

TALLINN UNIVERSITY OF TECHNOLOGY

School of Business and Governance

Gerda Fatal

**EDUCATION-JOB OR SKILLS-JOB MISMATCH: WHAT
MATTERS MORE FOR JOB SATISFACTION OF ESTONIAN
WORKERS?**

Master's thesis

Program Economic Analysis

Supervisor: Heili Hein, MA

Tallinn 2023

I hereby declare that I have compiled the thesis independently and all works, important standpoints and data by other authors have been properly referenced and the same paper has not been previously presented for grading.

The document length is 14887 words from the introduction to the end of the conclusion.

Gerda Fatal 08.05.2023

TABLE OF CONTENTS

ABSTRACT	5
INTRODUCTION	6
1. EDUCATIONAL AND SKILLS MISMATCHES: CONCEPTS, THEORETICAL EXPLANATIONS, AND MEASUREMENT	8
1.1. The concept of educational and skills mismatches	8
1.3. Theoretical foundations	9
1.3.1. Human capital theory	9
1.3.2. Job competition theory	10
1.3.3. Assignment theory	10
1.3.4. Signaling theory	11
1.3.5. Career mobility theory	11
1.4. Measurement	12
1.4.1. Measuring educational mismatch	12
1.4.2. Measuring skills mismatch	14
2. EMPIRICAL INSIGHT INTO EDUCATIONAL AND SKILL MISMATCHES	16
2.1. Prevalence of over- and undereducation	16
2.2. Prevalence of skills underutilization and deficits	17
2.3. Determinants of educational mismatch and skills mismatch	18
2.3.1. Gender, marital status, and children	18
2.3.2. Educational attainment	19
2.3.3. Field of education	20
2.3.4. Age, work experience, and training	20
2.3.5. Ability and skills	21
2.3.6. Job characteristics	22
2.3.7. Immigrant status	23
2.4. Effects on labor market outcomes	23
2.4.1. Effect on wages	24
2.4.3. Effect on job satisfaction	25
2.5. Labor market, education, and skills in Estonia	27
2.5.1. Labor market policies	27
2.5.2. Education and skills in Estonia	28

2.5.3. Empirical studies of mismatches in Estonia	32
3. METHODOLOGY AND DATA	33
3.1. Data.....	33
3.2. Educational mismatch indicator	33
3.3. Skills mismatch indicator	35
3.4. Variables.....	38
3.5. Estimation methods	40
4. RESULTS AND DISCUSSION.....	42
4.1. Mismatches.....	42
4.2. Job satisfaction	47
CONCLUSION	50
KOKKUVÕTE.....	52
LIST OF REFERENCES	55
APPENDICES	67
Appendix 1. List of variables used in the analysis	67
Appendix 1 continued.....	68
Appendix 1 continued.....	69
Appendix 2. Descriptive statistics.....	70
Appendix 3. Frequency distribution of control variables	71
Appendix 3 continued.....	72
Appendix 4. Marginal effects with mismatches as dependent variables	73
Appendix 4 continued.....	74
Appendix 4 continued.....	75
Appendix 5. Marginal effects with job satisfaction as dependent variable	76
Appendix 5 continued.....	77
Appendix 6. Non-exclusive licence.....	78

ABSTRACT

The objective of this master's study is to evaluate the relationship between education-job and skills-job mismatch in the Estonian labor market and to examine the effect of these two types of mismatches on job satisfaction. While some research has been conducted on educational mismatches in Estonia, little attention has been given to skills mismatches. Considering that job satisfaction serves as a significant indicator of labor market outcomes, and given that the impact of mismatches on job satisfaction has yet to be examined in the context of Estonia, it is essential to investigate this relationship further.

The subjective method is employed to measure educational mismatches and a realized method based on standardized proficiency scores from the Programme for the International Assessment of Adult Competencies (PIAAC) dataset is utilized to measure skill mismatches. Logistic regressions are carried out to estimate what factors determine educational and skills mismatches and an ordinal logistic regression is estimated to investigate the effects of mismatches on job satisfaction.

The following research questions are proposed in this thesis:

1. What factors contribute to educational and skills mismatches, and how do they differ for each type of mismatch?
2. To what degree do educational and skills mismatches impact job satisfaction, and which one is more influential?

The results suggest that several socio-demographic and job-specific factors determine mismatches and that these factors vary significantly depending on the type of mismatch. Furthermore, based on the findings of this study, only overeducation has a significant impact on job satisfaction, which suggests that educational mismatches are more influential than skills mismatches in this regard.

INTRODUCTION

It is well-established that workers who are overeducated or have more skills than necessary for their job are often paid less when compared to properly matched workers (Allen & van der Velden, 2001; Duncan & Hoffman, 1981; Green & Zhu, 2010; Groot & van den Brink, 1997; Hartog, 2000; Leuven & Oosterbeek, 2011; McGuinness, 2006). There is also evidence suggesting that these types of mismatches in the job market can increase the likelihood of becoming unemployed (Mavromaras et al., 2015; Sloane et al., 1999), increase company turnover (Alba-Ramírez, 1993), and decrease productivity (Tsang, 1987).

Numerous studies have investigated the disparities between education and employment, however, these discrepancies cannot only be traced to differences in education. Subsequent research has taken a closer look at the differences between educational and skills mismatches and has discovered that these differences are in fact substantial (Allen & van der Velden, 2001; Green & McIntosh, 2007; Mavromaras et al., 2013). Given the lack of research on this topic in Estonia, exploring these differences would be beneficial, and understanding their effects on job satisfaction and the resulting repercussions for the labor market could help identify improvement areas for policymakers. Job satisfaction has been shown to have significant effects on company turnover (Freeman, 1978) as well as on productivity and absenteeism (Iaffaldano & Muchinsky, 1985; Judge et al., 2001).

Measuring mismatches presents significant challenges, particularly in the context of skills. While it is relatively easy to determine an individual's current level of education, determining the required level of education for a particular job can be much more challenging (Dolton & Silles, 2008). The measurement of skills mismatch is even more complex, as self-assessment questions used to derive indicators of skills mismatch can have limited discriminative ability, and accounting for heterogeneity in individuals' skill levels can be problematic (Allen & van der Velden, 2001).

