a particular arrangement of words is to form a coherent sentence based on learned patterns from a large corpus of text data (Wu et al., 2023).

As of 2024, ChatGPT by OpenAI and Llama 3 by META stand out as NLP models capable of matching human performance in different linguistic and cognitive tasks (Wu et al., 2023). Practical applications of these models have shown their versatility, as they are able to make jokes, write computer programs, and make medical diagnoses (OECD, 2023). This advancement in AI communication attracted widespread attention, with the example of ChatGPT exceeding 100 million monthly active users by the end of January 2023, two months after its launch (Reuters, 2023).

The attention received by NLPs caused an interest to analyze how well these AI technologies perform in comparison to humans in different fields. For example, Geerling et al. (2023a) conducted a study which involved ChatGPT taking the Test of Understanding in College Economics (TUCE), which is a standardized test used in the

U.S. to measure basic economic knowledge[33]. The results of the study show that ChatGPT scored 63.3% on the microeconomics questions and 86.7% on the macroeconomics questions. This placed ChatGPT at the 91st percentile for microeconomics and the 99th percentile for macroeconomics when compared to students who typically complete this test at the end of their semester (Geerling et al., 2023a, 2023b). The research on NLP models is not just limited to economics, many studies have also shown their competence in other academic fields (See Sumbal et al., 2024 for medicine exams; Pursnani et al.,2023 for engineering exams; Choi et al., 2022 for law school exams). Overall, these findings show that an NLP model can achieve high levels of proficiency across various academic fields.

While diplomas continue to hold value, there is a growing demand in the job market for specific skills that traditional degree programs do not always provide. Rather than assuming that a worker with a certain degree has the necessary skills, employers are starting to look at whether candidates have the capabilities required for the tasks at hand. As a result, more employers are moving toward *skill-based hiring practices*, which evaluates candidates based on their performance in relevant tasks (McKinsey & Company, 2023).[34] This is evident in the technology sector, where companies like Google, Apple, and others have relaxed degree requirements in favor of demonstrated skills. Such a shift can lower the value attached to education as it challenges the traditional view that obtaining a degree automatically equips individuals with the necessary skills for the job market.

Still, while the relevance of degrees might be changing in some sectors due to the rapid pace of technological change and the increasing importance of technical skills, formal degrees continue to be valuable in many sectors. In many sectors, especially those that are heavily regulated, degrees are necessary credentials that certify individual

[33] The test includes two sections (microeconomics and macroeconomics), each comprising 30 multiple-choice questions, including three questions on international economics. The TUCE allows comparisons of students' knowledge across various skill levels and achieving around a 50% score is ideal.

[34] Skill-based hiring is an employment strategy that prioritizes specific skills and abilities over traditional qualifications. Employers assess candidates based on their ability to perform tasks or solve problems that are typical for the job. This can involve practical tests, simulations, or assessments during the interview process. Interviews are tailored to evaluate the specific skills needed for the job, often through behavioral and situational questions.

qualifications. Moreover, in fields that rely heavily on interpersonal skills and professional judgment, such as psychology, education, or healthcare, traditional degrees hold their value.

Historically, having a degree was also seen as a signal for general capability, soft skills, and potential to learn, which causes many employers to require a bachelor's degree. Over the years, as technology began transforming workplaces, there was an inclination to associate technological adeptness with higher educational attainment. This created a need for higher levels of education among workers to meet the demands of technological advancements and labor market conditions. The traditional view on having a university degree is still strong in Türkiye, and many families and students prioritize tertiary education as a path to secure employment. However, as Türkiye continues to integrate more closely with the global economy, the approach to hiring is gradually changing from traditional degree focused models to more skill-based practices.

A survey conducted by Coursera across 11 countries[35], including Türkiye, provides information about the change in hiring practices. The survey asks how prevalent skills-based hiring practices are and the results show that 22% of employers in Türkiye are already implementing skills-based hiring, while an additional 52% are considering it. Additionally, 16% are not currently using but are open to considering such practices in the future. Only 7%, are not engaging in skill-based hiring and are not inclined to consider it. In comparison to other countries, Türkiye's combined total of 74% (22% already using plus 52% considering) falls in the mid to higher range of moving towards skills-based hiring practices. The Coursera survey then asks employers to identify the main reasons for using or considering the implementation of skills-based hiring practices within their organizations. Totally, 85% of Turkish employers claim that they are motivated by the need to verify that candidates have the right skills for the job. Finally, the survey asks employers to identify the types of skills they find most difficult to find among recent university graduates[36]. The results show that in Türkiye,

[35] Australia, Egypt, France, Germany, India, Mexico, Saudi Arabia, Türkiye, the United Arab Emirates, the United Kingdom, and the United States.

[36] They are asked to rank the top 2 types of skills.

employers find technology skills, such as computer programming, to be the most challenging to find among recent university graduates, with 65% of employers indicating a deficit in this area. This is followed by data skills, including data analysis, where 54% of employers reported difficulties.

4.4.1. Changing Skill Demands in Response to AI and Advanced Technologies

How do the recent technological advancements affect skill demands in the labor market? Given that the widespread adoption of AI is a relatively new phenomenon, its transformative effects are not fully captured yet. Previous research has often focused on the potential for automation to replace human labor, analyzing tasks and occupations at risk, or utilized the adoption and integration of industrial robots as a proxy to understand the effect of advanced technologies on the labor market.

There are some early attempts in the literature to understand the effects of AI and advanced technologies on the labor market to find out how skill demands change. Felten et al. (2019) analyze the relationship between AI and labor through a new metric called the AI Occupational Impact (AIOI) to understand how occupations are affected, focusing on changes in wages, employment, and labor market polarization for the period from 2010 to 2016 for the United States. The results show that, on average, occupations impacted by AI see a small positive change in wages but no significant change in employment. Moreover, the positive correlation with wages is mainly driven by occupations that require a high level of software skills, indicating that certain skills can increase the benefits of AI. On the other hand, higher-income occupations show a positive relationship between AI and both employment and wages.

Alekseeva et al. (2021) examined the increasing demand for AI skills in various sectors, occupations, and firms in the U.S. from 2010 to 2019 by utilizing online job posting data (Lightcast data). The results indicate a rise in the demand for AI specialists, with the highest demand seen in IT occupations, followed by fields like architecture, engineering, and management. The research indicates that larger firms, particularly those with substantial investments in R&D, have a higher demand for AI skills. Additionally, the study documents a significant wage premium for AI related skills within the same firm and job title, suggesting that managerial occupations benefit

the most from AI skills. These findings suggest that the demand for AI related skills is not confined to IT-related industries and occupations.

Manca (2023) also uses Lightcast data from a broader set of countries including the United Kingdom, Canada, Australia, New Zealand, in addition to the US. The study finds that between 2012 and 2019, the demand for AI skills outpaced the average skill demand in these economies, showing the rapid adoption and integration of AI technologies. Moreover, the study finds that job postings requiring skills related with AI, such as Machine Learning, offer higher average wages across these countries. This is after accounting for factors such as educational attainment, job complexity, and geographical location, indicating that AI skills are highly valued in the labor market. Additionally, the study finds that AI-related jobs tend to demand higher-level cognitive skills, such as creative problem solving.

More recently, Acemoglu, Autor, Hazell and Restrepo (2022) (AAHR henceforward) examine the effects of AI on labor markets across the U.S., starting from the year 2010. They begin with the premise that the adoption of AI by firms can be inferred through the observable patterns in their recruitment, such as the hiring of professionals with expertise in 'AI-centric tasks'. To do so, AAHR compile a dataset at the establishment level, reflecting AI engagement, derived from online job postings in the U.S. and their specified skill requirements. To identify the tasks and occupations most affected by current AI technologies, AAHR utilize three indicators[37], and calculate the AI exposure of an establishment by evaluating its occupational structure during the baseline period of 2010 to 2012, using these indices. These baseline measures then act as proxies for the establishment's exposure to AI in the subsequent analysis. AAHR (2022) find that there is a significant increase in the number of AI-related job postings beginning in 2010, with an acceleration around 2015-2016. This aligns with the idea that the influence of AI is directly related with the compatibility of specific tasks within industries to the capabilities offered by current AI technologies. In fact, the

[37] (1) The AI occupational impact measure developed by Felten, Raj, and Seamans (2018, 2019); (2) the Suitability for Machine Learning (SML) index crafted by Brynjolfsson, Mitchell, and Rock (2018, 2019); and (3) Webb's (2020) AI exposure score.

results show that industries and workplaces with a higher initial (baseline) exposure to AI tend to post about 15% more AI-related job vacancies.

Additionally, AAHR (2022) indicates a significant relationship between exposure to AI and changes in the types of skills employers demand. Specifically, establishments with a higher exposure to AI tend to reduce their demand for certain previously sought-after skills while simultaneously showing an increased demand for new skills. This pattern suggests that AI is transforming the nature of work by automating tasks that were traditionally performed by humans and creating new roles that necessitate different competencies. Finally, AAHR (2022) reveals that exposure to AI is related with a decrease in hiring for both AI-related and overall positions. This decline in hiring coincides with the period of increased AI activity from 2014 to 2018, suggesting that the rise in AI is partly attributed to the automation of tasks previously carried out by humans. On the other hand, AAHR (2022) observe no relation between exposure to AI and changes in wage levels within specific occupations or industries.

Furthermore, surveys conducted by the OECD among workers and employers in the finance and manufacturing sectors across seven OECD countries showed noticeable changes in skill demands (Lane, Williams, and Broecke, 2023). Around half of the AI users reported that the introduction of AI had diminished the value of some of their skills, with 51% in the finance sector and 45% in manufacturing expressing this view. According to the OECD Employment Outlook (2023), the demand for AI-related skills is expected to increase due to two factors: the need to develop and maintain AI systems, and the requirement to use and interact with AI applications (See Table 35). Jobs related with the development and maintenance of AI systems are typically technical and often introduce new jobs where employees will undertake AI-specific tasks not previously seen in the job market. Moreover, within firms that use AI, employees may find themselves required to use AI technologies. While many of these roles are not new, the use of AI can cause changes in the tasks performed and the skills needed (OECD, 2023).

Those findings on the effect of AI on the labor market indicate that AI is having tangible effects on industries and occupations that are integrating this technology. There is an increase in job openings for AI specialists in establishments whose tasks

align with AI capabilities. A distinct pattern of skill turnover in AI-exposed establishments arises, marked by both a decline in demand for certain existing skills and the emergence of new skills; and a trend towards decreased hiring for non-AI roles in these establishments. These support the theory that AI algorithms are beginning to replace tasks traditionally performed by humans, even though the full extent of its influence on the wider economy remains to be seen (Autor et al., 2022).

Table 35. AI-Related Skills

Developing and Maintaining AI Systems	
Specialized AI Skills	• Fundamental AI concepts • In-depth knowledge of AI techniques • AI tools
Data Science Competencies	• Proficiency in data analysis and big data handling • Skills in programming languages • Data visualization and cloud computing capabilities
Additional Cognitive Abilities	• Creative problem-solving techniques
Cross-functional Skills	• Advanced social interaction abilities • Leadership and organizational management skills
Utilizing and Engaging with AI Applications	
Fundamental AI Understanding	• Understanding of machine learning basics
Digital Competencies	• Efficient use of computers or smartphones
Further Cognitive Abilities	• Strong analytical and problem-solving skills • Critical thinking and sound judgement • Creativity in tasks
Cross-disciplinary Skills	• Proficiency in communication • Ability to work collaboratively in teams • Effective multitasking skills

Note: This table was developed based on information derived from the OECD Employment Outlook 2023.

Overall, the research so far suggests that workers with strong digital skills, including those related to AI, may be better positioned to adapt to changes brought about by advanced automation and AI. Technical skills form the backbone of this skill set, with programming and coding in languages being foundational. Equally important is a deep understanding of Machine Learning and AI principles, which are essential for developing AI models and making data-driven decisions. Furthermore, these digital skills include not only technical skills directly related to AI but also digital literacy in a more general sense. Moreover, interpersonal skills, especially in teams that combine technical know-how with field-specific knowledge, are also important in this environment.

4.4.2. The "Bottleneck Skills"

While the RBTC literature suggests that routine tasks are highly susceptible to automation, there are some constraints that hinder the complete computerization of certain job tasks. Such constraints are considered to define the limits of computerizing tasks. According to Frey and Osborne (2013), these are *bottleneck skills* that limit the extent to which certain jobs can be automated or computerized. These bottlenecks refer to the current technological and practical limitations that prevent computers from performing certain tasks.

Frey and Osborne (2013) suggest that there are three bottleneck skills that currently limit job automation. These include perception and manipulation, creative intelligence, and social intelligence. Perception and manipulation tasks involve the ability to interact physically with the world, which includes understanding unstructured environments or handling irregular objects. Creative intelligence refers to the creation of new, innovative ideas or solutions, encompassing areas like art and literature. Social intelligence involves understanding and responding to complex human emotions.

However, some advancements have been made in addressing some of the bottleneck skills. For example, in terms of perception and manipulation, robotics with more sophisticated sensors and machine learning algorithms enhances robots' abilities to

perceive and interact with their environments. Nonetheless, despite these advancements, many challenges remain. For instance, advanced robots like Boston Dynamics' Atlas and Spot show advanced capabilities but are not yet widely adopted due to their costs. Furthermore, AI has made notable progress in creative fields. Algorithms can now generate art, music, and literary texts, as seen with AI tools like DALL-E. Yet, despite these capabilities, AI still lacks the understanding and emotional connection inherent to human creativity. Similarly, in social intelligence tasks, advancements in NLPs and 'affective computing' have led to more responsive and seemingly empathetic AI systems. However, AI lacks the ability to truly understand and respond appropriately to human emotional states in a context-sensitive way. Therefore, although the bottleneck skills in automation still exist, the advancements in technology always push the boundaries (McCormack and d'Inverno, 2019; Picard, 2000).

4.4.3. Developments in Türkiye

In 2023, Türkiye published the *Industry and Technology Strategy* which outlines Türkiye's national strategy towards industrial and technological development. This strategy report explains Türkiye's approach to improving its global competitiveness and securing its economic and technological independence through breakthroughs in critical technologies (The Ministry of Industry and Technology, 2023, p3). These policies are structured under the "National Technology Initiative," which aims to coordinate these efforts. The strategy mentions several areas including data governance, content moderation, and competition policy, which are essential for creating a sustainable and innovative technological environment. The strategy report also discusses AI, providing recommendations on the use of AI with a particular focus on data protection.

What factors are influencing the adoption of AI technologies within Turkish enterprises, and what growth in AI adoption has been observed in recent years? TURKSTAT (2023) conducted the Information Technology Usage in Enterprises Survey in Türkiye to gather data on the prevalence and nature of AI use within enterprises in Türkiye. The survey explains how widely AI is being adopted across different sizes of enterprises, identify the types of AI applications in use, and learn

about the main barriers to AI adoption [38]. The results show an increase in AI adoption among Turkish enterprises, with 5.5% of businesses reporting the use of AI technologies in 2023, which is a significant increase from 3.5% in the previous year. This increase is skewed among different firm sizes, with the largest usage seen in enterprises with 250 or more employees. However, the largest increase in terms of percentage points occurred in the smallest enterprise group (10-49 employees). This suggests that while larger enterprises may continue to use AI at a higher overall rate, the most significant growth over the past year has been among smaller enterprises, which saw the highest percentage point increase in AI adoption.

Table 36. Reasons for Not Adopting AI Technology in Turkish Enterprises (2023)

Reasons for Not Using AI Technology	**Total**	**10-49 employees**	**50-249 employees**	**250+ employees**
High Costs	60.0	60.7	62.4	52.4
Lack of Expertise in the Field	53.8	53.5	56.4	46.8
Incompatibility with Current Equipment, Software, or Systems	49.6	49.0	53.7	47.1
Existence of Challenges Regarding the Availability and Quality of Required Data	40.1	39.4	45.1	38.9
AI Technology Not Being Considered Useful for Entry into the Market	36.5	36.5	38.0	29.0
Uncertain Legal Consequences	36.3	35.5	40.7	38.3
Concerns About Data Protection and Privacy	35.9	35.2	40.3	36.9
Ethical Factors	31.3	30.9	34.5	30.4

[38] According to personal correspondence with TurkStat, the ICT Usage in Enterprises Survey does not directly ask enterprises whether they use AI in a yes-or-no format. Instead, the survey asks enterprises about their engagement across seven specific AI application areas. Firms indicating no use of AI to all of these domains are then prompted to specify reasons for non-adoption, by using a series of yes-or-no questions that allow multiple responses to identify various barriers to AI integration.

Note: Since respondents could select multiple reasons, the total may exceed 100%. Data sourced from the "Information Technology Usage in Enterprises Survey, 2023" by TURKSTAT.

What are the main reasons cited by enterprises in Türkiye for not adopting AI technologies? The reasons cited by Turkish enterprises (See Table 36) are mainly financial, with 60.7% of respondents saying that the high cost of AI technologies is a major barrier. Following this, 53.8% report a lack of relevant expertise within their firms as a reason for not adopting AI. Thirdly, nearly half of the enterprises (49.6%) report that existing equipment, software, or systems are not compatible with new AI technologies. Still, the fact that TURKSTAT, a government statistical agency, is conducting a survey on AI suggests there is a recognized importance of AI at a national level, indicating that the Turkish government sees AI as a critical area for future developments. This reflects an understanding that AI has the potential to drive productivity and economic growth, and there is a need to understand the current state of AI adoption to support this.

4.5. Data and Methodology

As was in the first two chapters of this thesis, we use the Survey of Adult Skills or PIAAC (The Programme for the International Assessment of Adult Competencies) from OECD[39]. The PIAAC survey is distinctive because it objectively measures foundational skills of individuals, such as their numeracy skills. The background questionnaire is an important component of the PIAAC and it collects information on participants' educational background, employment status, job characteristics, among others. Additionally, it includes information on the frequency of various job tasks performed by individuals. This allows for the creation of individual-level measures of task demand, which is different from the traditional occupation-level assessments (Pouliakas and Russo, 2015).

PIAAC is conducted through household surveys where participants are interviewed and tested directly. The assessment is carried out on computers or, if necessary, on paper. The first round of the PIAAC survey ("First Cycle") was conducted over the period from 2011 to 2012. Türkiye participated in the second round of PIAAC, which

[39] The details about the PIAAC data are explained in the first chapter of this thesis in more detail.

was carried out from 2014 to 2015. The PIAAC data collection in Türkiye involved 5,277 participants. For the purposes of our analysis, the sample from the PIAAC survey was reduced to individuals aged 20 to 54 years who were in full-time paid employment at the time of the survey. Furthermore, self-employed individuals and those working in the armed forces were excluded from the sample. These restrictions were implemented to ensure that the analysis focuses on wage-earning employees. After these, the number of observations for Türkiye was reduced to 1,388.

The wage data for Türkiye is presented only in deciles. Given this, the analysis employs OLS regression, rather than using an ordered probit model. Both OLS and ordered probit models were initially employed and the results from both models were consistent, supporting the decision to proceed with OLS for the analysis.

This approach simplifies the interpretation of results while maintaining the robustness of the findings. However, it is important to note that interpreting the coefficients from this model is different when decile-based data is used. In this context, a positive coefficient does not imply a direct percentage increase in wages. Instead, it indicates a relative improvement in the wage distribution, moving from a lower to a higher decile, for example.

4.5.1. Constructing Variables: ICT Requirements and the Level of ICT Use at Work

The PIAAC background questionnaire does not directly categorize ICT use and requirements into specific groups or categories in its background questionnaire but collects data on it. PIAAC assesses

- The frequency and types of computer and internet use,
- The complexity of software and applications used,
- The requirement of digital tasks for job performance.

In order to examine the wage effects of computer use and the relationship between ICT levels and routine task intensity of jobs, we construct two sets of variables based on PIAAC, which are task intensity variables and the “ICT use level at work” variable.

4.5.2. Constructing the Relevant Variables

4.5.2.1. ICT Use at Work Variable

The *"ICT Use at Work"* variable categorizes the level of computer use at work[40]. This variable categorizes the extent of ICT use in different jobs based on responses to five PIAAC questions about computer usage. The first question (G_Q04) establishes whether a computer is used in the job. If the response is "No," the ICT use level is categorized as "None". If the response is "Yes," the assessment progresses to determine the complexity of computer usage. Respondents are initially classified at the "Straightforward" level, which includes basic tasks, if they answer "yes" to the question G_Q05A, which asks if they use email for work more than once a month. Next, if respondents frequently use spreadsheet and word processing software, or if they also engage in programming, they are categorized to the "Complex" use level, reflecting a need for higher ICT skills.

4.5.2.2. Task Intensity Variables

The PIAAC background questionnaire collects information about the types of tasks performed at work, but it does not categorize tasks into groups like routine or cognitive within the questionnaire itself. In order to measure different task intensities in the workplace, we employ Principal Component Analysis (PCA)[41] to construct indices for measuring the intensity of different types of tasks at work. In this thesis, job tasks are grouped into three categories which are Routine, Interactive, and Cognitive.

Routine tasks are characterized by their codifiability and repeatability. Interactive tasks require communication and interaction with others. Cognitive tasks involve high levels of problem-solving and information processing. The PIAAC survey uses a Likert scale from 1 to 5 to rate the frequency or importance of these tasks, where a

[40] The "ICT use level at work" reflects the actual use of ICT by the worker in their job and measures how the worker uses computer technology, which might be different from the requirements of the job and the actual computer skill level of the worker.

[41] PCA is a statistical technique used to reduce the dimensionality of the data while retaining most of the variability. This method does this by transforming the original variables into a new set of variables, which are called as principal components (Jolliffe, 1990).

higher score indicates a more frequent or significant use of the skill. Tables 37 and 38 lists the PIAAC questions that are used to construct the three indices of task complexity.

In the PCA, the 1 to 5 scale responses for each task-related question are treated as quantitative data. These scores indicate how frequently each task is performed in jobs. The PCA transforms these responses into a set of principal components, which are new variables created by combining the original task scores to capture the largest variations among the tasks across all respondents. This reduces the information from multiple task questions into task indices, reducing the number of variables to composite scores that show the trends in the dataset. These composite scores are then used to quantify the intensity of routine, interactive, and cognitive tasks in easier to read way.

Table 37. Job Task Questions for Routine Intensity Indicator

Indicator	Variables	Question
Routine	F_Q03a	How often does your job usually involve planning your own activities?
	F_Q03b	How often does your job usually involve planning the activities of others?
	F_Q03c	How often does your job usually involve organizing your own time?
	D_Q11a	To what extent can you choose or change the sequence of your tasks?
	D_Q11b	To what extent can you choose or change how you do your work?

The index that measures the **routine intensity** of a job uses a set of questions designed to assess how much autonomy and flexibility an individual has in their daily work activities. To measure the routine intensity of jobs, the questions can be grouped into two components. The first component, *planning and organizing tasks*, includes questions about planning one's own activities, planning the activities of others, and

organizing one's own time. The question about planning one's own activities (F_Q03a) assesses how often employees are planning out their daily tasks. A high frequency indicates a lower routine intensity due to the variability and decision-making involved. Similarly, planning the activities of others (F_Q03b) involves coordination and leadership, again pointing to lower routine intensity. The ability to organize one's own time (F_Q03c) also shows the level of personal discretion and flexibility in a job, with higher autonomy relating with less routine work.

Table 38. Job Task Questions for Interactive and Cognitive Categories

Indicator	Variables	Question
Interactive	F_Q02a	How often does your job usually involve sharing work-related information with co-workers?
	F_Q02b	How often does your job usually involve instructing, training, or teaching people, individually or in groups?
	F_Q02c	How often does your job usually involve making speeches or giving presentations in front of five or more people?
	F_Q01b	In your main job, how often does it involve cooperating or collaborating with others in your workplace?
Cognitive	F_Q05a	How often are you usually faced by relatively simple problems that take no more than 5 minutes to find a good solution?
	F_Q05b	And how often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution?

The second component, *autonomy over task execution*, focuses on the freedom to choose or change the sequence of tasks (D_Q11a) and the methods of performing these

tasks (D_Q11b). The ability to change task sequences allows employees to adapt to different circumstances and tailor their work processes, which is characteristic of jobs with lower routine intensity. Similarly, having the flexibility to decide how to perform tasks further reduce the routine nature of the work.

Secondly, to measure the **interactive** index of jobs, the questions can be grouped into two components that emphasize communication and collaboration, and instruction and presentation. *Communication and collaboration* component combines the aspects of sharing work-related information with co-workers (F_Q02a) and cooperating or collaborating with others in the workplace (F_Q01b). These questions assess how frequently employees engage in direct communication and teamwork. Frequently sharing information shows that the job requires continuous interaction. Similarly, the need to cooperate or collaborate with others indicates that the job depends on teamwork. High frequency in these activities characterizes jobs with a high interactive index. The *Instruction and Presentation* component focuses on the more formal aspects of interaction, which are instructing, training, or teaching people (F_Q02b), and making speeches or giving presentations in front of five or more people (F_Q02c). These questions measure the extent to which a job involves educating others and presenting information to groups. Jobs that frequently involve these activities are highly interactive.

Finally, to measure the **cognitive** demands of jobs, we use two questions, combined into a single component that assesses problem-solving complexity. This *problem-solving complexity* component combines the frequency of encountering simple problems that take no more than 5 minutes to solve (F_Q05a) and the frequency of dealing with more complex problems that require at least 30 minutes to find a good solution (F_Q05b). Jobs that have a high frequency of complex problem-solving are indicative of jobs with significant cognitive demands, where workers must use analytical skills, critical thinking, and creativity.

To develop the indices of task complexity, we employ PCA to the scores of each group of questions. Table 39 also provides an overview of the PCA results and correlation coefficients for these task types. We determine the number of principal components needed in our application by checking explained variance and seeking that the grouped

tasks have a Cronbach's alpha reliability coefficient greater than 0.7. Cronbach's alpha is a measure of internal consistency, indicating how closely related a set of items are as a group and how well a set of variables or items measures a single, one-dimensional latent construct (Cronbach, 1951). The first two components for the routine and interactive indices and the first component for the cognitive index explain more than 70% of the variance in each group. The Alpha values for all task indices are above 0.7, which is regarded as a threshold indicating acceptable reliability, suggesting that the items for each task type are reliable and that they consistently measure the intended constructs.

Table 39. Summary of Component Analysis and Reliability Measures for Task Characteristics

		PCA		Correlation Coefficients			
	Number of Items	**Comp.**	**Explained Variance**	**Routine**	**Interactive**	**Cognitive**	**Cronbach's Alpha**
Routine	5	2	73.59%	1.0000	-	-	0.75
Interactive	4	2	83.07%	-0.4341	1.0000	-	0.71
Cognitive	2	1	78.66%	-0.3205	0.3888	1.0000	0.73

The correlation coefficients describe the relationships between different task types. There is a moderate negative correlation (-0.4341) between routine and interactive tasks which suggests that as the intensity of routine tasks increases, interactive tasks tend to decrease, and vice versa. Similarly, there is a moderate negative correlation (-0.3205) between routine and cognitive tasks, suggesting that jobs with higher routine task demands might have lower cognitive requirements. Finally, the positive

correlation between interactive and cognitive tasks (0.3888) indicates that tasks requiring higher levels of interaction often also require higher cognitive tasks.

4.5.3. The Effects of Computer Use on Wages

The methodology for measuring the wage effect of computer use builds on the work of Autor (1994) and DiNardo and Pischke (1996). These studies interacted educational attainment with a computer use dummy variable to analyze their combined effects on wages. In this thesis, we use both years of education and dummy variables for education levels to examine the effect of having a degree in separate models. After preliminary results, we continue with dummy variables for different levels of education. Furthermore, we categorize ICT use into two levels (straightforward and complex) to analyze the effects of different levels of ICT intensities and include the interactions of ICT use with education variables.

4.5.3.1.The Model for the Effect of ICT Use on Wages

For the OLS regression analysis focusing on the effect ICT usage on wage levels, we start with a baseline model that examines the effects of education, ICT use at different levels, and then we add their interaction on wages and numeracy scores in the subsequent models. The regression model can be shown mathematically as follows:

$$W_i = \alpha + \sum_j \beta_j E_{ij} + \sum_k \delta_k ICT_{ik} + \sum_j \sum_k \gamma_{jk}(E_{ij} \times ICT_{ik}) + \mu Num_i + \theta X' + \in_i$$

where W_i is the hourly earnings in deciles for individual i, E_{ij} represents the educational attainment dummy variables for individual i where j represents education levels ($j = 1$ for upper secondary and $j = 2$ for tertiary education)[42]. ICT_{ik} are dummy variables indicating the level of ICT use at work for individual i, specific to level k where k can be straightforward or complex[43]. The interaction term captures the combined effect of education and working at ICT level k. Num_i is the numeracy score of individual i and X includes controls for other variables including gender, marital

[42] Relative to having a lower secondary education or less.

[43] Relative to having no ICT use.

status, children, experience and experience squared, firm size and sector. $\in_i$ is the error term.

4.5.3.2.The Model for the Effect of Task Intensities on Wages

For the OLS regression analysis focusing on the effect of ICT usage on wage levels while also accounting for the effect of task intensities, the model includes these variables and is expressed mathematically as follows:

$$W_i = \alpha + \sum_j \beta_j E_{ij} + \sum_k \delta_k ICT_{ik} + \sigma_1 \text{Routine}_i + \sigma_2 Int_i + \sigma_3 Cog_i + \mu Num_i + \theta X' + \varepsilon_i$$

where W_i is the wage individual i expressed in deciles, E_{ij} are dummy variables indicating the level of education of individual i, and ICT_{ik} is a dummy variable representing the level of ICT use at work for individual i, specific to level k where k can be straightforward or complex. Routine_i is a continuous variable measuring the routine task intensity of individual i's job. Int_i and Cog_i are continuous variables measuring the interactive and cognitive task intensities, and Num_i is the numeracy score of individual i and X includes controls for other variables. ε_i is the error term.

According to the task-based approach, routine tasks are characterized by their repetitive and codifiable nature, making them more susceptible to automation and substitution by computers. In these models, cognitive and interpersonal task variables are used to see if it changes the relationships found in the previous model. This inclusion allows to analyze how routine intensity of jobs, alongside cognitive and interpersonal tasks, affect wages.

4.5.4. Descriptive Statistics

Table 6.1 provides descriptive statistics for our data set, demonstrating demographic characteristics of full-time wage earners, broken down by gender. The total number of observations is 1,388, with females comprising 22.57% and males comprising 77.43% of the sample. The data indicates that a larger proportion of individuals who work full-time fall within the age range of 30-44 and almost 26.7% of the individuals have a tertiary education degree (including professional degrees). Additionally, women tend to have higher tertiary educational attainment, with a larger proportion holding tertiary

Table 40. Descriptive Statistics (%)

	All	Female	Male
Age			
Entry age (20-29)	30.0	31.2	29.6
Prime age 1 (30-44)	53.5	56.0	52.8
Prime age 2 (45-54)	16.5	12.8	17.6
Education			
Lower secondary or less	48.1	34.7	52.0
Upper secondary	25.2	27.3	24.6
Professional degree	8.4	9.7	8.0
Bachelor's degree	15.3	24.3	12.7
Master/research degree	3.0	4.0	2.7
Firm Size			
Micro/small-sized enterprises	62.3	64.2	61.7
Medium-sized enterprises	20.0	21.7	19.4
Large-sized enterprises	17.8	14.1	18.8
Computer use at work			
Yes	44.9	54.6	42.1
No	55.1	45.4	57.9
Computer use at work for those with tertiary education			
Yes	86.2	91.2	83.8
No	13.9	8.8	16.3
Earnings			
Average hourly earnings decile	5.49	5.09	5.60
Observations	1,388	22.57%	77.43%

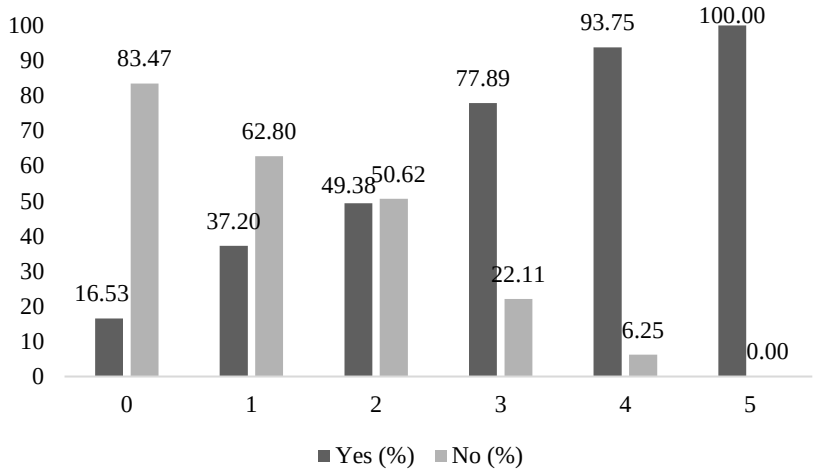


Figure 24. The percentages of respondents who use computers and those who do not use computers at work, categorized by different numeracy skill levels (2015)

(i.e. professional, bachelor's and master's) degrees compared to men. This suggests that the women who are full-time wage earners are a selective group. Computer usage is very high among women, especially among individuals with tertiary education. The data also indicates that males have higher average hourly earnings compared to females[44]. Sampling weights were used to ensure that the descriptive statistics accurately represent the population.

According to the SBTC theory, workers with higher skill levels are more likely to engage with and benefit from technological advancements. If this hypothesis is true, it is anticipated that workers with higher skills and/or education will have a higher probability of using computers in their jobs. Figures 23 and 24 illustrate the variation in computer usage at work among different levels of numeracy skill and education. Figure 23 demonstrates a direct relation between numeracy skills and computer usage in the workplace. At the lowest level of numeracy skills, which is level 0, only 16.53% of respondents use computers. The ratio increases gradually with each level of numeracy. This implies that individuals with higher numeracy skills tend to use computers more in their jobs.

[44] The t-test result shows a statistically significant difference in average hourly earnings in deciles between males and females, with males receiving a higher average. The difference between both means is 0.333, and it is marginally statistically significant with a p-value of 0.0535

Figure 24 shows the relationship between the level of attained education and computer usage at work. The data reveal that as the level of education increases, the use of computers at work also increases. Among individuals with a level of education below high school, the percentage of computer users is 16.26%. The proportion of computer usage at work increases with the education level, with the highest percentage of 97.62% observed among individuals holding a master's or research degree.

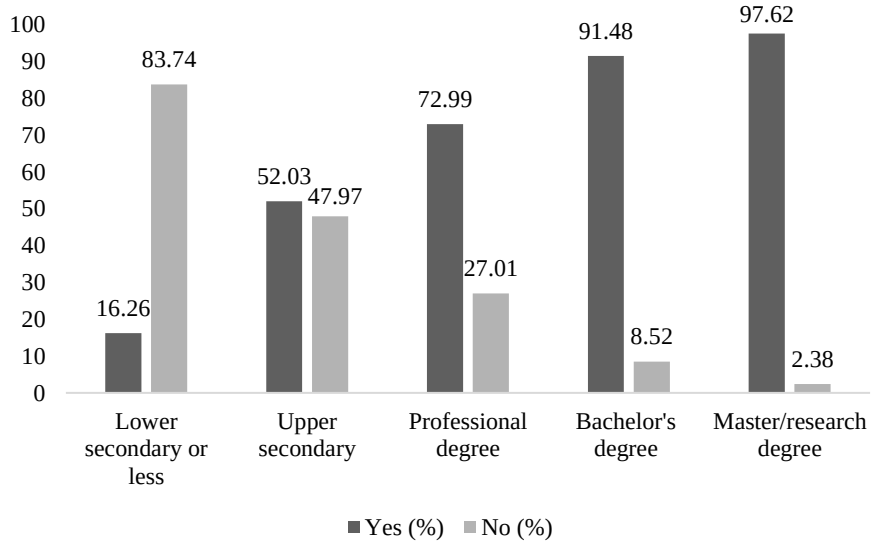


Figure 25. The percentages of respondents who use computers and those who do not use computers at work, categorized by their highest level of education attained (2015)

4.5.5. Job Characteristics

While SBTC focuses on how technology benefits workers with higher skills, the task-based approach and RBTC focus on the tasks themselves. In other words, under the task-based approach, the effect of technology on the labor market is analyzed by the tasks rather than focusing on the skills of workers. Table 41. categorizes jobs based on their characteristics and shows how they are distributed across the three levels of routine task intensity. The first job characteristic is the indicator of cognitive task intensity. It measures the complexity and frequency of problem-solving required in a job, categorizing it into three levels: low cognitive, medium cognitive, and high cognitive, based on thresholds at the 25th percentile (P25) and the 75th percentile (P75).

As the cognitive task intensity of a job increase, the proportion of jobs classified as

high routine intensive decreases. For jobs that have low cognitive task intensity, 57.3% are in the high routine category. Out of the jobs that have medium cognitive task intensity, 34.3% are classified as low routine, 22.7% are classified as medium routine, and 43.1% are classified as high routine. This shows that jobs with medium cognitive intensity are distributed more evenly across routine intensities, but a significant proportion is still in more routine-intensive settings. For jobs that require high cognitive task intensity, 44.6% are in the low routine category, 24.5% fall into the medium routine category, and 30.8% are in the high routine category.

Table 41. Distribution of Routine Task Intensity by Job Characteristics (%)

	Low-Routine Intensive	Medium-Routine Intensive	High-Routine Intensive
Cognitive Indicator			
Low Cognitive	24.8	17.9	57.3
Medium Cognitive	34.3	22.7	43.1
High Cognitive	44.6	24.5	30.8
Interactive Indicator			
Low Interactive	16.1	21.9	62.0
Medium Interactive	28.8	22.6	48.7
High Interactive	55.8	21.1	23.1
Firm Size			
Micro/Small-Sized (<50)	35.5	22.8	41.7
Medium-Sized (50-249)	35.2	21.6	43.2
Large-Sized (>249)	35.9	18.6	45.6
Sector			
Public	37.3	25.1	37.6
Tertiary Education			
Not Required	29.2	21.5	49.3
Required	56.4	22.6	21.0

The second job characteristic is the interactive task intensity indicator, which assesses the extent of interpersonal interaction required in a job. Among jobs that have low levels of interaction task intensity, 62.0% are classified as highly routine intensive, 21.9% fall into the medium routine group, and 16.1% are categorized as low routine. These findings indicate that jobs with less interaction are more likely to involve routine

tasks. Among jobs that include medium levels of interaction, 28.8% fall into the low routine category, 22.6% fall into the medium routine category, and 48.7% fall into the high routine category. Among jobs that include a high level of interactive tasks, 55.8% fall into the low routine group. This suggests that jobs that require a high amount of interaction are mostly found in less routine-intensive settings.