This master's thesis aims to assess the relationship between educational and skills mismatches in Estonia and examines the effect these mismatches have on job satisfaction.

Two research questions are proposed in the thesis as follows:

1. What factors contribute to educational and skills mismatches, and how do they differ for each type of mismatch?
2. To what degree do educational and skills mismatches impact job satisfaction, and which one is more influential?

To address the research questions, the PIAAC dataset is utilized. The subjective method is used in this study to measure educational mismatches, which involves assessing an individual's educational attainment and perceived required education level. For skill mismatches, Perry et al. (2014) methodology is employed, which standardizes numeracy proficiency scores and identifies deviations from the mean with specific boundaries as skill mismatches. A logistic regression is used to answer the first research question, which aims to identify the factors that contribute to educational and skills mismatches and what kind of differences can be observed for each type of mismatch. To assess the effects of mismatches on job satisfaction, an ordered logistic regression is used given the ordinal format of the survey question that measures job satisfaction.

The master's thesis is structured into four main parts. The first chapter explores the concept of mismatches and provides a theoretical background. The second part offers empirical insight into educational and skills mismatches by providing an overview of the existing literature. The third chapter covers the data and methods employed in this study, and the final chapter presents and analyzes the findings, providing a detailed explanation of the results and their significance.

1. EDUCATIONAL AND SKILLS MISMATCHES: CONCEPTS, THEORETICAL EXPLANATIONS, AND MEASUREMENT

The following chapter presents the concepts of educational and skills mismatches and discusses the theoretical explanations for the emergence and persistence of the phenomena. The chapter delves into the diverse theoretical frameworks that attempt to shed light on the causes of mismatch and reviews different methods used to estimate the prevalence of educational and skills mismatches.

1.1. The concept of educational and skills mismatches

The phenomenon of **educational mismatch** refers to the situation when individuals have more or less education than what is required for their jobs (Sicherman, 1991) or when their area of study does not align with the field they are working in (Sloane & Mavromaras, 2014).

Two main forms of educational mismatch are horizontal and vertical mismatch. Vertical mismatch occurs when a person's education or qualifications do not match the requirements of their job, resulting in either overeducation or undereducation (*Ibid.*). Horizontal mismatch, the other type of mismatch, arises when a person's field of study is not related to their job (*Ibid.*). Experiencing both vertical and horizontal mismatch is referred to as double mismatch (Falcke et al., 2020). Most studies on educational mismatch concentrate on the issue of vertical mismatch, with a specific emphasis on overeducation. The phenomenon of overqualification has been a more prominent focus of research than underqualification, primarily due to concerns that it could be the result of the rising supply of tertiary education graduates in recent decades (Quintini, 2011). Vertical mismatch is also the focus of this thesis and hence, the literature on horizontal mismatches is not discussed.

The current academic discourse has moved towards the idea that differences in skills among workers with the same education or qualifications may play a role in the occurrence of qualification mismatch (McGuinness et al., 2018). The concept of **skills mismatch** pertains to a situation where

the individual has surplus of deficits of skills for job performance (Perry et al., 2014). Overskilling occurs when individuals are employed in roles that only tap into a limited portion of their abilities and capacities. Conversely, underskilling is defined as a lack of necessary skills for a job, where the individual is not equipped with the required skillset. (Quintini, 2011)

In the past, policy concerns focused on potential skill shortages and deficits resulting from technological changes and an aging workforce which led to a need for skills upgrading and remedial training (OECD, 1996). However, it has been recognized that the issue is broader than this. Skill underutilization is now considered equally significant, with widespread implications for individual workers and the economy as a whole (Cedefop, 2010). Nevertheless, the literature on skills mismatch remains relatively scarce due to the complexities involved in measuring skills.

1.3. Theoretical foundations

There is no universally recognized explanation for mismatches. Instead, numerous theories strive to comprehend the phenomenon of mismatch in the labor market by taking either a supply-side or a demand-side perspective. These include human capital theory, job competition theory, career mobility theory, assignment theory, signaling theory, and career mobility theory. Theories related to human capital, signaling, and career mobility center around the supply side, while job competition theory emphasizes the demand side. Assignment theory encompasses both supply and demand.

1.3.1. Human capital theory

The human capital theory, first introduced by Becker (1964), posits that employees' compensation is directly tied to their marginal productivity, a function of their human capital. The association between education and productivity is typically explained through skills. Education, training, and work experience enhance the skills that make individuals more productive in their work. As Becker, (1964, 178) explains, "For education has little direct effect on earnings; it operates primarily indirectly through the effect on knowledge and skills."

The existence of overeducation seems to contradict human capital theory since it leads to worker underutilization and lower wages, which is inconsistent with the theory's claim that wages always equal workers' marginal product. McGuinness (2006) contends that this does not necessarily

discredit the theory, but serves as evidence that organizations may need time to fully harness the human capital stock. Thus, educational mismatch is regarded as a temporary phenomenon that is expected to subside as organizations respond to shifts in the relative supply of educated workers (McGuinness, 2003). However, Sloane et al. (1999) argue that mismatch can persist over an extended period. This presents a challenge to the theory and thus alternative theories may offer further insight.

1.3.2. Job competition theory

The job competition theory, proposed by Thurow (1975), posits that wages and rewards are influenced by job characteristics and wage-setting institutions, rather than worker productivity. It sheds light on the demand side of the mismatch and highlights the significance of an individual's position in the career development path. Career advancement of individuals is influenced by their competencies and experience, which need to align with the particular characteristics and skill requirements of a job. In this context, employers consider a range of personal characteristics, including education, in determining which individuals are suited for the available positions. Employers can use this information to determine the cost of further training for each candidate. Workers may pursue additional education to be competitive for higher-paying jobs, which may not necessarily require the extra qualifications, and employers may not always fully utilize these excess qualifications.

1.3.3. Assignment theory

The assignment theory, put forth by Sattinger (1993), integrates elements of both the human capital and job competition theories. This theory seeks to define the various types of employment available to employees, the distinctions between employees, the technology connecting the characteristics of employees and the output they generate, and the processes that allocate employees to specific careers. The theory suggests that the most efficient way to assign workers to jobs is based on skill level, with the most skilled workers assigned to the most skilled positions.

Contrary to job competition theory, the assignment process is not simply a matter of chance, but employees make conscious decisions to select jobs that maximize their financial gain and well-being (McGuinness, 2006). The employee's choice of education is determined by the costs and benefits of investing in education, while the job requirements determine whether the employee's skills are fully utilized (Groot & van den Brink, 1997). A fundamental characteristic of the theory,

as highlighted by Quintini (2011), is that while education generally enhances productivity, the level of realized productivity is also influenced by the complexity of the job held. Several studies (Duncan & Hoffman, 1981; Hartog & Oosterbeek, 1988; McGuinness, 2006; Sloane et al., 1999) have found that assignment theory is the most compatible with what is observed empirically.

1.3.4. Signaling theory

Signaling theory, developed by Spence (1973), differs from human capital theory in that it assumes that a person's years of education reveal their inherent productivity level rather than improve it. The model shares similarities with the job competition framework as both involve individual investments aimed at improving one's competitiveness in the labor market. However, in Spence's model, the level of education pursued is limited by the balance between potential income earned and the costs associated with obtaining said education.

Signaling theory offers a perspective on the relationship between education and skills, highlighting the role of education in enabling workers to signal their productivity, adaptability, and efficiency to potential employers. Employers have imperfect information about workers' abilities, which makes qualifications a key determinant in evaluating their potential. While education may not necessarily provide additional skills, it can still lead to improved job opportunities through signaling. (*Ibid.*) If companies find that the educational qualifications required for a position no longer guarantee that the candidate has the necessary skills, they are likely to increase the educational requirements for job seekers without changing job content (Quintini, 2011). This phenomenon, known as "qualification inflation", can lead to qualification mismatch without underlying skill mismatch (*Ibid.*).

1.3.5. Career mobility theory

The theory of career mobility, introduced by Rosen (1972), predicts that workers may temporarily work in jobs that allow them to acquire skills they can utilize later in higher-level jobs. Sicherman & Galor (1990) furthered this line of research, offering a framework for understanding educational mismatch within the context of human capital theory, suggesting that the total human capital, not just the years of education, affects productivity, and thus, overeducation may offset the absence of work experience, training, and tenure. Additionally, employers could benefit from recruiting overeducated workers by saving on training costs. As a result, overeducation may be a strategic decision that is beneficial for both employers and employees. Under the occupational mobility

theory, overeducation is considered a short-term situation since overeducated workers are thought to have a greater chance of being promoted or transitioning to higher-level jobs.

The theory of career mobility has limitations in explaining the occurrence of mismatches. It fails to offer a complete explanation for educational mismatch, as it does not explain the manifestation of undereducation. (Büchel & Mertens, 2004) Furthermore, empirical studies utilizing this theory have had limited success in explaining the mismatch phenomenon in the labor market (Büchel & Mertens, 2004; Grunau & Pecoraro, 2017; Sloane et al., 1999; Wen & Maani, 2019)

1.4. Measurement

This chapter investigates the common approaches of identifying educational and skill mismatches. A comprehensive overview is presented of the current methods utilized in research for measuring and assessing these mismatches. The goal is to improve understanding of the existing research on the subject by critically evaluating each approach and emphasizing its advantages and limitations.

1.4.1. Measuring educational mismatch

Education mismatches can be quantified through a comparison of an individual's present education with the educational requirements of a specific job. Although determining an individual's current educational attainment is relatively straightforward, acquiring information regarding the required education level presents a greater challenge (Dolton & Silles, 2008). Three methods for measuring educational mismatch exist, including subjective, objective, and statistical methods.

The **subjective method**, also known as the employee self-assessment method, is based on an individual's personal judgment of the level of education necessary for performing their job (Hartog, 2000). This method, used by Duncan & Hoffman (1981), F. Green & Zhu (2010), Naguib et al. (2019) and Sicherman (1991), involves employees being asked to assess the level of education they believe is necessary to perform their job duties. The discrepancy between their actual level of education and their perceived requirement is then used to determine whether they are over- or undereducated.

Studies utilizing this method have employed various questions to gather employees' perspectives, such as Duncan & Hoffman's (1981) inquiry into the amount of formal education needed to get a

job like theirs, and Alba-Ramírez' (1993) question about the type of education required for job performance. These questions highlight the different focuses of the method, with the first addressing the hiring standards and the second pertaining to the job performance requirements. McGuinness et al. (2018) highlight that the two approaches may result in different outcomes. Being overeducated both in terms of "doing the job" and "getting the job" indicates excess skills, whereas being overeducated only in terms of "doing the job" while being matched in terms of "getting the job" may be more indicative of excessive entry requirements. Nevertheless, there is evidence showing that the educational qualifications required to perform a job are generally in line with the educational qualifications required to obtain that job (Green et al., 1999).

Another problem, according to Hartog (2000), is that workers may overstate their job requirements, possibly due to a desire to feel more content with their job. Conversely, the subjective method may be more precise in reflecting the required education as it is determined through an evaluation of the specific job held by the employee (Rumberger, 1987). Individual self-assessments have the added benefit of being more likely to reflect current labor market demands in a rapidly changing job market (Santiago-Vela & Hall, 2022).

The **objective method**, or the job analysis method, involves a methodical evaluation conducted by experts, who assign the appropriate level of education for each occupation (Hartog, 2000). Widely recognized sources for such information include the Dictionary of Occupational Titles (DOT) in the US and the Standard Occupational Classification System (SOC) in the UK. These sources are utilized to assess any disparity between an individual's education and the requirements for a certain career by comparing the individual's current education with the expectations established through an occupational job analysis. (*Ibid.*) This method has been employed by Hartog & Oosterbeek (1988), Kiker et al. (1997), Rumberger (1987), among others.