The following characteristic is the size of the firm and the sector. The level of routine task intensity is rather consistent across three firm sizes. In relation to the sector, the public sector has a higher proportion of occupations in both the high and low routine intensity categories, whereas fewer jobs are classified as medium routine intensive. The high level of routine intensity observed in certain public sector jobs might reflect the regulatory and procedural characteristics of government work. On the other hand, the high percentage of public sector jobs in the low routine intensity category might reflect the jobs that involve complex decision-making and strategic planning. Finally, the tertiary education characteristic shows the correlation of higher educational requirements with the routine intensity of jobs. 49.3% of the jobs that do not require tertiary education fall into the high routine intensity category, suggesting that jobs which do not require higher education degrees tend to have more routine tasks. On the other hand, jobs requiring tertiary education are mostly found in the low routine intensity category.

4.6. The Effects of Computer Use on Wages in Türkiye

SBTC posits that technological advancements, such as in computing and information technology, require more advanced skills and higher levels of education. This leads to growing wage inequality based on skill levels and education. SBTC has two implications for the computer wage premium:

- Workers who use computers at work earn a wage premium compared to those who do not use computers. This premium reflects the higher productivity and demand for workers who can utilize these technologies effectively.

- The wage premium for computer use is generally higher for more educated workers.

Krueger (1993) and DiNardo and Pischke (1996) examined the impact of computer use on wages during the early stages of computer adoption in the 1980s and early 1990s. These studies found significant wage differentials associated with computer use. However, the analysis in this thesis uses data from 2015, a period when computer use is a lot more widespread and integrated into our lives and our jobs. Still, to build on these foundational studies, we conducted a similar analysis as a starting point to assess the impact of computer use on wages in Türkiye. Table 7.1 presents the findings for the wage effects associated with computer use in Türkiye, while accounting for the interaction between computer use and education.

In this exercise, Model 1 serves as the first baseline, focusing on the direct effects of years of education and computer use, and it includes numeracy skills as a control for unobserved ability. Model 2 builds upon Model 1 by adding an interaction term between education and computer use to see how the effect of computer use on wages might differ based on educational attainment. Model 3, the second baseline model, uses a different educational variable from Model 1. Instead of continuous years of education, it employs dummy variables for different education levels. Model 4 includes interaction terms between education levels and computer use, which help to assess the combined effects of these factors on wages. Other controls in these models include gender, experience, experience squared, marital status, having children, sector (public or private) and firm size.

Model 1 results show that each additional year of education is associated with an increase in the earnings decile by 0.190, suggesting a significant positive effect of educational attainment. The dummy variable for computer use at work also shows a strong positive effect (0.487), which indicates that workers who use computers are likely to be in higher earnings deciles compared to those who do not. Furthermore, by including numeracy skills as a control variable, we account for unobserved heterogeneity, so that the observed effects of education and computer use on wages are not affected from it. The finding aligns with the SBTC, which posits that technological advancements benefit workers with higher skills.

Model 2 results show that each additional year of education is associated with an increase in the earnings decile by 0.117, which is slightly lower than in Model 1 but

Table 42: Impact of Computer Use on Wages of Full-Time Workers in Türkiye (2015)

	Model 1	Model 2		Model 3	Model 4
Years of Education	0.190***	0.117***	Upper sec. education dummy	0.634***	0.683***
	(0.030)	(0.036)		(0.194)	(0.238)
Computer use (Y/N)	0.487***	-1.349**	Tertiary education dummy	1.637***	0.583*
	(0.185)	(0.621)		(0.240)	(0.335)
(Education x Computer Use)		0.180***	Computer use (Y/N)	0.475***	0.133
		(0.054)		(0.182)	(0.322)
Numeracy Skill	0.008***	0.008***	Upper Sec. x Computer Use		0.141
	(0.002)	(0.002)			(0.408)
Constant	-0.568	0.092	Tertiary x Computer Use		1.500***
	(0.428)	(0.475)			(0.431)
			Numeracy Skill	0.008***	0.008***
Observations	1,262	1,262		(0.002)	(0.002)
R-squared	0.414	0.422	Constant	0.642	0.771*
				(0.427)	(0.429)
			Observations	1,262	1,262
			R-squared	0.418	0.425

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. “Other Controls” in Model 2 include gender, experience, experience squared, marital status, children, sector and firm size.

still significant. Interestingly, the direct effect of computer use on wages is negative, suggesting that without considering the interaction with education, computer use alone is associated with a decrease in earnings. However, the interaction term between education and computer use is positive and significant, with a coefficient of 0.180. Given that the average years of education in the sample is 10.23 years, this interaction effect offsets the negative direct effect of computer use, resulting in an overall positive effect on earnings for individuals with average education levels. This finding indicates that the positive effect of computer use on earnings is conditional on the level of education, supporting capital-skill complementarity.

Model 3 shifts the focus from continuous years of education to categorical levels of education, using dummy variables for upper secondary and tertiary education. The results indicate that, compared to individuals with less than upper secondary education (the reference category), having upper secondary education is associated with an increase in the earnings decile by 0.634, while having tertiary education is associated with a larger increase of 1.637, both of which are significant. The dummy variable for computer use at work is significantly positive, suggesting that workers who use computers are likely to be in higher earnings deciles compared to those who do not.

Model 4 results show that having upper secondary education is associated with an increase in the earnings decile by 0.683 as compared to having less than upper secondary education, while having tertiary education (as opposed to having less than upper secondary education) causes an increase in wage deciles by 0.583, both of which are significant. The direct effect of computer use on wages is positive but not significant. However, the interaction terms give a more detailed picture. The interaction between upper secondary education and computer use is not significant, whereas the interaction between tertiary education and computer use is statistically significant, with a coefficient of 1.50, indicating that the combination of higher education and computer use substantially increases earnings. This effect was not explicitly modeled in Model 2, which used a general interaction term between continuous years of education and computer use, showing a positive effect, but without the distinction made in Model 4 for educational levels. Model 4 provides more detail

by examining how educational levels interact with computer use to influence wages. In Model 2, the direct effect of computer use is negative, but the interaction term suggests a mitigating effect when combined with education. On the other hand, Model 4 shows that while the direct effect of computer use is not significant, the interaction with tertiary education has a positive effect on wages, implying a more pronounced benefit of technology use for highly educated individuals.

4.6.1. Analyzing the Effect of Computer Use on Wage Deciles

A computer wage premium typically refers to the additional earnings that individuals receive due to their ability to use computers in their job. This premium is usually observed as a positive coefficient for computer use in regression models, indicating that using a computer at work is associated with higher wages. However, in our analysis, we cannot directly calculate this premium because our dependent variable is the earnings decile rather than actual wage amounts. However, it is possible to calculate the effect of computer use on wages by looking at the change in earnings decile position.

We can calculate the combined effect of computer use for an individual with the mean years of education (10.23 years[45]) as a percentage of the average hourly wage as[46]:

$$\text{Combined Effect} = \beta_{\text{Computer Use}} + (\text{Years of Education} \times \beta_{\text{Years of Edu x Computer Use}}) \quad (7)$$

$$\text{Effect of computer use} = \frac{\text{Combined Effect}}{\bar{W}} \times 100\%$$

[45] It should be noted the average educational attainment of the sample is relatively moderate and the mean years of education in the sample is 10.23 years, which corresponds to mid-high school level in Türkiye. It suggests that individuals with tertiary education are more educated than the average participant in the sample.

[46] The computer wage effect has been calculated for those levels of ICT use where the coefficients are statistically significant. When a coefficient is not statistically significant, it suggests that the evidence is insufficient to state that there is an effect of that level of ICT use on wages. If the coefficients are not significant, the wage effect for these skills cannot be calculated using the respective coefficients.

where $\overline{W}$ (= 5.4945) is the average hourly wage in deciles. The results show that, on average, using a computer at work is associated with an increase in hourly earning deciles by about 8.86%[47] in Model 1 and 8.96%[48] in Model 2 for individuals with 10.23 years of education. Similarly, in Model 3, the effect of using a computer at work is associated with an increase in hourly earning deciles by about 8.64%. This means that the overall effect of using a computer at work results in an upward shift in an individual's earnings position within the decile distribution.

4.6.2. Evidence on the Effects of Different Levels of ICT Use, Task Intensities and Education on Wages

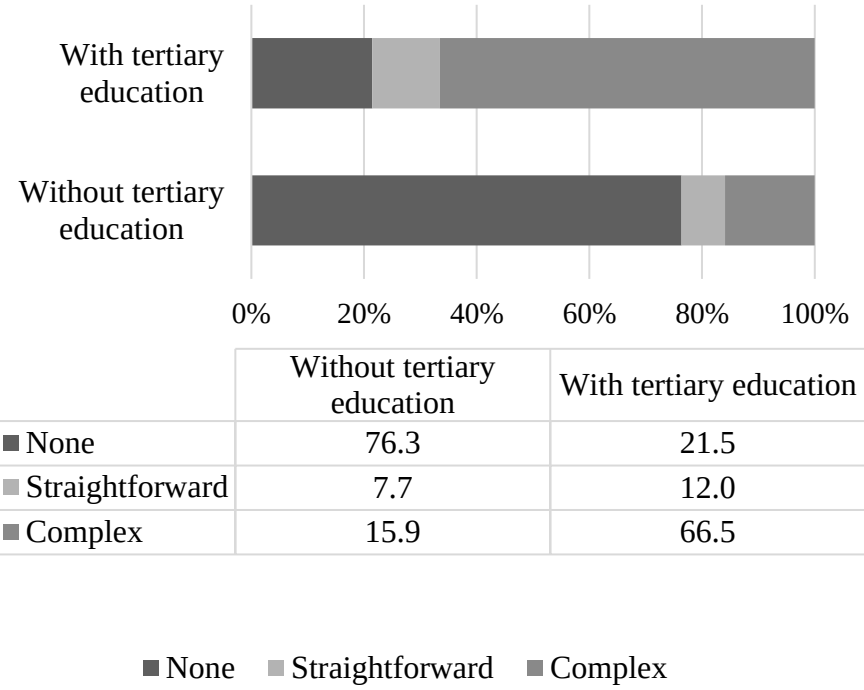
These findings align with the SBTC hypothesis that technology disproportionately benefits higher-skilled workers. However, if the computer use measured by a general variable that mostly involves medium-skill tasks, it might not capture all the benefits experienced by higher-skilled workers. The general "computer use" variable aggregates all levels of computer use, not accounting for the categorization within the workforce where different education levels might correspond to different types of computer use. More educated workers might be engaged in complex ICT tasks, while less educated workers might use computers for basic ICT tasks.

Figure 26 shows the distribution of ICT use at work by educational attainment. Among individuals without tertiary education, a substantial 76.3% do not use ICT at work. On the other hand, only 21.5% of those with tertiary education reporting no ICT use. Moreover, a significantly large percentage (66.5%) of the those with tertiary education uses complex levels of ICT at work. This difference suggests that higher education is related with more complex ICT use levels at work. Hence, by using different levels of ICT use, the models can better capture the relation between the type of computer tasks and the workers' education levels.

[47] Model 1: Combined Effect = (0.487/5.49) ×100% = 8.86%.

[48] Model 2: Combined Effect = -1.349+(10.23×0.180) = 0.4924 and %Δ = (0.4924/5.49) ×100% = 8.96%.

The method used in this chapter expands on Krueger (1993) and DiNardo and Pischke (1997) by introducing categories to account for the level of ICT usage from straightforward to complex. The aim is to understand whether the level of ICT use affects wage outcomes differently when accounting for educational attainment. Given the significant advancement of computer technology and educational attainment over the past few decades, this will show whether the wage premium associated with different levels of ICT use varies across different educational backgrounds. Moreover, in the following sections, we expand this analysis to include routine, cognitive and interpersonal job tasks. This addition aims to explain how different types of job tasks interact with education and technology use to influence wage outcomes.



	Without tertiary education	With tertiary education
None	76.3	21.5
Straightforward	7.7	12.0
Complex	15.9	66.5

Figure 26. Distribution of ICT use at work by educational attainment among full-time wage earners in Türkiye (2015)

As part of our analysis on the effects of the expansion of higher education in Türkiye, this study parallels Atasoy et al. (2021) but specifically focuses on the role of education in influencing the relationship between ICT skills and wage outcomes. Atasoy et al. (2021) find that basic IT skills are directly correlated with higher employment probabilities. While advanced IT skills do not significantly increase the probability of employment beyond the effect of basic IT skills, they are associated with higher-wage

jobs. This suggests that while basic skills may help secure a job, advanced skills are linked to better-paying jobs. Moreover, they find that advanced IT skills are more closely associated with higher wages in non-routine jobs.

However, the relationship between technology use and the probability of securing better-paying jobs may also be related with educational attainment. As technology progresses, the demand for more complex ICT skills increases, increasing wage levels particularly for those with higher educational backgrounds. To see this, this study examines how different levels of educational attainment influence wage outcomes in Türkiye, particularly through the interactions with different levels of ICT use. In this context, we are also analyzing how job task intensities effect the wages of individuals with different levels of ICT skills, complemented by varying educational backgrounds, in securing higher-paying job opportunities. To do so, this study constructs a routine intensity index by using individual-level responses to specific questions from the PIAAC survey. Similarly, indices for interactive and cognitive job tasks are also constructed based on individual responses. This approach ensures that the indices are directly reflective of the actual job experiences of individuals.

The remaining exercises will utilize the dummy variable specification. This approach will allow us to examine the returns on higher education in a context where Türkiye has significantly increased the number of tertiary education institutions and enrollment rates over recent years. By concentrating on levels of education, it will be possible assess whether this educational expansion translates into higher economic returns for graduates, which is essential for validating the effectiveness of educational policies. But more importantly, it will enable us to analyze how the integration of ICT skills within tertiary education correlates with wages.

4.6.2.1. The Model Results with ICT Level Interactions

This section concentrates on the relation between different levels of ICT usage at work and wage rates. The aim is to determine whether having a tertiary education degree affects wages of using different levels of ICT at work. Table 43 present the outcomes of our analyses. Model 1 includes education levels and ICT use, with no interaction terms or controls for unobserved ability. Model 2 extends Model 1 by adding

numeracy skill as a control variable. Model 3 further extends Model 2 by including interaction terms between education levels and ICT use.

The results of Model 1 are consistent with earlier findings, but they provide additional information about the effect of education levels and ICT use on earnings deciles. Similar with earlier findings, the analysis shows that having an upper secondary education is associated with an increase in earnings (0.847) while tertiary education leads to a larger increase of 1.971. More importantly, the first implication of SBTC, which posits that technological advancements benefit workers who can effectively use these technologies, is supported in both levels of ICT use for full-time wage earners in Türkiye. The coefficient for straightforward ICT use indicates an increase of 0.484 in earnings deciles, while complex ICT use is associated with a higher increase of 0.655. This differentiation between levels of ICT use shows that complex ICT use leads to a larger increase in earnings deciles compared to straightforward ICT use.

Model 2 builds upon the findings of Model 1 by incorporating numeracy skills as an additional control variable. The inclusion of numeracy skills, which has a significant positive effect on earnings, helps to control for unobserved cognitive abilities. Controlling for numeracy skills, the effect of different levels of ICT use does not change too much, which challenges the argument made by DiNardo and Pischke (1997) that the observed wage premiums could be attributed to unobserved heterogeneity – to the extent that numeracy skills correctly proxies for unobserved ability. Instead, these results suggest that the wage benefits associated with ICT use are not only a result of unobserved worker characteristics, but they contribute to productivity in a way that is valued in the labor market.

We can calculate the combined effect of computer use as a percentage of the average hourly wage deciles by using equation (7) above. The results show that

- Using straightforward ICT at work is associated with an increase in hourly earnings deciles by 8.81%.

- Using complex ICT at work leads to a higher increase in hourly earnings deciles by about 11.92%.

Table 43. The effect of education and different levels of ICT use on earnings for full-time wage earners in Türkiye, OLS results (2015)

	Model 1	Model 2	Model 3
Education Level			
Upper Secondary	0.847***	0.642***	0.637***
	(0.187)	(0.193)	(0.225)
Tertiary	1.971***	1.601***	1.246***
	(0.226)	(0.240)	(0.298)
ICT Use			
Straightforward	0.484**	0.435*	0.649*
	(0.239)	(0.228)	(0.391)
Complex	0.655***	0.554***	-0.035
	(0.194)	(0.194)	(0.496)
ICT Use x Education			
Upper secondary x Straightforward			-0.054
			(0.518)
Upper secondary x Complex			0.423
			(0.569)
Tertiary x Straightforward			-0.210
			(0.536)
Tertiary x Complex			1.071*
			(0.551)
Numeracy Skill		0.008***	0.008***
		(0.002)	(0.002)
Constant	2.400***	0.675	0.767*
	(0.293)	(0.427)	(0.427)
Observations	1,262	1,262	1,262
R-squared	0.404	0.418	0.422

*Note: Other controls include gender, experience and its square, marital status, children, sector and firm size. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

These findings suggest that while both basic and more advanced technological skills are beneficial in increasing wage outcomes, the use of complex ICT tasks is more

highly rewarded. These results support SBTC, which posits that technological advancements disproportionately benefit those with higher technological skills, leading to higher wage gains for workers who can use more complex levels of ICT.

Similar with the previous results, the results for Model 3 indicate that having an upper secondary education is associated with an increase in earnings deciles by 0.637, while tertiary education leads to a larger increase of 1.246. For ICT use, straightforward ICT use is associated with an increase in earnings deciles by 0.649, showing that a basic level of ICT use positively effects wages. However, the coefficient for complex ICT use is not significant, suggesting that the effect of complex ICT use might be influenced by other factors when combined with education levels. The interaction between tertiary education and complex ICT use is significant, with a coefficient of 1.071, indicating that the combination of higher education and complex ICT skills significantly increases earnings.In Model 3, the findings show that only significant interaction variable is between complex ICT use and tertiary education. This aligns with the second implication of the SBTC theory, which suggests that the wage premium for computer use is generally higher for more educated workers. The coefficient here is 1.104. This statistically significant positive interaction indicates that the combination of complex ICT use with tertiary education increases hourly earnings more than either factor alone. While the interaction terms for straightforward ICT use and tertiary education is not significant, this does not contradict the SBTC theory. For basic ICT use, this might indicate that a basic level of computer literacy is now considered a fundamental requirement in the job market. This finding suggests that not all technology-related skills provide an additional premium when combined with higher education.

On the other hand, the lack of significance of the interaction terms for upper secondary level could indicate that for this level of education, ICT skills do not translate into a wage premium as seen with tertiary education. This finding is particularly important in the context of SBTC, as it suggests that the premium for using advanced technology is not uniformly distributed across all education levels but is pronounced for those with higher education. This indicates that as technology continues to advance, the demand for more sophisticated ICT skills will likely increase, leading to higher wages.

However, this wage increase is likely to be pronounced for individuals with higher education.

4.6.2.2.The Model Results with Task Intensity Indices

How does the intensity of routine tasks, along with cognitive and interactive tasks, influence hourly earnings among full-time wage earners in Türkiye? DiNardo and Pischke (1997) suggest that wage premiums associated with using computers at work might not only reflect productivity gains but could be attributed to some job characteristics. Their research shows that even simple tools like pens and pencils are associated with significant wage premiums, similar to those of computer usage, indicating that factors related to the type of jobs might influence wage differences.