Rumberger (1987) highlights that the objective approach provides a more accurate and impartial assessment of the required education. However, this method assumes that all jobs with the same title have identical educational requirements. As McGuinness & Bennett (2007) point out, holding the same job title does not necessarily indicate that employees have the same job responsibilities and may require a different range of experiences and educational backgrounds. Furthermore, McGuinness (2006) argues that the educational prerequisites for various occupations will alter depending on changes in the supply of workers. This is a factor that the relatively static occupational classification systems may not account for.

The **statistical method**, or the realized matches method, is a quantitative method that can be computed using two strategies: the mean and the mode (Hartog, 2000). The mean approach, applied in the works of Groot & van den Brink (1997), Robst (2008), Verdugo & Verdugo (1989), and other scholars, involves determining the necessary level of education for a worker by computing the average educational attainment level of all individuals within the same profession (Verdugo & Verdugo, 1989). Employees whose educational attainment deviates more than one standard deviation from the average are considered over- or undereducated, while employees who fall within one standard deviation of the mean are considered to have a suitable match. In the mode approach, employed by Cohn & Khan (1995), Kiker et al. (1997) and Naguib et al. (2019), employees with educational levels above the mode value are categorized as overeducated, those below the mode as undereducated, and those equal to the mode value as well-matched (Kiker et al., 1997).

Similarly to the objective approach, the limitation of this method is the assumption that jobs sharing the same occupational title have the same educational requirements (Quintini, 2011). Furthermore, as McGuinness et al. (2018) note, this method represents the typical qualifications of all workers in a particular occupation, making it more relevant to the educational requirements needed to obtain a job rather than perform it effectively. However, the main benefit of the realized matches approach is its ease of implementation, as it can be applied to any available micro dataset that contains data on occupation and educational level (McGuinness et al., 2018).

1.4.2. Measuring skills mismatch

Skills mismatch is most commonly measured using the self-assessment method (Allen & van der Velden, 2001; Di Pietro & Urwin, 2006; McGuinness & Sloane, 2011). However, the available literature indicates that formulating questions to measure skill mismatches is challenging. The limited evidence on the impact of skill deficits on wages, job satisfaction, and job turnover has been attributed to the poor discriminative ability of self-assessment questions used to derive indicators of skill deficits (Allen & van der Velden, 2001).

Allen & van der Velden (2001) used data collected from the Higher Education and Graduate Employment in Europe study. They classified skill mismatch based on the responses to two survey questions: “Do you think you have the skills to cope with more demanding duties than those you are required to perform in their current job?” and “Do you think you would need further training

in order to cope well with your present duties?”. The use of this measure to evaluate skill mismatches is subject to the same limitations as its application in examining educational mismatches. Hartog (2000) cautions that overestimation by respondents can lead to measurement bias, resulting in an inflated overskilling. Further, Asai et al. (2020), point out that cross-country comparisons may be difficult due to cultural differences and translation issues.

Some authors have also utilized the realized method, in which the skill level of individuals is compared to each individual skill proficiency within occupations (Pellizzari & Fichen, 2013; Perry et al., 2014). Pellizzari & Fichen (2013) utilized PIAAC data and suggested a new methodology for defining the skill requirements of jobs. It establishes the minimum and maximum skill requirements for each occupation based on the proficiency levels of self-reported well-matched workers in that occupation. A worker is considered well-matched if their proficiency score falls within the established limits, while workers who exceed the maximum level are labeled as overskilled, and those who fall below the minimum are considered underskilled. Perry et al. (2014) expanded on this measure by standardizing the proficiency scores of individuals within occupations and using 1.5 standard deviations as cut-off points. Although the realized approach has the benefit of measuring the gap between an individual’s skills and the average level required, it has significant limitations. Asai et al. (2020) argue that the thresholds used in the realized approach lack precision. In addition, the approach relies on workers' self-assessment to identify skill mismatch, which poses the same challenges as the subjective method.

Allen et al. (2013) proposed another method to measure skill mismatch that relies on a comparison of skill use and skill level. The authors created a standardized index by subtracting the derived skill utilization measure from its corresponding skill level measure. If an individual is unable to utilize their skills completely at their job or overuses certain skills without possessing enough knowledge, it implies that they are poorly matched. Although this method eliminates the need to rely on self-reported measures of skill mismatch, it still has its limitations, as pointed out by Pellizzari & Fichen (2013). Their main criticism of this approach is that it compares skill level and skill use, which are distinct underlying concepts and cannot be measured on the same scale.

2. EMPIRICAL INSIGHT INTO EDUCATIONAL AND SKILL MISMATCHES

The following chapter provides an extensive overview of the available literature on the topic of mismatches. First, it features a comparison of the findings from different authors, and the approaches utilized to assess the prevalence of mismatches, emphasizing discrepancies in mismatch prevalence that may emerge when using different measurement approaches. Next, the chapter examines various factors that contribute to educational and skills mismatches. Finally, the effects of the mismatches on labor market outcomes are discussed.

2.1. Prevalence of over- and undereducation

Recent research conducted in different European countries indicates that overeducation is more prevalent among women and the incidence of surplus education varies significantly across countries. Boto-García & Escalonilla (2022), using Spanish survey data, found that the incidence of overeducation was 24% among men and 27% among women. Santiago-Vela & Mergener (2022) utilized a subjective approach on German data, and it revealed that 18.2% of men and 21.3% of women were overeducated. Castagnetti et al. (2018) carried out a study on overeducation in the Italian labor market employing the subjective approach. They indicated that 47.5% of men and 52.5% of women had more education than required for their job.

Groot & van den Brink (2000b) conducted a comprehensive meta-analysis of 25 studies on educational mismatch and reported that overeducation rates varied from 13–29%, while undereducation rates varied from 10–30% depending on the measurement methods employed. In another meta-analysis on the topic of mismatches, conducted by Quintini (2011), the incidence of overqualified workers was found to be highest in Sweden at 35%, with the lowest prevalence observed in Finland at 10%. The rest of the countries analyzed fell somewhere in between these two extremes.