SBTC suggests that as ICT becomes more complex, there should be an increasing premium on cognitive and interactive skills because these technologies often complement tasks that involve problem-solving and effective communication. The literature finds a shifting demand in the labor market towards these skills, driven by the rapid integration of technologies such as AI and machine learning, as explained in Chapter 4 above. These changes necessitate not only technical skills but also digital literacy, and problem solving and interpersonal capabilities (See Table 4.1 for changing skill demands).

In the literature, the intensity of routine tasks is often seen as a key factor of wage differentials. Routine tasks, typically associated with certain job types, are suggested to play an important role in wage determination. According to the literature, technological advancements increase the demand for tasks that require non-routine cognitive and interpersonal skills, leading to higher wages for these jobs (ALM, 2003; Acemoglu and Autor, 2011). By integrating routine task intensity index into our model, we aim to find out how the routine intensity interact with ICT use and educational levels to effect wages. By doing so, in a way, we are testing both the RBTC hypothesis that technological advancements disproportionately affect jobs that involve routine tasks and the claim by DiNardo and Pischke (1996).

Model 1 examines the direct effects of education levels and ICT use on earnings deciles and includes routine task intensity to assess its impact on wages. Model 2

builds on Model 1 by adding numeracy skills. Model 3 extends the analysis further by incorporating cognitive and interactive task intensities. Firstly, the results from Model 1 (see Table 44) indicate that both levels of education have significant positive effects on earnings deciles, with tertiary education showing a stronger effect. Compared to the reference group (i.e. individuals with lower secondary education and below), having upper secondary and tertiary education is associated with moving up by 0.823 and 1.885 deciles, respectively. We see a slight decrease in the coefficient for the education variable from 1.971 in Model 1 in Table 43 to 1.885 in Model 2. Secondly, both straightforward and complex ICT use have statistically significant positive effects on earnings, with complex ICT skills having a more pronounced effect. In Model 1 in Table 43, straightforward ICT use shows a coefficient of 0.484, and complex ICT use is at 0.655, both significantly increasing earnings. However, when routine task intensity is added in Model 1 in Table 44, these coefficients slightly decrease to 0.413 for straightforward and 0.570 for complex ICT use.

According to ALM (2003), routine tasks, which are repetitive and rule-based, are highly susceptible to automation and computerization. These tasks can be easily codified, leading to a decline in the demand for labor performing routine tasks. Our findings support these insights. The significant negative coefficient (-0.153) for routine intensity indicates that higher routine intensity is associated with lower wages, although its effect is relatively small compared to the effects tertiary education and ICT use.

In Model 2, numeracy skills are introduced as a control variable to account for unobserved cognitive abilities that could affect earnings. The results show that even after controlling for numeracy as a proxy for unobserved ability, both straightforward and complex ICT uses continue to positively affect earnings. On the other hand, routine intensity, which was previously statistically significant in Model 1, loses its significance in Model 2. This change suggests that the negative wage effects previously associated with routine tasks might not only be due to the nature of the tasks themselves but could be related to the lower numeracy skills of workers in those jobs, which were unaccounted for in Model 1.

Model 3 includes cognitive and interactive task intensities, together with routine task

intensity, to assess the wage outcomes. It should be noted that it is often challenging to directly measure these skills due to their abstract nature and the variability in how they are applied. In this exercise, the coefficients of these job tasks are interpreted as the coefficients for problem-solving and social skills. Because of the choice of questions (Table 38) used to construct measures of cognitive and interactive task intensities, our measures consist of the frequency of tasks that involve problem-solving, decision-making, communication, and collaboration. This allows us to assess how the use of these skills, together with ICT usage and education, influence wage outcomes. The SBTC theory would predict that as ICT becomes more complex, the premium for both cognitive and interactive skills should increase. This is because technology often complements cognitive skills like problem-solving and interactive skills. This leads to higher efficiency in jobs that demand these skills. For example, a positive coefficient for the interaction of cognitive tasks and routine intensity would suggest that engaging in cognitive tasks can counteract the negative wage effects of routine intensity.

In Model 3, both levels of education are positively and significantly related with earnings. There is a slight decrease in these coefficients across models, suggesting that task contents of jobs may absorb some of the effect attributed to education. The diminishing coefficients as more variables are introduced suggest that while education is important, its effects on wages are intertwined with job characteristics, such as the nature of the tasks involved. Higher education likely prepares individuals for jobs that require higher cognitive and interactive skills, which are themselves associated with higher earnings.Secondly, the coefficient for straightforward ICT use in Model 3 is reduced compared to Models 1 and 2 and becomes non-significant. This suggests that when cognitive and interactive task intensities are accounted for, the wage premium associated with basic ICT skills diminishes. This could indicate that basic ICT capabilities, while necessary, are not sufficient to command a higher wage in jobs that also require cognitive and interactive skills. It implies that straightforward ICT use has become a baseline requirement in many roles, providing little additional wage in contexts where more complex skills are also measured.

The coefficient for complex ICT use also decreases in Model 3 but remains significant, albeit at a lower level than in previous models. This indicates that while advanced ICT

Table 44. The effect of education, different levels of ICT use and task intensities on earnings for full-time wage earners in Türkiye, OLS results (2015)

	Model 1	Model 2	Model 3
Education Level			
Upper Secondary	0.823***	0.637***	0.597***
	(0.186)	(0.193)	(0.192)
Tertiary	1.885***	1.559***	1.449***
	(0.228)	(0.242)	(0.242)
ICT Use			
Straightforward	0.413*	0.388*	0.354
	(0.242)	(0.230)	(0.232)
Complex	0.570***	0.500**	0.426**
	(0.200)	(0.198)	(0.200)
Routine Intensity	-0.153**	-0.111	-0.051
	(0.068)	(0.067)	(0.070)
Cognitive Task Intensity			0.017
			(0.063)
Interactive Task Intensity			0.234***
			(0.083)
Numeracy Skill		0.008***	0.007***
		(0.002)	(0.002)
Constant	2.480***	0.835*	1.051**
	(0.294)	(0.428)	(0.441)
Observations	1,261	1,261	1,257
R-squared	0.407	0.420	0.426

*Note: Other controls include gender, experience and its square, marital status, children, sector and firm size. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

skills increase wages, their relative effect is moderated by the presence of cognitive and interactive tasks. This finding may suggest that complex ICT skills are complementary to other task-based skills, increasing earnings particularly in jobs that also value cognitive and interactive abilities, which aligns with studies on changing job demands in the labor market.

The coefficient for cognitive task intensity in Model 3 is not significant, suggesting that the level of cognitive demands associated with a job does not independently affect earnings in a statistically significant way. On the other hand, the coefficient for interactive task intensity is significantly positive, indicating that jobs requiring high levels of interpersonal interaction are associated with higher earnings. The importance of these skills may reflect the increasing emphasis on collaborative work environments in modern economies, where interaction can directly influence productivity and career advancement.

Overall, these analyses sheds light on the determinants of wage levels in Türkiye about job tasks and their impacts on wages. Initially, routine tasks are found to negatively influence wages, suggesting that roles characterized by repetitive and automatable activities might result in lower wages. However, this negative effect dissipates when the models account for numeracy skills. Furthermore, the positive significance of interactive task intensity in influencing wages supports the idea that the labor market highly values interpersonal skills.

4.6.2.3.Other Controls

Model 4 includes additional control variables, some of which incorporates supply-side factors of the labor market, including gender, experience and its squared term, firm size and sector (public vs. private). Including these characteristics helps control for worker and job characteristics that could bias the estimates of the main effects and interactions explained previously. These control variables provide additional information on the factors influencing hourly earnings. Notably, the inclusion of firm size and sector variables result in significant effects in wage outcomes. Larger firms and the public sector employment increase earnings. Additionally, the model addresses gender effects. The results show a significant negative coefficient for females in all models, suggesting that women earn significantly less than their male counterparts for similar jobs. Finally, the significant positive coefficients for the linear experience term and the significant negative coefficients for its squared term indicate that, while wages increase with experience initially, the rate of increase slows down as employees continue to accumulate more years of work. The significant effects from these additional controls are in line with the expectations after controlling for ICT use.

4.7. Conclusion

In the fourth chapter of this thesis, we conducted a comprehensive analysis of the relationships between education, ICT use, job tasks, and wage outcomes in Türkiye. Our analysis focused on understanding how different levels of ICT use effect wages and how these effects vary with educational attainment. Given the emphasis on job tasks of the contemporaneous theories, we also examined the role of routine, cognitive, and interactive tasks in shaping wage outcomes, alongside ICT use and education.

While conducting this study, we acknowledge the likely effect of unobserved abilities on economic outcomes, particularly in relation to the use of ICT. By utilizing the PIAAC data, which provides direct assessments of numeracy skills, this study can capture these unobserved abilities. Numeracy scores from PIAAC serve not only as indicators of an individual's quantifiable skills but also as proxies for unobserved cognitive abilities that may influence the economic returns of ICT in the workplace.

Our analysis reveals several important findings. First, workers who use ICT at work, especially those who use complex ICT, tend to be in higher earnings deciles compared to those who do not use computers, supporting the SBTC theory. Furthermore, we find that the wage effect of complex ICT use is higher for more educated workers, particularly those with tertiary education, showing the capital-skill complementarity in advanced technological contexts. Additionally, our analysis of job tasks indicates that routine task intensity is associated with lower wages, but this effect diminishes when controlling for cognitive abilities such as numeracy skills, while interactive task intensity shows a significant positive correlation with wages.

These findings contribute to the broader literature by providing empirical support for SBTC and capital-skill complementarity within the context of Türkiye. SBTC posits that technological advancements disproportionately benefit more-skilled workers, increasing the demand for their labor relative to less-skilled workers. This theory explains why technological changes often lead to increased wage inequality as they enhance the productivity of more-educated and higher-skilled workers more than that of less-educated and lower-skilled workers. Our results align with this theory, showing that complex ICT skills significantly increase wages in Türkiye, especially for those with higher education.

On the other hand, task-based and RBTC approaches focus on the specific tasks performed by workers and how these tasks interact with technology. They categorize tasks into routine and non-routine tasks, examining how technology substitutes for or complements them. Routine tasks, which are repetitive and easily automated, are more likely to be displaced by technology, while non-routine tasks, which require human judgment and interaction, are more likely to be complemented by technology. Our study supports this perspective by showing that routine task intensity negatively effects wages, whereas interactive tasks increase earnings. However, this effect becomes less pronounced when accounting for unobserved abilities, indicating that the observed wage penalties might also be related to the lower skills of workers in routine-intensive jobs.

These findings are very important and if they can be generalized with more detailed and up-to-date research they have strong implications for the recent higher education expansion in Türkiye. In the context of the "race between education and technology," these imply that while formal education is important, the rapid pace of technological advancement and the corresponding demand for workers with advanced digital skills mean that having technical ICT skills, or even improving the basic skills, can be very important in determining labor market success.

Given the advancements in AI and the findings from our study, efforts should be directed towards developing a workforce capable of adapting to and complementing AI technologies. This involves investing in education and training programs that emphasize both cognitive and technical skills. Enhancing digital literacy is essential to ensure that workers can keep pace with technological changes and mitigate potential negative effects.

Lastly, there are some limitations to this study. The data is from 2015, and it may not fully reflect the current situation of the labor market, particularly given the significant brain drain from Türkiye. Future research should incorporate more recent data to better reflect these contemporary trends and their impacts on the labor market. Additionally, adopting a longitudinal approach could explain better how these relationships change over time, especially considering continuous technological advancements in today’s world.

CHAPTER 5

CONCLUSION

This thesis examines the alignment between the education system and labor market demands in Türkiye, by focusing on the implications on labor market outcomes. The thesis is structured into three main chapters, which not only analyzes different types of mismatches between individuals' education, skills, fields and their job requirements but also investigates how technological proficiency interacts with educational attainment to influence wages. Each type of mismatch represents a different aspect of the alignment between education and labor market needs:

- **Education mismatch concerns the *quantity* of education** that individuals possess relative to what is required for their jobs. This mismatch occurs when individuals have either more or less education than is necessary for their jobs, leading to overeducation or undereducation, respectively.

- **Skill mismatch is related with the *quality* of education.** This type of mismatch assesses whether the skills individuals possess are sufficient for their job.

- **Field-of-study mismatch examines the *relevance* of education,** specifically whether individuals' fields of study align with their jobs.

In addition to examining these mismatches, the fourth chapter analyzes the role of technology use in the Turkish labor market, focusing on how different levels of technology use and different job tasks affect wages of full-time workers.

The findings indicate that:

Overeducation is more prevalent than undereducation in Türkiye.

We find that despite substantial investments in education in Türkiye, there is a mismatch in the labor market where the qualifications provided by the education system are not aligned with the labor market requirements. Using both objective and subjective methods, we find that 42% of full-time wage earners in Türkiye are mismatched according to objective method, with 31% being overeducated and 11% undereducated. Subjective assessments reveal that 29% of workers are mismatched, with 16% overeducated and 13% undereducated. The high incidence of education mismatch among workers in Türkiye, as found by using two different methods, suggests a significant challenge in the alignment between educational qualifications and job market requirements. When contextualized against previous research, these figures are worrying. For example, international studies reviewed by McGuinness (2006) reported an average overeducation incidence of around 22% based on objective measures across various countries.

This finding suggests an issue regarding the quantity of education, where the labor market is unable to absorb high levels of educational attainment among workers. Many individuals possess higher educational qualifications than their jobs require. This might indicate of an oversupply of higher education relative to the demands of the labor market. This suggests that the high incidence of education mismatch in Türkiye might be relevant with the rapid expansion in higher education during the last two decades, without corresponding growth in high-skill employment opportunities.

Skill mismatches, particularly overskilling, are also prevalent in Türkiye.

Complementing the analysis of education mismatch, we also focus on skill mismatches. This exercise reveals that 41% of the full-time wage earners in Türkiye experiences skill mismatches where 28% are overskilled, and 13% are underskilled. This signals a significant misalignment between the skills workers possess and those required by their jobs. Moreover, among the overeducated workers, around 38% are also overskilled, and around 54% are well-matched in terms of numeracy skills. The significant intersection between overeducation and overskilling suggests a dual mismatch, where workers are both overeducated and underutilized in terms of their skills.

The findings on the incidence of education and skill mismatches reveal two problems.

Firstly, the incidence of dual mismatch is significant, with 38% of overeducated individuals also being overskilled. This indicates inefficiencies within the labor market, suggesting that Turkish labor market could not effectively absorb or utilize the educated workforce. Secondly, the observation that more than half of overeducated individuals are well-matched in terms of skills despite their higher educational levels, implies a problem within the education system: while these individuals attain higher education levels, their skills remain within the range of what their jobs require (and their jobs require a lower level of education), pointing to inefficiencies in the education system's ability to increase skill levels in line with educational attainment. This finding implies that more education does not necessarily equate to higher skills, raising questions about the quality of education in Türkiye.

Gender and type of education significantly influence the likelihood of education and skill mismatches.

Firstly, the analysis on correlates on labor market mismatch shows that women are less likely to be overeducated (significant only in the objective method results) compared to men. This could be due to selectivity. Women in the labor force, especially those in full-time jobs, may face more rigid criteria in their job search, leading to situations where only those with closely matched education levels secure employment.

Moreover, women are more likely to be underskilled compared to men. When examining the distribution of numeracy skill scores for women, it is observed that women in the underskilled category have significantly lower scores (Figure 7.1 in Chapter 2). This might reflect their lower participation in education. This could suggest that women at lower skill levels have had fewer opportunities or less access to enhance their numeracy skills through formal education, contributing to the differences seen in the scores. Secondly, there are serious challenges associated with the alignment of vocational education with the labor market in Türkiye. Vocational education is associated with a higher likelihood of being mismatched in terms of skills and education (except self-assessed undereducation where the effect is also positive but not significant). These findings imply that vocational education in its current form may not be effectively preparing individuals for the labor market.

Education mismatch and overskilling leads to wage penalties for affected workers.

Although some models show insignificant results (see Table 45), we show that education mismatch and overskilling leads to wage penalties for affected workers:

(a) Each additional year of overeducation results in a positive return when objective method is used, but this return is less than the return for years of education that match job requirements. This indicates that while overeducated workers earn more for each additional year of education, this return is lower compared to those whose education level is well-matched to their job. Supporting this result, we find that workers who are overeducated earn significantly less than their counterparts with similar education levels who are adequately matched to their jobs.

(b) Each additional year of undereducation leads to a statistically significant negative return, indicating that having fewer years of education than required for the job results in lower wages. However, this effect is not significant when employing a dummy variable approach, when the objective method is used to measure education mismatch. This is likely due to the influence of minimum wages. The high prevalence of minimum wage in Türkiye suggests a compressed wage distribution at the lower end, which likely conceals the wage penalties associated with undereducation when a dummy variable is used. Furthermore, undereducated workers earn more compared to those that have the same level of education but work in adequately matched jobs when self-assessments are used to measure the required level of education. This occurs because undereducated workers are in jobs that require a higher level of education, which come with higher wages due to the premium placed on the required education.

(c) When subjective methods are used, overeducation shows a larger wage penalty (-0.820***) compared to overskilling (-0.425**)[49]. When objective methods are employed, the wage penalty for overskilling (-0.432**) exceeds that for overeducation (-0.354**). This reveals that being overskilled has a larger

[49] To compare the effects of overeducation and overskilling on wages, we can examine the results from models that include both overeducation and overskilling as dummy variables. Since overskilling is also represented as a dummy variable, we can evaluate their relative effect consistently this way.

negative impact on wages than being overeducated when education mismatch is objectively measured. Furthermore, the coefficients for overskilling indicate that the negative effect of being overskilled is consistent and does not change much regardless of how the education mismatch is measured.

Table 45. Summary of Education and Skill Mismatch Coefficients for Wage Outcomes and Interpretations

	Mismatch Type	**Method**	**Coefficient**	**Interpretation**
Education Mismatch ORU Specification	**Required Education**		0.317 to 0.352	Each additional year of required education results in a positive return.
	Over-education	Objective	0.222 to 0.224	Each additional year of overeducation results in a positive return, but less than required education.
		Subjective	Not significant	The effect is not statistically significant.
	Under-education	Objective	-0.238 to -0.242	Each additional year of undereducation leads to a negative return.
		Subjective	-0.192 to -0.190	Each additional year of undereducation leads to a negative return
Education Mismatch Dummy Variable Specification	**Actual Education**		0.273 to 0.293	Each additional year of actual education results in a positive return.
	Over-education	Objective	-0.395 to -0.354	Overeducated workers earn significantly less than well-matched counterparts (with same level of education).
		Subjective	-0.848 to -0.820	Overeducated workers earn significantly less than well-matched counterparts.

	Under-education	Objective	Not significant	The effect is not statistically significant.
		Subjective	0.446 to 0.433	Undereducated workers earn more than well-matched counterparts with same level of education.
Skill Mismatch	**Over-skilling**	Hybrid	-0.382 to -0.432	Overskilled workers earn less than those with same level of skill but well-matched to their jobs in terms of skills.
	Under-skilling		Not significant	The effect is not statistically significant.

The significant positive effect of undereducation on job satisfaction (based on self-assessment for measuring education mismatch) indicates that undereducated individuals feel more satisfied with their work. Similarly, being underskilled has a significantly positive effect on job satisfaction in all models.

The results related to job satisfaction are statistically significant after controlling for wages, which indicates that the influence of being underskilled or undereducated on job satisfaction is independent of wage levels. This might be because undereducated and underskilled individuals perceive themselves as having surpassed expectations or having achieved upward mobility, which can lead to increased job satisfaction due to a sense of achievement.

Moreover, jobs requiring higher education levels often offer better non-wage benefits, such as improved working conditions, more comprehensive health benefits, or higher job security. These factors could also contribute to the higher job satisfaction reported by underskilled or undereducated workers.

There is a high incidence of field-of-study mismatch among full-time wage earners with tertiary education in Türkiye.

The findings reveal that 34% of full-time wage earners among the higher educated are

working in jobs unrelated to their fields of study. This mismatch often coincides with overeducation, as 45% of those experiencing a field-of-study mismatch are also overeducated. This dual mismatch indicates that nearly one in every six tertiary-educated workers is not only employed in jobs unrelated to their field of study but also exceeds the educational requirements of their jobs. Additionally, among those well-matched in terms of education level, 25% are still working in jobs that do not align with their field of study.

The analysis of field-of-study mismatch by specific fields in Türkiye indicates significant variability across different disciplines.

For example, "Science, Mathematics, and Computing" graduates face a field-of-study mismatch rate of 66% and an overeducation rate of 52%. These findings suggest that many graduates from these fields struggle to find jobs related to their studies, and even when they do, the jobs often do not require their level of education. On the other hand, "Teacher Training and Education Science" has a relatively low field-of-study mismatch rate of 23% and a low overeducation rate at 22%, indicating better alignment between education and labor market needs in this field. Additionally, "Social Sciences, Business, and Law" graduates have a lower field-of-study mismatch rate of 22%, but a high overeducation rate of 56%, showing that while they find related employment with their field, the jobs often do not utilize their full educational qualifications.

However, the mismatch rates should be interpreted carefully, as they consist different disciplines with different job market requirements and professional standards. For example, for the "Social Sciences, Business, and Law" field, the high overeducation rate suggests that there may be an oversupply of graduates. However, this field encompasses a wide range of disciplines, which can lead to a broad interpretation of what constitutes a match between field of study and employment. For example, law is a field that requires specific credentials whereas some jobs related with business and social sciences may not strictly require a specific degree.

Field-of-study mismatch is as detrimental to wages as mismatches in education (when measured objectively) and skills for tertiary-educated workers in Türkiye.

The results show that field-of-study mismatches lead to wage penalties, but the impact

varies depending on the measurement method. When considering all mismatch types (i.e. field-of-study, overeducation, and overskilling) the effects on wages are significant and similar in magnitude when education level is objectively measured. However, when education mismatch is assessed subjectively, field-of-study mismatch does not significantly affect wages, whereas when objective methods are used to assess education mismatch, field-of-study mismatch has a significantly negative effect on wages.

The lack of significance in the field-of-study mismatch variable in models using subjective measures of overeducation suggests that individuals' perceptions significantly influence their interpretation of educational mismatches and their subsequent effects on earnings. Figure A2 in the appendix of Chapter 3 shows this by presenting box plots of hourly earnings deciles for tertiary-educated wage earners, categorized by their educational match status using both objective and subjective methods. The plots indicate that individuals self-assessing as overeducated typically report lower earnings and greater variability in these earnings compared to those identified as overeducated with the objective method. This implies that, among tertiary educated, individuals who self-assess as overeducated tend to be in lower-paying jobs, whereas self-assessed well-matched individuals tend to be clustered in well-paying jobs. Thus, when both mismatches are included in the model (for subjective method), the dominance of education mismatch on wages mask the less pronounced effects from field-of-study mismatch.

The analysis of job satisfaction among tertiary-educated full-time wage earners in Türkiye show that labor market mismatches (i.e. overeducation, overskilling and field-of-study mismatch) do not significantly affect job satisfaction.

On the other hand, earnings have a statistically significant effect, with higher wages correlating positively with increased job satisfaction. This indicates that for this demographic, financial compensation is important in determining job satisfaction.

Workers who use computers at work improve their positions in earning deciles compared to those who do not use computers in Türkiye. Furthermore, the wage effect of computer use is higher for more educated workers, particularly for those with tertiary education using complex ICT.

The findings show that straightforward and complex levels of ICT use are associated with statistically significant increases in earnings deciles. This aligns with the Skill-Biased Technological Change (SBTC) literature, which posits that technological advancements benefit workers who are equipped to use these technologies effectively, thereby increasing their earnings. Moreover, the positive effect of computer use on wages is statistically significant for workers with tertiary education who use complex ICT. On the other hand, there is no statistically significant wage effect for workers with higher education using straightforward ICT. For workers with upper secondary education, there is no significant interaction between their education level and ICT use (both straightforward and complex).

Our findings show the importance of digital literacy in the labor market. We find that basic ICT skills significantly increase wages. However, for individuals with tertiary education, basic ICT skills are likely considered a minimum requirement rather than a distinct advantage that enhances earnings potential, as the interaction between basic ICT skills and tertiary education does not yield a statistically significant additional wage benefit for those with higher education. However, the interaction between complex ICT skills and tertiary education indicates that advanced digital skills provide an additional benefit for those with higher education. This implies that, if educational institutions provide better digital skills, this may help mitigate the wage effects of labor market mismatches by enhancing overall earnings.

Jobs with a high intensity of routine tasks tend to pay lower wages, but this relationship is relatively weak. On the other hand, jobs requiring high levels of interpersonal interaction are associated with higher earnings.

We find that although routine tasks have some negative effect on wages, when considering workers' cognitive abilities (such as numeracy skills), the negative wage effect of routine tasks diminishes. This implies that the lower wages in routine-intensive jobs are partly because these jobs attract workers with lower cognitive abilities. Furthermore, the positive significance of interactive task intensity in influencing wages supports the idea that the labor market highly values interpersonal skills.

Collectively, our findings reveal worrying misalignments between the education

system and labor market needs in Türkiye, as evidenced by prevalent labor market mismatches. Our results show that a majority of higher education graduates (78%) experience some form of mismatch. The high incidence of overeducation in Türkiye indicates that the labor market is not absorbing the increased levels of educational attainment. This points to an inefficiency in the labor market where the demand for high-skilled jobs is not keeping pace with the supply of educated workers. Additionally, the significant rates of skill mismatches indicate a misalignment between the skills provided by the education system and those required by the labor market. Moreover, overeducated and overskilled workers earn less than their well-matched counterparts, indicating that the labor market does not effectively utilize the higher education and skills of these individuals.

The education and skill mismatches in Türkiye can be attributed to a combination of education planning and sectoral structure issues. Firstly, ineffective education planning leads to misalignments between the education system and the labor market, contributing to the high rates of labor market mismatches in Türkiye. This can result from outdated curricula, lack of coordination with industry, and insufficient labor market information guiding educational planning. However, the challenge of education-to-employment alignment in Türkiye extends beyond curriculum relevance to include the overall quality of education, which is very important in preparing graduates for the labor market. This quality is not only determined by the curriculum but also by the instructional methods, teacher training, and educational resources available. Without high-quality teaching that encourages critical thinking, problem-solving, and adaptive learning, even a well-designed curriculum may fail to equip students adequately for the labor market.

Secondly, sectoral structure also contributes to the observed mismatches. The high incidence of field-of-study mismatch, where 34% of tertiary-educated workers are employed in jobs unrelated to their fields of study, indicates that the sectors which should ideally absorb these graduates are either not expanding at the same rate as educational outputs or are not aligned with the skills produced by the education system. This variability suggests that certain sectors are better aligned with the education system than others, reflecting issues within both the sectoral structure of Türkiye’s economy and the education planning process. Additionally, the positive

effect of advanced ICT skills on wages for tertiary-educated workers suggests that sectors requiring high technology use are better aligned with education outcomes. This indicates that some industries are more adept at integrating technological advancements than others.

To address these challenges, comprehensive policies can help improve the alignment between education and labor market demands. To that end, several policies can be suggested based on CEDEFOP (2016) recommendations. Firstly, enhancing labor market information systems (LMIs) to provide timely and accurate data on labor market needs can help students make informed educational and career choices, aligning their qualifications with market demands. Secondly, strengthening vocational education and training (VET) programs to align with industry needs is also very important. This involves regularly updating curricula and forming partnerships between educational institutions and businesses.

Thirdly, promoting lifelong learning and continuous skill development is also very important to address skill obsolescence and the rapid pace of technological change. Policies encouraging ongoing education and training can help to achieve this. Furthermore, implementing sector-specific strategies can address specific needs within different industries. For example, focusing on advanced ICT skills for technology sectors and technical and vocational skills for traditional manufacturing sectors can improve alignment. Additionally, addressing gender disparities in education and employment through targeted policies can reduce mismatches, ensuring equal opportunities for skill development and career advancement (CEDEFOP, 2010; 2016).

Future research should continue to investigate the misalignment between educational outcomes and labor market demands, especially given the rapid pace of technological and economic changes. Firstly, the availability of longitudinal data would be instrumental in analyzing the long-term effects of the current expansion in higher education on labor market mismatches in Türkiye. Such studies can track the development of skill and educational mismatches over time and identify contributing factors to their persistence. This would offer important information about the relationship between educational policies and labor market conditions.

Secondly, future research should also examine the role of non-cognitive skills in labor market outcomes, as these skills gain more recognition in the literature for their importance alongside cognitive abilities. However, despite this growing recognition, the availability of empirical data for these skills are very limited. If such data becomes available, studying non-cognitive skills in the context of educational and labor market alignment could provide valuable information, especially about their role in mitigating the negative effects of education and skill mismatches.

Finally, an important direction for future research is the two-way relationship between brain drain and the misalignment between educational outcomes and labor market demands. This research should investigate how labor market mismatches encourage highly educated and skilled individuals to emigrate from their home countries seeking better opportunities abroad. Similarly, it should also examine how the outflow of human capital due to brain drain is exacerbating these mismatches as the domestic labor market loses highly educated and skilled individuals that can contribute to economic growth and innovation. This can show how this phenomenon affects the domestic labor markets and what long-term consequences it may have on the Turkish economy.

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APPENDICES

A1. METHODS OF MEASURING LABOR MARKET MISMATCH

Type of mismatch

(1) Education mismatch

Method 1: Self-assessment (SA) method

1) Create 6-category versions of the actual education level and the required education level variables

2) Compare and create variables to store education mismatch

Method 2: Realized matches (RM) method

1) Create a variable to store the mode of required education level by occupation

2) Create variables to store education mismatch:

• If the individual's actual education level is lower than the required education level by occupation, set edu_cat_rm to "undereducated"

• If the individual's actual education level is higher than the required education level by occupation, set edu_cat_rm to "overeducated"

• If the individual's actual education level is equal to the required education level by occupation, set edu_cat_rm to to "well-matched"

(2) Field-of-study mismatch

Create categories for different fields of study and compare them with the current occupation for each individual, following Montt (2017).

(3) Skill mismatch

First step: create a quantitative scale of skills

1) Create a new variable to store the proficiency scores of individuals who claim to be well-matched

2) Calculate the mode of well_matched_score by 1-digit ISCO code

Second step:

3) Calculate the 20th and 80th percentile of well_matched_score by 1-digit ISCO code

Third step: categorize workers as well-matched, over-skilled, or under-skilled

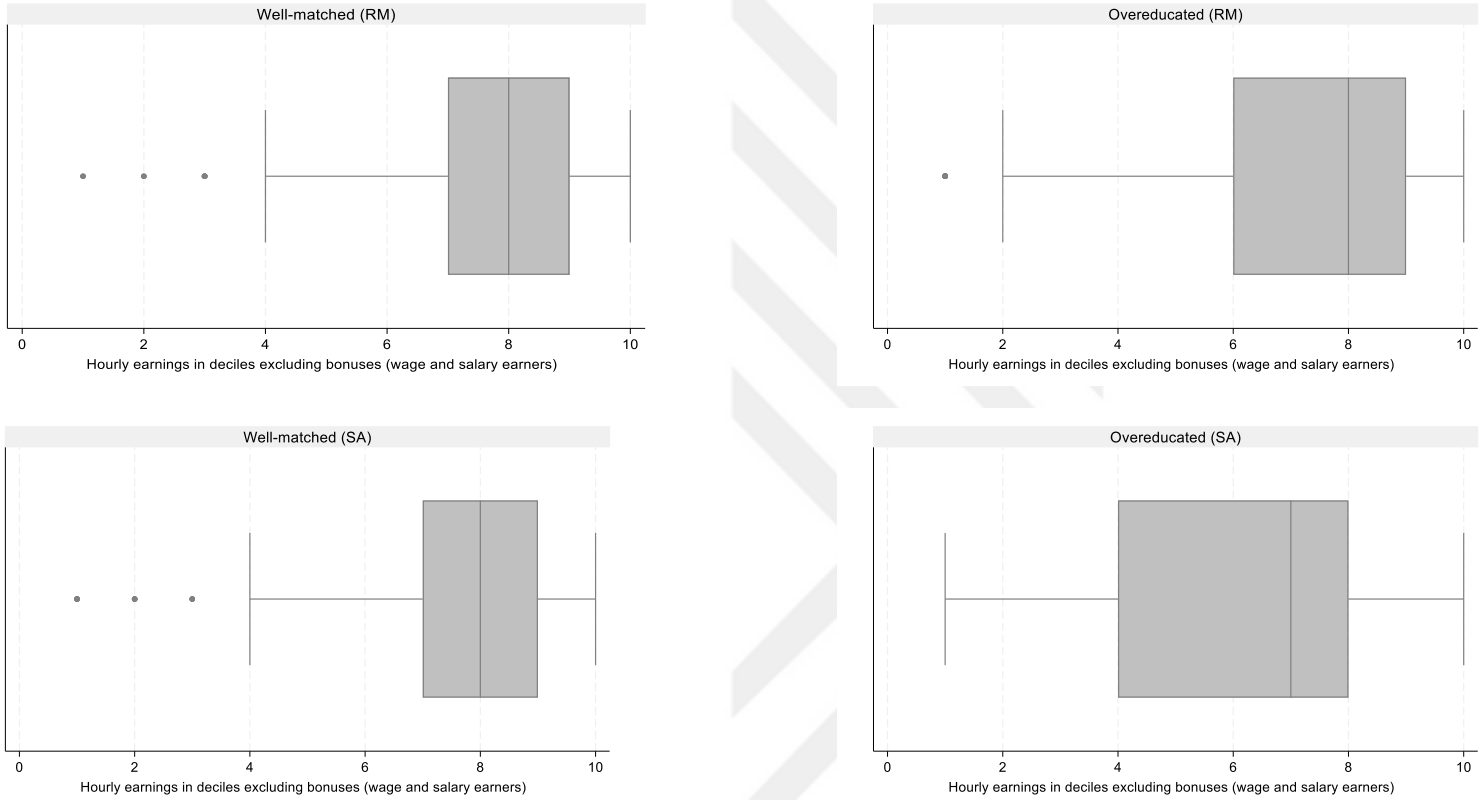
4) Create a new variable to store the skills mismatch status for each individual

• If the individual's proficiency score is less than the minimum threshold value, set skills_mm to "underskilled"

• If the individual's proficiency score is greater than the maximum threshold value, set skills_mm to "overskilled"

• If the individual's proficiency score is within the minimum and maximum threshold values, set skills_mm to "well-matched"

Figure A2. Hourly Earnings in Deciles Distribution for Well-Matched and Overeducated Full-Time Wage Earners with Tertiary Education in Turkey, by Subjective Assessment and Real Matches Methods (2015)



A3. DESCRIPTIVE STATISTICS

For full-time employed workers

	MALE (76.80%)	FEMALE (23.20%)	ALL	N
AGE GROUP				1685
Entry Age (20-29)	23.88	30.69	25.46	
Prime Age 1 (30-44)	58.81	57.80	58.58	
Prime Age 2 (45-54)	17.31	11.51	11.51	
EDUCATION LEVEL				1685
Lower secondary or less	47.30	31.97	43.74	
Upper secondary	26.66	24.81	26.23	
Associate degree	6.72	10.49	7.60	
Bachelor degree (ISCED 5A)	17.00	28.13	19.58	
Master/research degree	2.32	4.60	2.85	
ECONOMIC SECTOR				1682
Private sector	84.43	75.19	82.28	
Public sector	15.26	24.04	17.30	
A non-profit organization	0.31	0.77	0.42	
WORKPLACE SIZE				1356
1 to 10 people	34.06	32.66	33.70	
11 to 50 people	27.81	31.81	28.83	
51 to 250 people	20.26	19.77	20.13	
251 to 1000 people	10.13	9.46	9.96	
More than 1000 people	7.75	6.30	7.37	

A4. CORRELATES OF FIELD-OF-STUDY MISMATCH IN TÜRKİYE

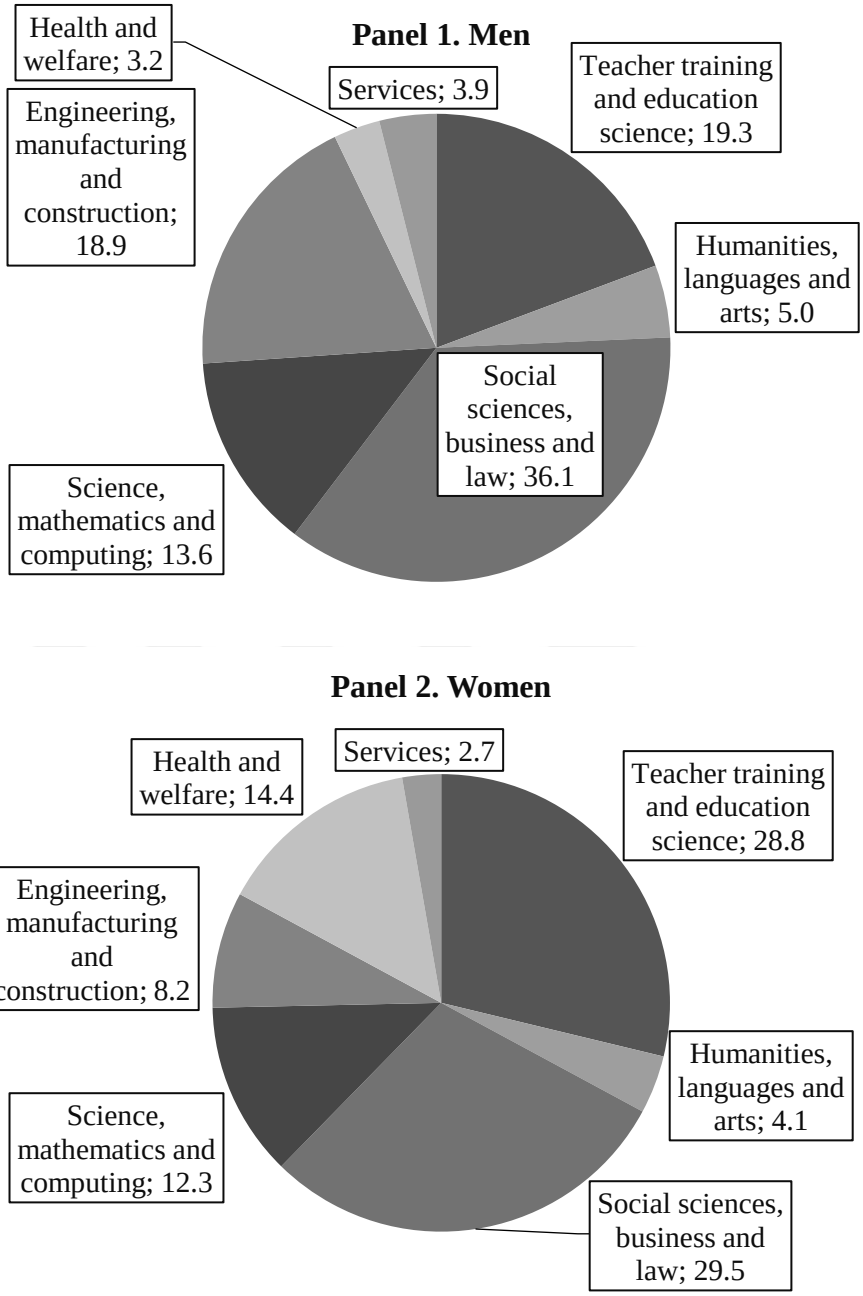
Including undereducated and underskilled categories, 2015 (Probit results)

	Coefficient estimates (standard errors)	
Edu. mismatch method	**RM Method**	**SA Method**
Overeducated	0.496***	0.765***
	(0.161)	(0.168)
Undereducated	0.852***	-1.047**
	(0.329)	(0.490)
Overskilled	0.449**	0.495**
	(0.191)	(0.193)
Underskilled	-0.994**	-1.005**
	(0.396)	(0.401)
Female	-0.334**	-0.257
	(0.165)	(0.163)
Attained education	-0.133*	-0.234***
	(0.069)	(0.070)
Entry age (20-29)	0.249	0.221
	(0.202)	(0.205)
Prime age 2 (45-54)	-1.293**	-1.225**
	(0.527)	(0.513)
Experience	-0.017	-0.038
	(0.050)	(0.048)
Experience squared (1/100)	0.138	0.234
	(0.192)	(0.187)
Numeracy skill	-0.003	-0.004
	(0.003)	(0.003)
Ready to learn	0.101	0.178**
	(0.087)	(0.086)
Public	-0.034	-0.042
	(0.168)	(0.164)
Manual	-0.162	-0.242
	(0.152)	(0.156)
Constant	1.714	3.275***
	(1.133)	(1.162)
Observations	425	425

*Note: SA stands for self-assessment method and RM stands for realized matches method. Robust standard errors in parentheses. Experience squared divided by 100. *** p<0.01, ** p<0.05, * p<0.1*

A5. PERCENTAGE DISTRIBUTION OF ACADEMIC FIELDS

For Tertiary-Educated Full-Time Wage Earners in Türkiye (2015), by gender



Source: Own calculations from PIAAC.