The prevalence of excess education is influenced by the way required education is measured. Some scholars have evaluated this prevalence by employing more than one measuring technique on identical datasets. Kiker et al. (1997) employed the job analysis method, statistical mean, and mode method to examine overeducation rates, and found that overeducation incidence was 9.4% with

the mean approach, 25.5% with the mode approach, and 33.1% with the job analyst approach. In contrast, undereducation rates were 5%, 17%, and 37.5%, respectively. Groot & van den Brink (2000a) found that the statistical mean method indicated the prevalence of overeducation to be 11.5% and undereducation – 16.7%. The job analysis method, however, showed that 12.3% of workers were overeducated and 13.3% were undereducated. Using the subjective method, they estimated that 8.7% of workers were overeducated and 3.8% were undereducated. These outcomes illustrate the substantial disparities that may arise with different measurement techniques.

2.2. Prevalence of skills underutilization and deficits

Limited empirical investigation has been dedicated to skills mismatch, with most studies relying on subjective measurement approaches. One of the pioneering studies examining the interplay between qualification and skill mismatch was by Allen & van der Velden (2001). Their study derived measures of skills mismatches on self-reported skill underutilization or deficits. The findings indicated that around 14% of Dutch university graduates and 15% of tertiary vocational graduates experience skill underutilization, while roughly half of each group exhibit skill deficits. The authors also noted a weak correlation between overeducation and overskilling.

A study conducted by Green & McIntosh (2007) in the UK found that the levels of overskilling were ranging between 35–53% and the incidence of underskilling was 13%. Like Allen & van der Velden (2001), they found a weak correlation between educational mismatch and skills mismatch. McGuinness & Wooden (2009) investigated the persistence of overskilling in the Australian workforce. They discovered that despite being more inclined to switch jobs, only a small fraction of overskilled employees manage to find a job that aligns with their skills. Specifically, among workers who voluntarily left their jobs in 2001, merely 19% found jobs that were a good fit the next year, and only 23% found well-matched jobs three years later. Vieira (2005) investigated the phenomenon of skill mismatch in Portugal and found the incidence of overskilling to be 47%.

Pellizzari & Fichen (2013), utilizing their novel and more precise approach to measuring skill mismatches found that around 9% of workers are underskilled and 16% are overskilled. One of the most recent findings comes from the study of German workers by Santiago-Vela & Hall (2022) in which they determined that the rate of overskilling is roughly 10%, while around 20% of workers have insufficient skills.

2.3. Determinants of educational mismatch and skills mismatch

The following section delves into various determinants that researchers have identified as contributing factors to educational and skills mismatches. Drawing on a comprehensive range of studies, the nuanced relationship between personal characteristics, educational attainment, field of education, work experience, abilities and skills, job characteristics, and immigrant status, the probability of experiencing a mismatch is investigated.

2.3.1. Gender, marital status, and children

According to Groot (1996), the employment of men seems to be less effective than that of women as men have a higher probability of being mismatched concerning education compared to women. He proposed the explanation that women might choose to leave the labor market if their skills do not align with the job and focus on housework and childcare instead. Similarly, Kiker et al. (1997) observed that men were more likely to experience overeducation among Portugal workers. In contrast, in his study of applied sciences graduates in the Netherlands, Falcke et al. (2020) found that women were less likely to be well-matched.

The results of Groot's (1996) study also indicated that married men were more likely to be overqualified in their jobs as compared to single men, which the author attributed to the pressure of providing for their families leading them to accept jobs regardless of their qualifications. Likewise, Green & McIntosh (2007) discovered that individuals who are married are more inclined to secure jobs that require higher qualifications than they actually hold. Sloane et al. (1999) found that married men are more susceptible to undereducation, which they link to the increased financial responsibilities that men bear, thus, men may have a greater incentive to fully utilize the education they have obtained. It is worth noting that the same line of reasoning, concerning the greater financial burden of men, as explained earlier, was used by Groot (1996) to explain why married men could be more predisposed to overeducation.

Regarding having children, Green & McIntosh (2007) found evidence to suggest that having children may increase the likelihood of an individual working in a job that exceeds their qualifications. The authors' argument was that the presence of children could restrict the flexibility of parents in the job market, leading them to opt for jobs that are more flexible to their schedules but may not match their educational qualifications. They also identified that gender differences exist, with female parents being more susceptible to overeducation.

The relationship between gender and skills mismatch has received limited attention in the literature. Krahn & Lowe (1998) noted from their research of Canadian workers that women were more likely to underutilize their skills. However, Green & McIntosh (2007) found no evidence to suggest that women experience a higher degree of skills mismatch. In contrast, Pellizzari & Fichen (2013) reported that males had a higher likelihood of being overskilled compared to females, while there were only minor gender differences in underskilling. The authors found the results surprising because it is commonly assumed that women, who often face more employment barriers than men, may take jobs that do not match their skill set. However, they point to OECD (2013) review of PIAAC results which shows that women use their skills less than men because of the nature of their jobs. Thus, the authors suggest, being in jobs that do not require the frequent use of skills may reduce the likelihood of a skills mismatch.

Although Green & McIntosh (2007) did not find evidence of gender differences regarding skill mismatches, they did find that married individuals have a lower likelihood of experiencing skills mismatch in comparison to single individuals. They also investigated if the disproportionate burden of childcare falling primarily on women was contributing to their higher likelihood of working in jobs that exceeded their qualifications. To examine this hypothesis, the authors included an interaction term for gender and the number of children. The results indicated that the impact of having children on the probability of being overqualified for a job is 60% greater for women compared to men, but this finding was not statistically significant.