A6. MINIMUM ACHIEVEMENT RANKS

For Higher Education Programs in Türkiye, 2015-2021

Program	Score Type	Min. Achievement Rank		
		2015	2017	2021
Medicine	Quantitative	40,000	40,000	50,000
Law	Equal Weight	150,000	150,000	125,000
Engineering	Quantitative		240,000	300,000 [50]
Architecture	Quantitative		200,000	250,000
Pharmacy	Quantitative			100,000
Dentistry	Quantitative			80,000
Teaching	Quant., Verbal, Lang, EW		240,000	300,000 [51]

Source: CoHE, SSPC (Student Selection and Placement Center)

[50] Excludes: Forestry, Agriculture, Fisheries, Wood Products

[51] Includes: Guidance and Psychological Counseling (PDR)

A7. MINIMUM SCORE REQUIREMENTS

For Tertiary Education in Türkiye, 2015-2022

Year	System	Bachelor's Degree Programs	Associate Degree Programs[52]
2015	YGS	180	140
2016	YGS	180	150
2017 - 2020	YKS	180	150
2021	YKS	180	150
2021 AP	YKS	170	140
2022 - 2023	YKS	The minimum score requirement has been removed.	

[52] Associate Degree Programs, Distance Learning Associate Degree Programs, and Special Talent-Based Undergraduate Programs

B. CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: PLEVNELİ DÜZÇAY, Deniz

EDUCATION

Degree	Institution	Year of Graduation
MS	METU Economics	2014
BS	METU Economics	2010
High School	TED Ankara College High School, Ankara	2005

WORK EXPERIENCE

Year	Place	Enrollment
2011-2017	METU Department of Economics	Research Assistant
2017 November	Central Bank of Republic of Türkiye	Assistant Specialist

FOREIGN LANGUAGES

Advanced English

C. TURKISH SUMMARY / TÜRKÇE ÖZET

Eğitim, iş gücünün beşerî sermayesini artırmanın yanı sıra yeni bilgi ve teknolojilerin gelişimini kolaylaştırarak bir ülkenin inovasyon kapasitesini artırır ve gelişmiş teknolojilerin etkin kullanımını teşvik ederek ekonomik büyümeye katkı verir. Bu kapsamda eğitim, ekonomik büyümeyi teşvik eden temel bir faktördür. Eğitim yatırımlarının temel amacı, sadece daha geniş bir iş gücü üretmek değil, aynı zamanda teknolojik ilerlemeyi destekleyecek şekilde daha nitelikli bir iş gücü oluşturmaktır. Bu süreçte en önemli bir zorluklardan biri, eğitim sistemini iş piyasasının ihtiyaçlarıyla uyumlu hale getirerek iş gücünü bu ihtiyaçlara uygun şekilde hazırlamaktır.

Eğitim çıktıları ile işgücü piyasası talepleri arasındaki uyumsuzluk, eğitim yatırımlarının etkinliğini belirleyen önemli bir faktördür. İşgücü piyasası uyumsuzluğu, bireylerin sahip oldukları eğitim ve becerilerin işlerinin gerektirdiği eğitim ve becerilerle uyumsuz olduğu durumu ifade eder. Bu tür uyumsuzluklar hem bireyler için hem de ekonomi için verimlilik kayıplarına yol açabilir. İşgücü piyasası uyumsuzlukları, genel olarak üç ana kategoride incelenmektedir:

1. Eğitim Uyumsuzluğu (Education Mismatch):

Eğitim uyumsuzluğu, bireylerin sahip oldukları eğitim seviyesinin işlerinin gerektirdiği eğitim seviyesinden farklı olması durumunu ifade eder. Bu durum, fazla eğitimli (overeducation) veya yetersiz eğitimli (undereducation) olma şeklinde ortaya çıkabilir.

2. Beceri Uyumsuzluğu (Skill Mismatch):

Beceri uyumsuzluğu, bireylerin sahip oldukları becerilerin işlerinin gerektirdiği becerilerle uyuşmaması durumunu ifade eder. Bu durum, fazla becerili (overskilled) veya yetersiz becerili (underskilled) olma şeklinde ortaya çıkabilir.

3. Alan Uyumsuzluğu (Field-of-Study Mismatch):

Alan uyumsuzluğu, bireylerin eğitim aldıkları alanın, çalıştıkları işin gerektirdiği alanla uyuşmaması durumunu ifade eder. Bu durum, bireylerin eğitim aldıkları alanda çalışmamaları veya çalıştıkları işin eğitim aldıkları alanla ilgili olmaması şeklinde ortaya çıkar.

Bu tez, eğitim uyumsuzluğu, beceri uyumsuzluğu ve alan uyumsuzluğu olmak üzere Türkiye'de iş gücü piyasasında bu üç tür uyumsuzluğun görülme sıklığını ve sonuçlarını nicel olarak belirlemeyi ve teknoloji kullanımının ücretler üzerindeki etkisini değerlendirmeyi amaçlamaktadır. Tezin savı, Türkiye'de, eğitim sistemi ile iş gücü piyasası ihtiyaçları arasında önemli uyumsuzluklar bulunması ve bu durumun ekonomik anlamda olumsuz sonuçlara yol açıyor olmasıdır. Teknolojinin, bu uyumsuzlukların sonuçlarına hem kötüleştiren bir faktör olarak (teknolojik ilerlemenin eğitimsel adaptasyondan daha hızlı olması durumunda) hem de bir çözüm olarak (gelişmiş dijital okuryazarlık ve teknoloji entegreli eğitim yoluyla) etki edebileceği düşünülmektedir.

Tez üç ana bölümden oluşmakta ve her bölüm Türkiye'deki eğitim ve işgücü piyasası arasındaki uyumsuzlukları farklı açılardan ele almaktadır. İlk ana bölüm, Türkiye'deki eğitim ve beceri uyumsuzluklarının görülme sıklığını, bu uyumsuzluklara neden olan faktörleri ve bunların sonuçlarını incelemeyi amaçlamaktadır. Bu bölümde, işgücü piyasasında eğitim ve beceri uyumsuzluklarının teorik temelleri tartışılmakta ve ardından Türkiye'deki durum analiz edilmekte ve eğitim ve beceri uyumsuzluklarının iş tatmini ve ücretler üzerindeki etkileri değerlendirilmektedir. İkinci ana bölümde, yüksek eğitimli (önlisans, lisans ve yüksek lisans/doktora mezunu) bireylerin çalıştıkları alanların eğitim aldıkları alanlarla ne kadar uyumlu olduğunu analiz edilmekte, alan uyumsuzluklarının sıklığı ve bunların ücretler ve iş tatmini üzerindeki etkileri incelenmektedir. Üçüncü ve son ana bölüm, teknolojik gelişmeler, eğitim ve ücretler arasındaki ilişkiye yoğunlaşmaktadır. Türkiye'deki işgücü piyasasında farklı düzeylerdeki bilgi ve iletişim teknolojileri (BİT) kullanımı ve iş görevlerinin niteliği incelenmekte, bu faktörlerin ücretler üzerindeki etkileri değerlendirilmektedir. Bölüm, ayrıca, beceri yanlı teknik değişim (SBTC), rutin yanlı teknik değişim (RBTC) ve görev bazlı yaklaşımlara (task-based approach) Türkiye bağlamında destek verecek ampirik bulgulara ulaşmaktadır.

Bu tez, Türkiye'deki eğitim ve işgücü piyasası arasındaki uyumsuzlukları kapsamlı bir şekilde ele alarak literatüre üç temel katkıda bulunmaktadır. İlk olarak, Türkiye için eğitim uyumsuzluğunu inceleyen çalışmalar yapılmış olmasına rağmen, beceri uyumsuzluklarına ilişkin benzer çalışmalar bulunmamaktadır. Bu çalışma, Türkiye'deki beceri uyumsuzlukları üzerine yapılan ilk kapsamlı çalışmalardan biridir. Bu kapsamda, beceri uyumsuzluklarının ücretler ve iş tatmini üzerindeki etkileri, diğer iş gücü piyasası uyumsuzluklarını da kapsayan bir analiz ile detaylı bir şekilde incelenmiştir. Bu analizler, Türkiye'deki işgücü piyasası ve eğitim sistemi arasındaki uyumsuzlukları anlamak için yeni ve tamamlayıcı bilgiler sunmaktadır. İkinci olarak, SBTC ve RBTC teorilerine Türkiye bağlamında ampirik kanıtlar sunulmaktadır. Üçüncü olarak ise, işgücü piyasası uyumsuzluklarının etkileri analiz edilirken gizli beceriler (unobserved abilities) kontrol edilmektedir. Bu sayede, işgücü piyasası uyumsuzluklarının etkilerini değerlendirirken yanlılıklar minimize edilmekte ve daha güvenilir sonuçlara ulaşılmaktadır.

Birinci Bölüm: Türkiye'de İşgücü Piyasası Uyumsuzluğunun Yaygınlığı, Korelasyonları ve Sonuçları

Tezin ilk ana bölümü, Türkiye'deki işgücü piyasasında eğitim ve beceri uyumsuzluklarının görülme sıklığını, bu uyumsuzluklara neden olan faktörleri ve bunların sonuçlarını incelemektedir. Teorik anlamda, işgücü piyasası uyumsuzluklarını açıklayan dört temel teorik çerçeveden söz edilebilir. İnsan Sermayesi Teorisi, bireylerin eğitim ve becerilere yaptıkları yatırımların onların verimliliklerini artırdığını ve bu verimlilik artışının ücretlere yansıdığını öne sürer. Ancak, işgücü piyasasında bilgi eksiklikleri ve iş arama maliyetleri nedeniyle bireyler uygun işleri bulana kadar geçici olarak uyumsuzluklar yaşayabilirler. İş Rekabet Teorisi, iş piyasasında bireylerin eğitim düzeylerinin, işverenlerin onları sıralamak için kullandığı bir kriter olduğunu savunur. Bu teoriye göre, aşırı eğitimli bireyler daha az eğitimli bireyleri iş bulma sıralamasında geride bırakır ve bu da uyumsuzluklara neden olur. Sinyal Teorisi, eğitim seviyesinin işverenlere bireylerin verimliliği hakkında bilgi veren bir sinyal olduğunu belirtir; ancak, eğitim düzeyi her zaman bireyin gerçek becerilerini yansıtmayabilir ve bu da uyumsuzluklara yol açabilir. Atama Teorisi ise, işgücü piyasasında bireylerin becerileri ile işlerin gerektirdiği nitelikler arasında tam bir uyum olmadığında uyumsuzlukların ortaya çıktığını

savunur. Bu durum, bireylerin becerilerinin tam olarak kullanılamamasına ve işverenlerin de beklenen verimliliği elde edememesine neden olur.

Bu bölümde kullanılan veriler, OECD tarafından yürütülen Uluslararası Yetişkin Yeterlikleri Değerlendirme Programı (PIAAC) anketinden elde edilmiştir. PIAAC verisinin önemi, bireylerin sahip oldukları becerileri objektif olarak ölçmesi ve bu becerilerin iş piyasasındaki gereksinimlerle ne kadar uyumlu olduğunu değerlendirmeye olanak tanımasıdır. PIAAC uluslararası bir çalışma olup 16-65 yaş arasındaki yetişkinlerin okuryazarlık (literacy), sayısal beceriler (numeracy) ve problem çözme (problem-solving) yetkinliklerini objektif bir şekilde değerlendirmektedir. Okuryazarlık ve sayısal beceriler, temel yetkinlikler (foundational skills) olarak kabul edilmekte olup, bu becerilerin eksikliği bireylerin iş bulma ve kariyerlerinde ilerleme olanaklarını sınırlayabilir. PIAAC verisi, bu nedenle, eğitim ve beceri uyumsuzluklarını analiz etmek için ideal bir kaynak sunar.

Öte yandan, PIAAC verisinin gözlem sayısının düşük olması, temsiliyet gücüne ilişkin soru işaretleri yaratmaktadır. Bu kapsamda, PIAAC verisi Türkiye'deki Hanehalkı İşgücü Anketi (HIA) ile karşılaştırılmıştır. Bu karşılaştırma sonucunda, PIAAC verilerinin Türkiye'nin genel nüfus yapısını ve işgücü piyasasını temsil etmede uygun olduğu tespit edilmiştir. PIAAC, HIA'ya kıyasla bireylerin beceri düzeyleri hakkında daha detaylı bilgi sağlamaktadır. Bu nedenle, PIAAC verisi, Türkiye'deki eğitim ve işgücü piyasası arasındaki uyumsuzlukları anlamak ve bu uyumsuzlukların ekonomik sonuçlarını kapsamlı bir şekilde analiz etmek için tercih edilmiştir.

İşlerin eğitim gereksinimlerini belirlemek için literatürde kullanılan üç ana yöntem vardır: öz değerlendirme, gerçekleştirilmiş eşleşmeler ve iş analizi. Öz değerlendirme yöntemi (SA), çalışanların kendi eğitim düzeylerinin işlerinin gereksinimleriyle ne kadar uyumlu olduğunu kendilerinin değerlendirmesi üzerine kurulu bir yaklaşımdır. Bu yöntemde bireylere işlerinin gerektirdiği eğitim düzeyi sorularak, bu düzey kendi eğitim düzeyleri ile karşılaştırılmaktadır. SA yönteminin avantajı, kişi seviyesinde değerlendirme yapmaya olanak sağlamasıdır; ancak, bireylerin kendi eğitim ve beceri düzeylerini fazla veya eksik değerlendirme olasılığı nedeniyle sonuçlar yanlı olabilir. Gerçekleştirilmiş eşleşmeler yöntemi (RM) ise, bir iş pozisyonundaki çalışanların ortalama veya mod eğitim düzeylerine dayanarak uyumluluğu belirler. Bu yöntemde,

bir işteki tipik eğitim düzeyi belirlenir ve çalışanların bu belirlenen eğitim düzeyine göre uyumlu, fazla eğitimli veya yetersiz eğitimli olup olmadıkları değerlendirilir. RM yöntemi, daha objektif bir yaklaşım sunar, ancak bireysel farklılıkları göz ardı edebilir ve eğitim seviyesinin zamanla değişebileceği durumlarda güncelliğini yitirebilir. İş analizi yöntemi (JA) ise, iş gereksinimlerini belirlemek için sistematik değerlendirmeler yapan profesyonel iş analistlerinin kullanıldığı bir yaklaşımdır. Bu yöntemde, belirli iş pozisyonları için gerekli eğitim düzeyleri detaylı bir şekilde analiz edilerek belirlenir, ancak uygulanması maliyetli ve zaman alıcı olabilir. Bu üç yöntem, işgücü piyasasındaki eğitim ve beceri uyumsuzluklarını anlamak için farklı perspektifler sunar ve eğitim sistemi ile iş piyasası arasındaki uyumu değerlendirmek için değerli bilgiler sağlar. Bu tezde SA ve RM yöntemleri kullanılmıştır.

Beceri uyumsuzluğu analizinde kullanılan yöntemler, öz değerlendirme, doğrudan ölçüm ve bu iki yöntemin kombinasyonundan oluşur. Öz değerlendirme yönteminde, çalışanlar kendi becerilerini değerlendirir. Ancak, bireylerin kendilerini değerlendirmede objektif olamama veya işlerinin gereksinimlerini tam olarak bilmemesi gibi dezavantajları vardır. Doğrudan ölçüm yöntemi, çalışanların becerilerini doğrudan yeterlilik puanlarıyla ölçer ve bunları iş yerlerindeki beceri kullanımıyla karşılaştırır. Bu yöntem, büyük ölçekli değerlendirmelerde veri toplanmasını gerektirir ve maliyetlidir.

Hibrit model ise, öz değerlendirme ve doğrudan ölçüm yöntemlerinin kombinasyonunu kullanır. OECD PIAAC verileri, bireylerin becerileri ve iş yeri özellikleri hakkında kapsamlı bilgiler sağladığı için bu modeli kullanmayı mümkün kılar. Hibrit model hem öz değerlendirme bilgilerini hem de farklı alanlardaki yeterlilik bilgilerini birleştirir. İlk adımda, öz değerlendirme yöntemi kullanılır. Bu, bireylerin öz değerlendirme sorularına verdikleri yanıtlarla gerçekleştirilir. Bireylere "Şu anki işinizde gerekenden daha fazla yetenekli olduğunuzu düşünüyor musunuz?" ve "İşinizi etkili bir şekilde yapabilmek için daha fazla eğitime ihtiyacınız var mı?" soruları sorulur. Bu sorulara "Hayır" cevabı veren bireyler, kendilerini işlerine uygun becerilere sahip olarak görürler. İkinci adımda, bireylerin becerileri objektif olarak değerlendirilir. Bu aşamada, PIAAC'tan elde edilen sayısal beceri puanları kullanılır. Öz değerlendirmeye göre beceri ve işleri uyumlu olarak tespit edilen çalışanların sayısal beceri puanlarının dağılımına bakılarak, belirli yüzde dilimleri (örneğin, P20

ve P80) belirlenir. Bu yüzde dilimleri, her bir iş kategorisi için minimum ve maksimum beceri gereksinimlerini belirler. P20, bir iş kategorisi için gerekli olan en düşük beceri seviyesini temsil ederken, P80, gerekli olan en yüksek beceri seviyesini temsil eder. Son adımda, bireylerin sayısal beceri puanları, belirlenen minimum ve maksimum eşik değerlerle karşılaştırılır. Eğer bir bireyin puanı belirlenen maksimum değerin üzerindeyse, o birey fazla becerili olarak sınıflandırılır. Aynı şekilde, puanı minimum değerin altındaysa, yetersiz becerili olarak sınıflandırılır. Bu yöntem, beceri uyumsuzluklarını daha objektif bir şekilde belirlemeyi sağlar, aynı zamanda çok yüksek ve çok düşük değerlerin dışarıda kalmasını sağlayarak analiz sonuçlarının daha tutarlı olmasına katkıda bulunur.