2.3.2. Educational attainment

Some authors posit that the relationship between educational attainment and educational mismatch is positive (Frenette, 2004; Wirz & Atukeren, 2004). In support of this assumption, Wirz & Atukeren (2004) demonstrated that individuals holding a university degree are more susceptible to an educational mismatch in comparison to those with non-university qualifications. Similarly, Frenette (2004) found that individuals holding a master's degree were more likely to experience educational mismatch compared to those with a bachelor's degree. Furthermore, Pellizzari & Fichen (2013) examined skill mismatches and observed that individuals with tertiary education are less likely to be underskilled compared to those with lower levels of education, but they are more prone to being overskilled.

On the contrary, other researchers have presented empirical evidence that challenges this hypothesis arguing that the likelihood of educational mismatch decreases with higher qualifications (Dolton & Vignoles, 2000; McGuinness & Bennett, 2007; Pietro & Cutillo, 2006; Robst, 2008). For instance, Robst (2007) research in the US suggested that individuals with master's or doctoral degrees have a lower likelihood of being mismatched in comparison to those with a bachelor's degree. Pietro & Cutillo (2006) in Italy also found that individuals holding postgraduate degrees were more likely to hold positions that aligned with their qualifications compared to those with other types of education levels. This may be because postgraduate qualifications may provide graduates with valuable skills that are in demand by employers (*Ibid.*). The job competition model and signaling theory complement these findings, as they propose that individuals with higher levels of education are more likely to be hired because they possess the necessary skills.

2.3.3. Field of education

Studies in the academic literature have widely shown that individuals with a general education background, such as the arts, humanities, social sciences, and language, are more susceptible to educational mismatch compared to those with specialized education in subjects like medicine, accounting, engineering, and architecture (Dolton & Silles, 2008; Dolton & Vignoles, 2000; Green & McIntosh, 2007; Pietro & Cutillo, 2006). This distinction can be attributed to the specificity of skills obtained through specific degrees, which align with particular careers, making these graduates more in demand in the job market. This is in line with findings from several studies, including McGuinness (2003), that discovered a lower likelihood of educational mismatch for individuals who majored in math, engineering, medicine, and other related fields, compared to those with social science backgrounds.

2.3.4. Age, work experience, and training

An essential understanding of human capital theory is that there is a balance between education and other factors such as work experience and training that contribute to an individual's human capital (Becker, 1994). Studies have shown that educational mismatch can be an indication of shortcomings in other areas of human capital development, leading to support for the substitutability hypothesis. It suggests that work experience and training are negatively correlated with the likelihood of experiencing educational mismatch (Büchel & Pollmann-Schult, 2004;

Green & McIntosh, 2007; Pietro & Cutillo, 2006; Sloane et al., 1999) and skills mismatch (Green & McIntosh, 2007; Mavromaras et al., 2009).

Extensive research suggests that youth are more likely to experience overqualification than adults (Crompton, 2002; Dekker et al., 2002; Frei & Sousa-Poza, 2012; Vahey, 2000). These findings have been explained through various arguments, such as the limited work experience or the lack of visibility of their skills to potential employers. Additionally, Duncan & Hoffman (1981) discovered that workers with long job tenures were the least likely to report having surplus education and the most likely to report having less education than their job requires, suggesting that job-specific training may act as a substitute for formal education.

The evidence presented in this section suggests that these mismatches may occur in the early years of a person's professional life and may not necessarily be a long-term issue. However, limited research indicates that mismatch is typically a persistent problem (Cedefop, 2010; Dolton & Silles, 2008; Dolton & Vignoles, 2000; Frenette, 2004). According to Dolton & Silles (2008), individuals who were overeducated in their first job face a greater risk of being overeducated in their current job. McGuinness & Wooden (2009) conducted a study spanning two survey waves that were three years apart and observed that among the severely overskilled in the first wave, only 19.2% were appropriately matched three years later.

2.3.5. Ability and skills

The heterogeneity of individual skills and abilities can impact the phenomenon of educational mismatch. It is challenging to determine the extent to which employees who experience educational mismatch are less capable compared to those who do not. Green et al. (1999) used a numeracy test as a proxy for abilities and skills and found that higher scores on the mathematics test were correlated with a reduced likelihood of educational mismatch. In the same vein, Green & McIntosh (2007) reveal that UK graduates who performed well in mathematics had a decreased likelihood of being mismatched.

Chevalier (2003) separated those who experienced educational mismatch into two categories based on their level of satisfaction with their job-education match: genuine, in which the respondents were dissatisfied with the match, and apparent educational mismatch, where the respondents were satisfied with the match. This was done to account for the heterogeneity in job characteristics and to factor in unobservable skills. He established that the likelihood of apparent educational

mismatch was lower than that of genuine educational mismatch. The findings indicated that overeducation was primarily caused by a lack of skills among graduates. Chevalier asserted that this could be due to universities giving less attention to students, leading to more people having inadequate skills and becoming overeducated after graduation.

Chevalier & Lindley (2009) expanded on Chevalier's research by differentiating between two types of skills – academic skills (communication, foreign language, numerical ability, and computer skills) and professional skills (entrepreneurship, teamwork, leadership, and management). They determined that the likelihood of experiencing a genuine or apparent mismatch between one's education and job was contingent upon the individual's possession of academic or professional skills. The results indicated that with regard to educational mismatch, overall academic skills had no significant effect. The only exception was writing skills which were found to increase the chance of apparent educational mismatch by 9 percent. Conversely, the results further demonstrated that professional skills such as management and leadership skills were found to significantly decrease the likelihood of genuine educational mismatch, by approximately 6 and 11 percentage points, respectively.

2.3.6. Job characteristics

The phenomenon of qualifications mismatch is further determined by job characteristics such as part-time employment, shift work, and sector of employment as demonstrated in studies by Dolton & Silles (2008), Green & McIntosh (2007), Pietro & Cutillo (2006) and Sloane et al. (1999). According to Pietro & Cutillo (2006), having a permanent job increases the probability of graduates being overqualified. The authors attributed this to the fact that graduates may be more inclined to accept non-graduate roles if they come with a secure and long-term contract. Additionally, their research reveals that the probability of being overqualified also increases with a part-time job, as some graduates may take such jobs temporarily to ease the job search process.

Green & McIntosh (2007) research revealed that part-time jobs, jobs with shift work, and jobs in the private sector are strongly linked to the likelihood of overqualification as well as underutilization of skills. The authors observe that while job characteristics seem to dominate over individual characteristics, they also acknowledge that these factors are intertwined, leading to the potential overlap of their effects.

2.3.7. Immigrant status

The phenomenon of overeducation among migrant workers has been acknowledged in the literature by various studies (Falcke et al., 2020; Green et al., 2007; Joonas et al., 2014; Lindley, 2009; Quintini, 2011). The disparities in overqualification rates among immigrants and ethnic groups have been attributed to several factors, including discrimination, inadequate language skills, limitations in the transferability of qualifications acquired in the home country, and incomplete information regarding such qualifications.

Green et al. (2007) examine the prevalence of overeducation among recently arrived immigrants in Australia. The findings indicate that immigrants are more susceptible to overeducation compared to the native population, even if they were granted skill-assessed visas. According to the study by Lindley (2009), immigrants displayed a greater propensity to be both overeducated and undereducated.

Pellizzari & Fichten (2013) observe that foreign workers are over twice as likely to be underskilled compared to native workers, and significantly less prone to skill underutilization. In particular, the data indicates that foreign workers have a significantly lower likelihood of being overskilled in numeracy by 70% and in literacy by 40% compared to native workers. This disparity makes sense when considering that they may not be fluent in the language of the host country. Yet, given the common finding that immigrants often hold formal educational qualifications that exceed their job requirements, the lower prevalence of overskilling in numeracy is unexpected. Although many studies attribute this to the difficulty of recognizing educational qualifications across countries, this disparity might reflect differences in the quality of education across countries.

2.4. Effects on labor market outcomes

The labor market is a crucial element in any economy, so it is imperative to have a skilled and educated workforce to ensure sustainable economic growth. However, educational and skills mismatches occur when the supply and demand of skills do not align, which results in significant consequences for labor market outcomes. This section provides a detailed review of the pertinent literature on the topic, compares and contrasts the findings from different studies, and discusses the implications of educational and skills mismatches on the labor market.

2.4.1. Effect on wages

Numerous studies (Allen & van der Velden, 2001; Duncan & Hoffman, 1981; Green & Zhu, 2010; Groot & van den Brink, 1997; Hartog, 2000; Leuven & Oosterbeek, 2011; McGuinness, 2006) have demonstrated the impact of educational mismatches on wages. McGuinness (2006) conducted a review of 21 different studies that investigated the wage effects on educational mismatches. He reported that the returns to overeducation varied between 2.6% to 7% with three studies (Groot, 1993, 1996; Groot & van den Brink, 2000a) estimating negative returns to education. This means that the overeducated have generally been found to earn more than well-matched workers doing the same job. In terms of undereducation, most studies found negative returns, while Groot (1993, 1996) and Groot & van den Brink (2000a) observed positive returns. Given these findings, the consensus is that undereducated earn less than those with matching qualifications doing the same job. All studies examined, with the exception of one (McGuinness, 2003), comparing the overqualified workers with the same qualifications but in well-matched jobs, estimated a negative wage penalty to overeducated workers. These studies further indicated that undereducated workers earn more than workers with the same level of education but whose job matches their education level. In a later, more comprehensive meta-analysis, Quintini (2011) examined a total of 38 studies related to the wage effects of educational mismatches, which complemented and expanded upon the earlier work of McGuinness (2006). The meta-analysis determined that the conclusions from the earlier studies were consistent with the overall findings of the included papers.

Lower wages received by overqualified workers may be reflective of their inferior abilities. Chevalier (2003) reported that the apparently overeducated graduates earn between 5% to 10% less than those whose qualifications align with the position. However, for genuinely overeducated graduates, the pay penalty is much more severe, ranging from 22% to 26%. He argues that the broadening of higher education accessibility in the UK has contributed to an increase in graduate heterogeneity, with lower-ability students pursuing tertiary education. Hence, certain estimates of overqualification may overstate the phenomenon since some graduates may lack the necessary skills for graduate jobs. Mavromaras et al. (2009) discovered an intriguing trend where the likelihood of being overskilled decreases as one's highest educational attainment rises, but the wage penalty for those who are overskilled actually increases. The reason behind this, the author argues, is that these individuals possess a greater potential for productivity, but are constrained by job-related factors, resulting in a more significant wage penalty.

2.4.3. Effect on job satisfaction

Job satisfaction, as defined by Vroom (1964, 99), is "...affective orientations on the part of individuals toward work roles which they are presently occupying.". Freeman (1978) is recognized as one of the early economists to introduce the concept of job satisfaction in the field of economics. He observed that job satisfaction and employee turnover have an inverse relationship. Additionally, research has found that job satisfaction has an impact on worker productivity and absenteeism (Iaffaldano & Muchinsky, 1985; Judge et al., 2001). Therefore, it is evident that job satisfaction has significant implications for the labor market.

Several studies have examined the impact of overeducation on job satisfaction, but the findings are inconclusive. Some studies suggest that overeducation leads to reduced job satisfaction (Tsang & Levin, 1985; Verhaest & Omeij, 2006; Verhofstadt & Omeij, 2003; Vieira, 2005; Vila et al., 2007), while other studies show that this is only the case when overeducation is coupled with overskilling (Allen & van der Velden, 2001; Green & Zhu, 2010; Sloane & Mavromaras, 2014).

Empirical studies have identified the quality of match as a crucial factor in determining job satisfaction (Battu et al., 2000; Fleming & Kler, 2008; Hersch, 1995; Johnson & Johnson, 2000; Tsang, 1987), yet the underlying mechanisms remain uncertain. In general, there appear to be two main focuses regarding the mechanisms behind job satisfaction and quality of match: the direct effect of autonomy and the effect of lower earnings. The first theory, proposed by Tsang & Levin (1985) connects educational mismatch to job satisfaction and the likelihood of quitting. According to this theory, employees who are overqualified for their jobs have lower job satisfaction because they expect a more challenging and autonomous work environment that would align with their higher level of education, but these expectations are not met. This leads to decreased productivity and lower job satisfaction. The second theory suggests and has found empirical support, that workers experiencing an educational mismatch in their job are likely to receive lower wages compared to their peers with equivalent education who possess job roles that align with their education, which may result in decreased job satisfaction (Fleming & Kler, 2008).