İşgücü piyasası uyumsuzluklarının gelir üzerindeki etkilerini ölçmede kullanılan iki temel yöntem ORU (Over-Required-Undereducation) ve kukla değişken (dummy variable) yöntemleridir. ORU yöntemi, Duncan ve Hoffman (1981) tarafından geliştirilen ve eğitim uyumsuzluklarının detaylı bir analizini sunan bir yaklaşımdır. Bu yöntemde, bireylerin eğitim düzeyleri işin gerektirdiği eğitim süresi (years of required education), fazla eğitim süresi ve yetersiz eğitim süresi olmak üzere üç bileşene ayrılarak incelenir. Bireyin sahip olduğu eğitim yılları, işinin gerektirdiği eğitim yılları ile karşılaştırılarak bu kategorilere ayrılır. Örneğin, bir işin gerektirdiği eğitim seviyesi 12 yıl ise ve bireyin eğitim seviyesi 14 yıl ise, birey 2 yıl fazla eğitimli kabul edilir. Aynı şekilde, bireyin eğitim seviyesi 10 yıl ise, 2 yıl yetersiz eğitimli olarak değerlendirilir. Bu yöntemde, fazla eğitim ve yetersiz eğitim bileşenlerinin her biri ayrı ayrı değerlendirilir ve bu bileşenlerin ücretler üzerindeki etkileri analiz edilir. Bu yöntem ile yapılan analizlerde, çoğunlukla, fazladan eğitimli yılların pozitif fakat gerekli eğitim yıllarına kıyasla daha düşük bir katsayıya sahip olduğu, yetersiz eğitimli yılların ise negatif bir katsayıya sahip olduğu bulunmaktadır.

Kukla değişken yöntemi, Verdugo ve Verdugo (1989) ile Kiker vd. (1997) tarafından yaygınlaştırılan bir başka yaklaşımdır. Bu yöntemde, eğitim uyumsuzluklarını analiz etmek için kişinin eğitim süresini gösteren bir değişkenin (actual education) yanı sıra "fazla eğitim" ve "yetersiz eğitim" olmak üzere iki kukla değişken kullanılır. Fazla eğitim kukla değişkeni, bireyin sahip olduğu eğitim seviyesinin işin gerektirdiği eğitim seviyesinden daha yüksek olduğu durumlarda 1 değerini alır. Literatürde yer alan çalışmalarda çoğunlukla bu değişkenin katsayısı negatif olarak bulunmaktadır. Bu,

aşırı eğitimli bireylerin, eğitim seviyeleri kendileriyle aynı olan ancak uygun işlerde çalışan bireylere kıyasla daha düşük ücret aldığını gösterir. Yetersiz eğitim kukla değişkeni ise, bireyin sahip olduğu eğitim seviyesinin işin gerektirdiği eğitim seviyesinden daha düşük olduğu durumlarda 1 değerini alır. Bu kukla değişkenin katsayısının pozitif olması, yetersiz eğitimli bireylerin kendi eğitim seviyelerine uygun işlerde çalışanlara kıyasla daha fazla ücret aldığını göstermektedir.

Bu ters işaretli katsayılar, yöntemlerin farklı analiz yaklaşımlarını ve eğitim uyumsuzluklarının farklı boyutlarını yansıtmakta olup, birbirleriyle çelişkili değildir. ORU yöntemi kullanıldığında, fazla eğitimli yılların genellikle pozitif bir katsayıya sahip olması beklenir çünkü daha fazla eğitim, genel olarak daha yüksek ücretlerle ilişkilendirilir. Ancak, fazla eğitim yıllarının katsayısı, gerekli eğitim yıllarına kıyasla daha düşüktür. Kukla değişken yönteminde fazla eğitimin katsayısının negatif olması, fazla eğitimli bireylerin, eğitim seviyeleri kendileriyle aynı olan ancak uygun işlerde çalışan bireylere kıyasla daha düşük ücret aldığını gösterir. Bu durum, ORU yönteminde gözlemlenen, gerekli eğitim getirisinin fazla eğitim getirisinden daha yüksek olduğu bulgusuyla tutarlıdır.

Genel olarak, işgücü piyasası uyumsuzlukları üzerine yapılan araştırmalar, eğitim ve beceri uyumsuzluklarının ücretler ve iş tatmini üzerindeki etkilerini ele almaktadır. Eğitim uyumsuzluğu üzerine yapılan çalışmalar, fazla eğitimli veya yetersiz eğitimli bireylerin iş piyasasında nasıl konumlandıklarını ve bu durumun ücretlerine nasıl yansıdığını incelemiştir. Benzer şekilde, beceri uyumsuzluğu üzerine yapılan çalışmalar da bireylerin sahip oldukları becerilerin işlerinin gerektirdiği becerilerle ne kadar uyumlu olduğunu ve bu uyumsuzluğun iş tatmini ve iş performansı üzerindeki etkilerini değerlendirmiştir. Ampirik bulgular, genellikle eğitim ve beceri uyumsuzluklarının hem bireysel hem de ekonomik düzeyde olumsuz sonuçlara yol açtığını göstermektedir. Özellikle fazla eğitimli bireylerin genellikle ücret kayıpları yaşadıkları, beceri uyumsuzluklarının ise iş tatmini üzerinde etkileri olduğu bulgulanmıştır. Türkiye özelinde yapılan araştırmalar da benzer sonuçlar ortaya koymuş ve ülkedeki eğitim uyumsuzluklarının iş gücü piyasasında önemli bir sorun olduğunu vurgulamıştır (örn. Filiztekin, 2011). Bu araştırmalar, uyumsuzlukların yaygınlığını, nedenlerini ve sonuçlarını ortaya koyarak, eğitim sistemi ve iş gücü piyasası arasında daha iyi bir uyum sağlanması gerektiğini göstermektedir.

Bu tezde, PIAAC verisi kullanılarak, Türkiye'de eğitim ve beceri uyumsuzluklarının görülme sıklığı, bağlantılı faktörleri ve sonuçları incelenmiş ve araştırma sonucunda, literatürdeki bulgularla tutarlı sonuçlar elde edilmiştir. İlk olarak, Türkiye'de eğitim uyumsuzluklarının oldukça yaygın olduğu bulunmuştur. Öz değerlendirme sonuçlarına göre, çalışanların %29'u eğitim düzeyleri açısından uyumsuzdur; bunların %16'sı fazla eğitimli, %13'ü ise yetersiz eğitimlidir. Objektif yöntemlerle yapılan değerlendirmeler, öz değerlendirmelere kıyasla daha yüksek bir fazla eğitim oranı göstermektedir. Objektif yaklaşıma göre, çalışanların %42'si eğitim açısından uyumsuzdur; bunların %31'i fazla eğitimli ve %11'i yetersiz eğitimlidir. Buna ek olarak, araştırma sonuçları Türkiye'de beceri uyumsuzluklarının da yüksek düzeyde olduğunu göstermektedir. Bulgulara göre, çalışanların %41'i beceri düzeyleri açısından uyumsuzdur ve iş gereklerine göre bu kişilerin %28'i fazla becerilere, yüzde 13'ü ise eksik becerilere sahiptir.

Bunun ardından, ORU ve kukla değişken yöntemleri kullanarak yapılan analiz sonuçları, Türkiye'de eğitim ve beceri uyumsuzluklarının ücretler üzerinde olumsuz etkileri olduğunu ortaya koymaktadır. Fazla eğitimli çalışanlar, kendileri ile aynı eğitim seviyesine sahip ancak eğitim seviyesi işinin gereklilikleri ile uyumlu çalışanlara kıyasla daha düşük gelir elde etmektedir. Aynı zamanda bu kişiler, objektif yöntemler kullanıldığında, eşdeğer işlerde çalışan ve eğitimleriyle işleri uyumlu olan bireylerden daha yüksek ücretler kazanmaktadır. Yetersiz eğitimli çalışanlar, benzer bir işte çalışan ve eğitimleriyle uyumlu çalışanlardan daha düşük ücret alırlar, ancak kendileri ile aynı eğitim seviyesine sahip ve eğitimleriyle uyumlu işçilerden (SA yöntemi kullanıldığında) daha fazla kazanırlar.

Benzer şekilde, fazla becerili olmanın da ücretler üzerinde olumsuz etkisi bulunmaktadır. Ancak, yetersiz becerili olmanın ücretler üzerinde anlamlı bir etkisi bulunmamaktadır. Ayrıca, iş tatmini üzerine yapılan analizin sonucunda, eğitim ve beceri uyumsuzluklarının iş tatmini üzerindeki etkilerinin farklılık gösterdiği görülmüştür. Fazla eğitimli olmanın iş tatmin düzeylerine etkisinin olmadığı, ancak yetersiz eğitimli bireylerin işlerinden memnun olma olasılıklarının daha yüksek olduğu bulunmuştur.

Özetle, ilk bölümden elde edilen bulgular, eğitim ve işgücü piyasası arasındaki

uyumun artırılması için politika ve stratejilerin geliştirilmesi gerekliliğini açıkça ortaya koymaktadır. Literatürdeki bulgularla uyumlu olarak, Türkiye'deki eğitim ve beceri uyumsuzluklarının yaygınlığının ve bu uyumsuzlukların olumsuz sonuçlarının, işgücü piyasasının etkinliğini ve bireylerin ekonomik refahını olumsuz yönde etkileyebileceği görülmektedir.

İkinci Bölüm: Türkiye'de Yüksek Eğitimli Çalışanlar Arasında Alan Uyumsuzluğu

1960'lardan bu yana Türkiye, tarım ekonomisinden sanayi ve hizmet sektörlerine dayalı bir ekonomiye geçiş yapmıştır. İthal ikameci sanayileşme politikaları, şehirlerde sanayilerin gelişimini teşvik etmiş ve kırsal alanlardan kentsel alanlara olan göç, yeni sanayiler için gerekli işgücünü sağlamıştır. Ancak, tarım işgücünün diğer sektörlere geçişi beklenen ölçüde başarılı olmamıştır (İlkkaracan ve Tunalı, 2010; Günçavdı ve diğerleri, 2013). 1980'ler ve sonrasında, Türkiye daha liberal ekonomik politikalara geçiş yapmış ve bu dönemde kırsal işgücünün, kentsel alanlara göçü devam etmiştir (Aydin, 2013; Günçavdı ve diğerleri, 2013). Türkiye'de yaşanan bu ekonomik dönüşüm, vasıflı işgücünü ihtiyaç kılmıştır. Bu ihtiyaçlara yanıt olarak, 1990'lardan itibaren, Türkiye'nin yükseköğrenim sistemi, üniversite sayısında hızlı bir artışla karakterize edilen bir dönüşüm geçirmiştir. İlk önemli genişleme dalgası 1990'ların başında gerçekleşmiş, ikinci genişleme dalgası ise 2000'lerin ortalarında ve devamında özel kurumların hızla kurulmasıyla gerçekleşmiştir. Ancak, bu hızlı artış, eğitimin kalitesi ve planlaması konularında endişelere yol açmıştır.

Bu bölümde, Türkiye'de yüksek eğitim alan bireylere odaklanılarak işgücü piyasasında görülen alan uyumsuzlukları analiz edilmiştir. Alan uyumsuzluğu, bireylerin eğitim aldıkları alan ile çalıştıkları işin gerektirdiği beceriler arasındaki uyuşmazlığı ifade eder. Bu uyumsuzluğun, işgücü piyasasında bireylerin verimliliklerini, iş tatminlerini ve ücretlerini olumsuz yönde etkileyebilen bir faktör olması, son dönemde literatürde önemli bir araştırma konusu olmasına neden olmaktadır. Örneğin, Robst (2007), alan uyumsuzluğunun bireylerin ücretlerini ve iş tatminini olumsuz etkilediğini belirlemiş ve bu uyumsuzluğun daha yüksek iş değiştirme oranlarına yol açtığını vurgulamıştır. Bu bulgular, alan uyumsuzluğunun bireylerin ekonomik refahı üzerinde önemli etkileri olduğunu göstermektedir.

Türkiye'deki yüksek eğitimli bireyler arasında yapılan çalışmalar da benzer sonuçlar ortaya koymakta ve eğitim sistemi ile işgücü piyasası arasındaki uyumun artırılması gerektiğini göstermektedir (örn. Ege ve Erdil, 2023).

Tezin bu ikinci temel bölümünde, yüksek eğitimli bireyler arasında alan ve iş uyumsuzluğunun yaygınlığı, ilişkili faktörler ve bu uyumsuzluğun ücretler ve iş tatmini üzerindeki etkileri analiz edilmiştir. Bu kapsamda, Türkiye işgücü piyasasında eğitim uyumsuzluğu, alan uyumsuzluğu ve beceri uyumsuzluğu birlikte ele alınarak, bu üç uyumsuzluk türünün işgücü piyasası sonuçları üzerindeki etkilerine bakılmaktadır. Alt örneklem olarak yüksek eğitimli bireyler alınmış ve bu bireylerin işgücü piyasasındaki durumları analiz edilmiştir. Bu analiz için OECD tarafından sağlanan PIAAC verisi kullanılmaya devam edilmiştir. Bu veri seti, alan uyumsuzluğunu değerlendirmek için de uygun bir kaynak oluşturmaktadır.

İlk bölümle benzer olarak, bireylerin eğitim düzeyleri ve işlerinin gerektirdiği eğitim düzeyleri karşılaştırılarak eğitim uyumsuzlukları (fazla eğitim ve yetersiz eğitim) belirlenmiştir. Aynı şekilde, bireylerin sahip oldukları beceriler ile işlerinin gerektirdiği beceriler karşılaştırılarak beceri uyumsuzlukları (fazla becerili ve yetersiz becerili) analiz edilmiştir. Eğitim ve beceri uyumsuzluklarının analizi önceki bölümde kullanılan yöntemlerle gerçekleştirilmiştir.

Bunların yanı sıra bu bölümde, alan uyumsuzluğunu ölçmek için, bireylerin eğitim aldıkları alan ile çalıştıkları işin gerektirdiği alan arasındaki uyum da değerlendirilmiştir. Alan uyumsuzluğunu ölçmek için, bireylerin eğitim aldıkları alan ile çalıştıkları işin gerektirdiği alan arasındaki uyum değerlendirilmiştir. Bunlar, bireylerin PIAAC verisinde belirtilen eğitim programlarına göre sınıflandırılmıştır. Alan uyumsuzluğunu belirlemek için Montt (2017) tarafından kullanılan yöntem izlenmiştir. Bu yöntem, bireylerin eğitim alanı kodları ile Uluslararası Standart Meslek Sınıflaması (ISCO) kodları karşılaştırılarak uyumsuzluk durumlarını belirlememizi sağlamaktadır.

Bu bölümde yapılan analizler, Türkiye'de yüksek eğitimli tam zamanlı ücretli çalışanların %34'ünün alan uyumsuzluğu yaşadığını göstermektedir. Analizler ayrıca, alan uyumsuzluğu ile eğitim ve beceri uyumsuzluklarının örtüşme oranlarını da ortaya koymuştur. Yüksek eğitimli tam zamanlı çalışanların %18'inin hem alan uyumsuzluğu

hem de (gerekli eğitim seviyesi objektif yöntem kullanılarak belirlendiğinde) fazla eğitimli olduğu bulunmuştur. Buna ek olarak, eğitim düzeyi açısından iyi uyum sağlamış olanların %25'inin hala eğitim alanlarıyla uyumlu olmayan işlerde çalıştığı tespit edilmiştir. Bu bulgular, eğitim sistemi ile işgücü piyasası arasındaki uyumun sağlanmasında ciddi eksiklikler olduğunu göstermektedir.

Alan uyumsuzluğu bölümler bazında incelendiğinde, farklı alanlarda önemli farklılıklar gözlemlenmiştir. "Beşeri Bilimler, Diller ve Sanatlar" mezunları arasında alan uyumsuzluk oranı %70 ile en yüksek seviyededir. Bunu %66 ile "Fen, Matematik ve Bilgisayar Bilimleri" mezunları takip etmektedir. Öte yandan, "Öğretmen Eğitimi ve Eğitim Bilimleri" ile "Sosyal Bilimler, İşletme ve Hukuk" mezunları arasında alan uyumsuzluk oranları daha düşük seviyededir. “Öğretmenlik ve Eğitim Bilimleri” alanından mezun olan bireyler arasında alan uyumsuzluğu oranı %23 olup, fazla eğitimli oranı ise %22’dir. Bu oranlar, bu alandan mezun olan bireylerin genellikle eğitimleriyle uyumlu işlerde çalıştıklarını göstermektedir. “Sosyal Bilimler, İşletme ve Hukuk” alanından mezun olan bireyler arasında alan uyumsuzluğu oranı %22 olarak tespit edilmiştir. Bununla birlikte, bu alandaki mezunların %56'sı fazla eğitimli olarak bulunmuştur. Bu da, bu mezunların çoğunun eğitimlerinin gerektirdiği düzeyde iş bulamadığını göstermektedir. Bu bulgular, farklı eğitim alanlarından mezun olan bireylerin işgücü piyasasında karşılaştıkları uyumsuzlukların çeşitlilik gösterdiğini ve bazı alanlarda bu uyumsuzlukların daha yaygın olduğunu göstermektedir.

Bu bölümde ulaşılan bulgular, alan uyumsuzluğu yaşayan bireylerin, uyumlu olan akranlarına kıyasla daha düşük ücret aldığını ortaya koymaktadır. Bu durum, bireylerin sahip oldukları eğitim ve becerileri tam olarak kullanamadıkları işlerde çalışmaları nedeniyle verimliliklerinin ve dolayısıyla ücretlerinin düşük olmasından kaynaklanmaktadır. Nesnel yöntemlerle ölçülen eğitim uyumsuzluğu ve beceri uyumsuzluğu da benzer şekilde ücretleri olumsuz etkilemektedir. Bu etkiler, eğitim gereksinim düzeyi nesnel olarak ölçüldüğünde, alan uyumsuzluğunun etkisi ile aynı büyüklükte olmaktadır. Yani, alan uyumsuzluğu, eğitim uyumsuzluğu ve beceri uyumsuzluğunun her üçü de Türkiye'deki yüksek eğitimli ücretli çalışanlar için ücret sonuçları üzerinde eşit derecede önemli ve olumsuz etkilere sahiptir. Ayrıca, öz-değerlendirme yöntemi kullanılarak ölçülen eğitim uyumsuzluğunda, alan uyumsuzluğunun ücretler üzerindeki etkisi anlamlı bulunmamıştır. Bu durum, kişisel

algıların eğitim uyumsuzluklarını nasıl yorumladıkları üzerinde önemli bir etkiye sahip olduğunu ve bu algıların alan uyumsuzluğunun etkilerini gizleyebileceğini göstermektedir.

Bununla birlikte, analiz sonuçları, alan uyumsuzluğunun iş tatmini üzerinde istatistiksel olarak anlamlı bir etkisi olmadığını göstermektedir. Bu, bireylerin alan uyumsuzluğu yaşasalar bile genel iş tatminlerinin bundan büyük ölçüde etkilenmediğini göstermektedir. Ancak, bu durum alan uyumsuzluğunun dolaylı etkilerini göz ardı etmemelidir. Örneğin, düşük ücretler iş tatminini olumsuz etkileyebilir ve alan uyumsuzluğu genellikle düşük ücretlerle ilişkilendirildiğinden, dolaylı yoldan iş tatminini etkileyebilir. Nitekim gelir, iş tatmini üzerinde önemli ve pozitif bir etkiye sahip olarak bulunmaktadır.

Özetle, bu bölümde elde edilen bulgular, yüksek eğitimli bireylerin önemli bir kısmının eğitim ve becerilerinin işlerinin gerektirdiği düzeyle uyumsuz olduğunu ortaya koymuştur. Türkiye'deki yükseköğrenim mezunlarının %78'inin bu üç tür işgücü piyasası uyumsuzluğundan en az birini yaşadığı göz önüne alındığında, eğitim politikalarının işgücü piyasasının ihtiyaçlarına daha iyi cevap verecek şekilde yeniden yapılandırılması gerektiği açıktır. Sonuç olarak, bu bölümde eğitim ve beceri uyumsuzluklarının yanı sıra alan uyumsuzluğunun da önemli bir sorun olduğu belirlenmiştir. Bu bulgular, eğitim ve işgücü piyasası arasındaki uyumun artırılması ve mezunların eğitim aldıkları alanlarda istihdam edilmesini destekleyecek politikaların önemini vurgulamaktadır.

Üçüncü Bölüm: Türkiye'de Sermaye-Beceri Tamamlayıcılığı, Teknoloji Kullanımı ve Eğitim

Bu bölüm, Türkiye'deki işgücü piyasasındaki teknoloji kullanımı ve sermaye-beceri tamamlayıcılığının yanı sıra iş görevlerinin doğasını da dikkate alarak, bu faktörlerin ücret sonuçları üzerinde eğitim düzeyiyle birlikte nasıl bir etkileşimde bulunduğunu incelemektedir. Bölüm, BİT kullanımının çalışanlar için nasıl ücret avantajları sağladığını ve bu avantajların eğitim seviyesi ile iş görevlerinin yoğunluğuna göre nasıl değiştiğini detaylandırmaktadır.

Sermaye-beceri tamamlayıcılığı, teknolojik gelişmelerin ve sermaye yatırımlarının

vasıflı işgücü ile olan olumlu etkileşimini ifade eder ve SBTC yazını ile bağlantılıdır. SBTC'nin temel önermesi, teknolojik yeniliklerin yaygınlaşması ile, bu teknolojileri kullanabilen, yüksek beceri düzeyine sahip çalışanlara olan talebin artmasıdır. Bir diğer ifadeyle, SBTC, teknolojik ilerlemelerin vasıflı işçilerin verimliliğini vasıfsız işçilerinkinden daha fazla artırma eğiliminde olduğunu ve böylece vasıfsız işgücüne kıyasla vasıflı işgücüne olan talebi artırdığını öne sürmektedir. Bu durum işgücü piyasasında vasıflı işçiler lehine değişimlere yol açarak vasıflı ve vasıfsız işçiler arasındaki ücret farkının artmasına katkıda bulunabilir.

RBTC literatürü ise, özellikle BİT ilerlemelerinin rutin ve kodlanabilir görevleri otomasyona uygun hale getirerek bu işleri nasıl etkilediğini anlamak için bir çerçeve sunmaktadır. RBTC, teknolojik ilerlemenin iyi tanımlanmış prosedürleri takip eden görevlerin (yani kodlanabilir görevler) otomasyonuna giderek daha fazla izin verdiğini öne sürmektedir. Buna bağlı olarak, teknolojik yenilikler (örneğin, robotik ve yapay zeka gibi) rutin görevleri otomasyona uygun hale getirerek, bu görevleri yerine getiren çalışanlara olan talebi azaltır. Bunun sonucunda rutin olmayan işlerde çalışan çalışanların ücretleri artarken, rutin görevleri yerine getiren çalışanların ücretleri baskı altında kalabilir veya düşebilir.

Krueger (1993), işyerinde bilgisayar kullanımı ile ücretler arasındaki ilişkiyi inceleyerek SBTC hipotezi için önemli kanıtlar sunmuştur. Krueger, işyerinde bilgisayar kullanan işçilerin kullanmayanlara kıyasla yaklaşık %10 ila %15 daha yüksek ücret aldığını ortaya koymuştur. Bu ücret primi, bilgisayar kullanımının sağladığı artan verimliliğe atfedilmiştir. Bulgular, teknolojik ilerlemelerin, özellikle bilgisayar kullanımının, vasıflı işçileri orantısız bir şekilde faydalandırdığını ve bu nedenle bu işçilere olan talebin arttığını ve ücret eşitsizliğine katkıda bulunduğunu ima etmektedir. Buna karşılık, DiNardo ve Pischke (1997), bilgisayar kullanımına bağlanan ücret farklılıklarının gerçekten verimlilik artışlarını mı yansıttığını yoksa gözlemlenmeyen heterojenlikten mi kaynaklandığını sorgulamışlardır. DiNardo ve Pischke, bilgisayarların yanı sıra kalem ve kağıt gibi diğer basit ofis araçlarının da önemli ücret farklılıklarıyla ilişkili olduğunu bulmuşlardır. Eğer bu tür basit ve verimliliği artırması pek olası olmayan araçlar, bilgisayarlarla benzer ücret primleri gösteriyorsa, gözlemlenen ücret farklılıklarının yalnızca teknolojiden değil, işin doğası veya bu araçları kullanan çalışanların gözlemlenemeyen özelliklerinden de

kaynaklanabileceğini öne sürmüşlerdir.

Bu çalışmada, Krueger (1993) ve DiNardo ve Pischke (1997) çalışmalarından esinlenerek Türkiye'de teknoloji kullanımının ve iş görevlerinin ücretler üzerindeki etkisi analiz edilmiştir. Bu amaçla, OECD'nin PIAAC verileri kullanılarak iki yeni değişken oluşturulmuştur. BİT kullanımı ile ilgili değişkenler, bireylerin iş yerinde BİT kullanma düzeylerini ölçmektedir. İş görevleri ile ilgili değişkenler ise iş görevlerinin doğasını ve yoğunluğunu ölçmektedir ve rutin görev yoğunluğu, bilişsel görev yoğunluğu ve etkileşimsel görev yoğunluğu olmak üzere üç kategoriye ayrılmıştır. Rutin görevler, tekrarlayan ve belirli kurallara dayalı görevleri; bilişsel görevler, analitik düşünme ve problem çözme gerektiren görevleri; etkileşimsel görevler ise sosyal beceriler ve iletişim gerektiren görevleri kapsamaktadır.

Farklı seviyelerde BİT kullanımının ücretler üzerindeki etkilerini daha iyi anlamak amacıyla, PIAAC'ta yer alan teknoloji kullanımı sorularından faydalanılarak basit ve karmaşık seviyelerde BİT kullanımını ayrıştıracak birer kukla değişken yaratılmıştır. İş görevi yoğunluklarının analizi için oluşturulan rutin, etkileşimsel ve bilişsel görev yoğunlukları endeksleri için ise ana bileşenler analizi (PCA) kullanılmıştır. Bu yöntem, çok sayıda değişkenin yer aldığı verileri daha az sayıda bileşen ile temsil etmeyi ve böylece verilerin daha anlaşılır ve okunabilir hale gelmesini sağlar. PIAAC anketinde yer alan ve iş görevlerini belirleyen sorular, bireylerin işlerinde gerçekleştirdikleri görevlerin sıklığını ve önemini 1'den 5'e kadar derecelendiren Likert ölçeği ile değerlendirilmiştir. Bu yanıtlar kullanılarak, farklı görevlerin yoğunluklarını ölçen yeni değişkenler oluşturulmuştur.

Bu çalışmada, ayrıca, işgücü piyasası analizlerinde önemli bir faktör olan gizli yetkinlikler (unobserved ability) dikkate alınmıştır. Gizli yetkinlikler, bireylerin gözlemlenmeyen veya ölçülemeyen yetenekleri, motivasyonları ve diğer kişisel özellikleridir. Bu faktörler, ücretler ve işgücü piyasası sonuçları üzerinde önemli etkilere sahip olabilir ve analizlerde göz ardı edilmesi, sonuçların yanlı olmasına yol açabilir. Gizli yetkinliklerin etkisini kontrol etmek amacıyla, PIAAC verilerindeki doğrudan ölçülen bilişsel beceriler (sayısal beceriler) kullanılmıştır. Bu yaklaşım, gizli yetkinliklerin göz ardı edilmesi durumunda ortaya çıkabilecek yanlılıkları minimize etmeyi amaçlamaktadır. Özellikle yüksek eğitimli ve BİT kullanan bireylerin, yalnızca

bu faktörler nedeniyle değil, aynı zamanda gözlemlenmeyen yetkinlikleri nedeniyle de daha yüksek ücretler alabileceği göz önünde bulundurulmuştur. Bu nedenle, analizlerin sonuçları, gizli yetkinliklerin etkilerini dikkate alarak daha doğru ve güvenilir bir şekilde yorumlanmıştır.

Bu bölümde yer alan ilk modelde, eğitim seviyesi ve farklı düzeylerde BİT kullanımının ücretler üzerindeki etkileri incelenmiştir. Bu analizlerde, eğitim seviyeleri ve BİT kullanımı, önce etkileşim terimleri olmadan değerlendirilmiş; ardından sayısal beceriler kontrol değişkeni olarak eklenmiş ve ardından eğitim seviyesi ile BİT kullanımı arasındaki etkileşim terimleri dahil edilmiştir.

İkinci modelde, BİT kullanımının yanı sıra iş görev yoğunluklarının (rutin, bilişsel ve etkileşimsel görevler) ücretler üzerindeki etkisi dikkate alınmıştır. Bu modelde, rutin görev yoğunluğu, etkileşimsel görev yoğunluğu ve bilişsel görev yoğunluğu değişkenleri kullanılarak analizler yapılmıştır. Bu yaklaşım, farklı eğitim seviyelerindeki bireylerin ücret sonuçlarının, iş görevlerinin doğası ve BİT kullanımı ile nasıl ilişkini olduğunu anlamayı hedeflemektedir.

Farklı seviyelerde BİT kullanımının ücretler üzerindeki etkisini gösteren ilk modelde, bireyin eğitim seviyesini gösteren kukla değişkenler, işinde kullandığı BİT kullanımını gösteren kukla değişkenler ve BİT kullanımı ile eğitim seviyesi arasındaki etkileşim terimleri yer almaktadır. İş görev yoğunluklarının ücretler üzerindeki etkisini gösteren ikinci modelde ise bireyin eğitim seviyesini gösteren kukla değişkenler, işinde kullandığı BİT kullanımını gösteren kukla değişkenler ve görev yoğunluklarını gösteren sürekli değişkenler yer almaktadır. Bu modellerin ikisinde de bireylerin sayısal becerileri kontrol edilmektedir.

İlk modelin bulguları, iş yerinde BİT kullanmanın, kullanmamaya göre daha yüksek ücretler ile ilişkili olduğunu göstermektedir. Bu bulgu, BİT kullanımının çalışanların verimliliğini artırdığı ve bunun ücretlere yansıdığına dair Krueger (1993) tarafından ortaya konulan sonuçları ve SBTC'yi desteklemektedir. BİT kullanımının ücretler üzerindeki etkisi, istatistiksel olarak anlamlı ve pozitiftir ve BİT kullanımı daha kompleks seviyelere geldikçe bu etki daha büyük olmaktadır. Ayrıca, eğitim seviyesi ve BİT kullanımı arasındaki etkileşim terimleri, yüksek eğitim seviyelerine sahip çalışanların, kompleks BİT kullanımından daha fazla ücret elde ettiğini

göstermektedir. Bu bulgu, teknolojik becerilere sahip olmanın, özellikle yüksek eğitimli çalışanlar için önemli bir avantaj sağladığını ortaya koymaktadır. Son olarak, sayısal beceriler kontrol değişkeni olarak eklendiğinde, BİT kullanımının ücretler üzerindeki olumlu etkisi devam etmektedir. Bu, BİT kullanımının sağladığı ücret faydasının, çalışanların sayısal becerilerinden bağımsız olarak da mevcut olduğunu göstermektedir.

İkinci modelin bulguları, rutin görev yoğunluğu yüksek olan işlerde çalışmanın, rutin görev yoğunluğu düşük olan işlerde çalışmaya kıyasla daha düşük ücretler ile ilgili olduğunu göstermektedir. Rutin görev yoğunluğu yüksek işlerde çalışanların daha düşük ücretler alması, teknolojik değişimin rutin işleri nasıl olumsuz etkilediğini ve bu tür işlerde çalışanların dezavantajlı durumda olduğunu ortaya koymaktadır. Ancak, gizli yetkinlikler (unobserved abilities) kontrol edildiğinde, rutin görev yoğunluğunun ücretler üzerindeki etkisi istatistiksel olarak anlamlı olmaktan çıkmıştır. Bu durum, rutin görevlerin ücretler üzerindeki etkisinin büyük ölçüde çalışanların gözlemlenmeyen yetkinliklerine bağlı olduğunu göstermektedir.

Bu modelin sonuçları, etkileşimsel (interactive) görev yoğunluğunun, pozitif ve istatistiksel olarak anlamlı bir katsayıya sahip olduğunu göstermektedir. Bu da etkileşimsel görevlerin yoğunluğunun ücretler üzerinde olumlu bir etkisi olduğunu ima etmektedir. Bu bulgu, sosyal becerilerin ve iletişimin işgücü piyasasında önemli bir değer taşıdığını göstermektedir. Bilişsel (cognitive) görev yoğunluğu ise ücretler üzerinde istatistiksel olarak anlamlı bir etkiye sahip değildir. Bu, bilişsel görevlerin doğrudan ücretler üzerinde belirgin bir etkisi olmadığını göstermektedir. Ancak, bilişsel görevlerin genel iş performansı ve diğer faktörlerle ilişkili olabileceği göz önünde bulundurulmalıdır.

Sonuç olarak, bu bölümde elde edilen bulgular, teknoloji kullanımı ve iş görevlerinin doğasının ücretler üzerinde nasıl belirleyici olduğunu anlamamıza yardımcı olmaktadır. İleri teknolojilerin kullanımının artması, işgücü piyasasında gerekli beceri setlerini değiştirmektedir. Teknolojiyle uyumlu olabilmek için çalışanların daha karmaşık ve analitik becerilere sahip olması gereklidir. Türkiye'nin eğitim sistemi ve işgücü piyasası arasındaki bu dinamiklerin anlaşılması, eğitim politikaları açısından büyük öneme sahiptir. Eğitim sisteminin, teknolojik ilerlemelerle uyumlu bir şekilde

yapılandırılması, ekonomik büyümenin sürdürülebilirliği ve toplumsal eşitsizliklerin azaltılması açısından önemlidir. Bu bağlamda, Türkiye'nin eğitim politikalarının, sermaye-beceri tamamlayıcılığını ve teknolojik değişimleri göz önünde bulundurarak yeniden şekillendirilmesi gerektiği sonucuna varılmaktadır. Bu, hem işgücü piyasasında daha dengeli bir yapının oluşturulmasına hem de ülkenin rekabet gücünün artırılmasına katkı sağlayacaktır.

Sonuç ve Çalışmanın Önemi

Bu tez, Türkiye'de eğitim sistemi ile işgücü piyasası talepleri arasındaki uyumu incelemekte ve bunun işgücü piyasası sonuçlarına etkilerini değerlendirmektedir. Tez, bireylerin eğitim, beceri ve alan uyumsuzluklarını analiz ederken, teknolojik yeterliliklerin eğitim seviyeleri ile nasıl etkileşime girdiğini ve ücretleri nasıl etkilediğini de araştırmaktadır. Çalışmanın bulguları, eğitim ve işgücü piyasası arasındaki uyumsuzlukların ücretler üzerindeki olumsuz etkilerini ortaya koymaktadır. Önerilen politikalar şunlardır:

1. İşgücü Piyasası Bilgi Sistemlerinin (LMIs) Geliştirilmesi: İşgücü piyasası ihtiyaçlarına dair zamanında ve doğru veri sağlamak, öğrencilerin eğitim ve kariyer seçimlerini bilinçli yapmalarına yardımcı olabilir.

2. Mesleki Eğitim ve Öğretim (VET) Programlarının Güçlendirilmesi: Bu programların sanayi ihtiyaçlarıyla uyumlu hale getirilmesi, müfredatın düzenli olarak güncellenmesini ve eğitim kurumları ile işletmeler arasında işbirliği oluşturulmasını gerektirir.

3. Yaşam Boyu Öğrenme ve Sürekli Beceri Geliştirme: Hızlı teknolojik değişimlere uyum sağlamak için sürekli eğitim ve beceri geliştirme teşvik edilmelidir.

4. Sektörel Stratejiler: Belirli sektörlerdeki ihtiyaçları karşılamak için özel stratejiler uygulanmalıdır. Örneğin, teknoloji sektörleri için ileri düzey BİT becerilerine ve imalat sektörleri için teknik ve mesleki becerilere odaklanılabilir.

5. Cinsiyet Eşitsizliklerinin Giderilmesi: Eğitim ve istihdamda cinsiyet

eşitsizliklerini azaltmaya yönelik politikalar, beceri geliştirme ve kariyer ilerlemesi için eşit fırsatlar sağlayarak uyumsuzlukları azaltabilir.

Gelecek araştırmalar, eğitim çıktıları ile işgücü piyasası talepleri arasındaki uyumsuzlukları incelemeye devam etmelidir. Özellikle zaman serisi verilerin yaygınlaşması, yükseköğrenim genişlemesinin işgücü piyasası üzerindeki uzun vadeli etkilerini analiz etmek için büyük öneme sahiptir. Ayrıca, bilişsel olmayan (non-cognitive) becerilerin işgücü piyasası sonuçlarındaki rolünü incelemek, bu becerilerin eğitim ve işgücü piyasası uyumunu nasıl etkilediği hakkında değerli bilgiler sağlayabilir. Beyin göçü ve eğitim çıktıları ile işgücü piyasası talepleri arasındaki iki yönlü ilişki de gelecekteki araştırmalar için önemli bir alan olarak öne çıkmaktadır.

Sonuç olarak, bu çalışma Türkiye'deki eğitim sistemi ile işgücü piyasası arasındaki uyumsuzlukların giderilmesinin, ekonomik verimliliği artırmada önemli olduğunu göstermektedir. Eğitim ve işgücü piyasası politikalarının, bireylerin yetkinliklerini ve eğitimlerini daha iyi değerlendirmelerini sağlayacak şekilde düzenlenmesi gerekmektedir. Bu çalışma, gelecekteki araştırmalar için de bir temel oluşturarak, eğitim ve işgücü piyasası uyumsuzluklarının daha detaylı ve güncel verilerle incelenmesi gerektiğini vurgulamaktadır.

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TEZİN ADI / TITLE OF THE THESIS (**İngilizce** / English): Aligning Education and Labor Markets: Understanding Labor Market Mismatches And Technology Use In Türkiye

TEZİN TÜRÜ / DEGREE: **Yüksek Lisans** / Master ☐ **Doktora** / PhD ☒

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