Tsang (1987) sought to evaluate the validity of the Tsang and Levin model by utilizing data obtained from Bell Communication companies. The results indicated job satisfaction decreases when there is a discrepancy between the required education level and the education level possessed by the employee. Specifically, for each year of excess education, there was a nearly 12% decline

in job satisfaction. In a follow-up study conducted by Tsang et al. (1991), the findings echoed the results of the prior research, indicating that employees who faced an educational mismatch were at an increased risk of job dissatisfaction, with a likelihood of 8 to 13% higher compared to their well-matched counterparts. The authors also note that women were the most impacted demographic, with the highest levels of dissatisfaction observed among them.

Hersch (1991) conducted a study using a sample of employees from 18 US firms. The main finding aligned with prior research, demonstrating that employees with an educational mismatch were more susceptible to job dissatisfaction. However, his research suggested the probability of being dissatisfied was at 4% compared to those with a well-matched education. Battu et al. (2000) used data of British graduates and found that job satisfaction was higher among employees who had an education that was well-aligned with their job requirements compared to those who had an educational mismatch. The authors suggested that this may be due to a perceived lack of promotional prospects or employers not upgrading the tasks of these employees. Vila et al. (2007) explored the effect of the mismatch between education and employment on job satisfaction of young European graduates in seven countries in Europe. The study revealed that graduates who can put their education to use in their jobs typically exhibit higher job satisfaction. The abovementioned findings were also corroborated by other scholars such as Belfield & Harris (2002) and Verhaest & Omey (2006, 2010).

Allen & van der Velden (2001) contend that skills mismatch is a better indicator of job satisfaction than educational mismatch. Their research revealed that job satisfaction is significantly affected by the underutilization of skills, while educational mismatch was statistically insignificant only when estimated separately. Sloane & Mavromaras (2014) also presented evidence suggesting that being overskilled significantly diminishes job satisfaction, even after controlling for individual unobserved heterogeneity. According to Vieira (2005), skill underutilization leads to a decrease in overall job satisfaction, as well as satisfaction with various dimensions such as pay, job security, type of work, and number of hours worked.

Contrary to most literature on the subject, Büchel (2002), utilizing a sample of German firms, failed to establish a connection between job satisfaction and educational mismatch, and instead found that those with educational mismatch were healthier, more career-oriented, received more on-the-job training and had longer tenures than those with adequate education. However, it is important to note that this sample was restricted to individuals working in low-skilled jobs that

required few formal qualifications. Similarly, Naguib et al. (2019) used data of early career master graduates from a university in Switzerland and their analysis found no strong statistical evidence of a negative impact of educational mismatch on job satisfaction, but this research also is limited to a specific sub-population, and thus it may not be straightforward to extrapolate these findings to the entire population.

2.5. Labor market, education, and skills in Estonia

This section delves into various labor market policies that have been implemented to improve the alignment of skills and jobs and promote the development of skills in the Estonian workforce. Additionally, it evaluates the current educational and skill proficiency of the labor force in Estonia and reviews Estonian-specific empirical literature on educational and skills mismatches.

2.5.1. Labor market policies

Estonia has placed significant emphasis on skills governance, implementing various programs and strategies, including the OSKA initiative. Launched in 2015, OSKA serves as an anticipation and monitoring system for labor and skills demand in Estonia, analyzing the labor and skills needs required for the country's economic development over the next decade. OSKA focuses on three key questions: (1) how many people and which skills are needed in the labor market today and tomorrow, (2) where and how can these skills be acquired, and (3) what changes should be made in the education system to meet future needs. One notable finding from OSKA's research is that the number of young people graduating from higher education or vocational training institutions in Estonia does not meet the anticipated labor force demand in the future. (Estonian Qualifications Authority, n.d.)

In 2014, Estonia launched a comprehensive strategy called the Lifelong Learning Strategy to determine funding decisions and establish priorities for adult education. The objective of the Estonian Lifelong Learning Strategy is to provide customized educational options that meet the unique requirements and potential of individuals across their lifespan, with the goal of maximizing self-realization in various aspects of life. The adult learning program is designed to help adults return to formal education, strengthen on-the-job training and retraining, and improve the relevance of training to the labor market. (Estonian Ministry of Education and Research, 2014) In continuation of the Estonian Lifelong Learning Strategy, the Education Strategy 2021-2035 lays

out the major educational objectives for the next 15 years. The aim is in line with the previous strategy. (Jākobsone, 2022)

Since 2009, Estonia has been offering State-Commissioned Short Courses, which are offered at no cost and designed to boost adult education participation, particularly among individuals who do not typically enroll in such courses. The initiative seeks to achieve two objectives: to raise participation in adult learning and to improve the competitiveness of the adult population in the labor market. It should be highlighted that paid study leave for non-formal courses has been available since 2009, which has been instrumental in encouraging individuals to participate in the program. (OECD, 2020) Estonia has also adopted Active Labor Market Policy (ALMP) to improve the skills and qualifications of individuals who are not meeting the needs of the labor market. This policy also supports employed individuals to prevent unemployment and provides assistance during job transitions, helping them to remain employed. (OECD, 2020)

2.5.2. Education and skills in Estonia

In 2013, Estonia implemented a reform in higher education that eliminated tuition fees, making higher education free for full-time students who study in the national language (Estonian Ministry of Education and Research, n.d.). The composition of educational attainment in Estonia is presented in Figure 2.1, illustrating significant changes that occurred over the last decade. According to Statistics Estonia (2023), only 32% of Estonians had tertiary degrees at the start of the millennium – this has risen almost to 43% by 2021. Notably, during the two decades, there has been a decrease in the share of individuals with basic or lower education from rates as high as 19% recorded back in 2000 down to 12% in 2021.

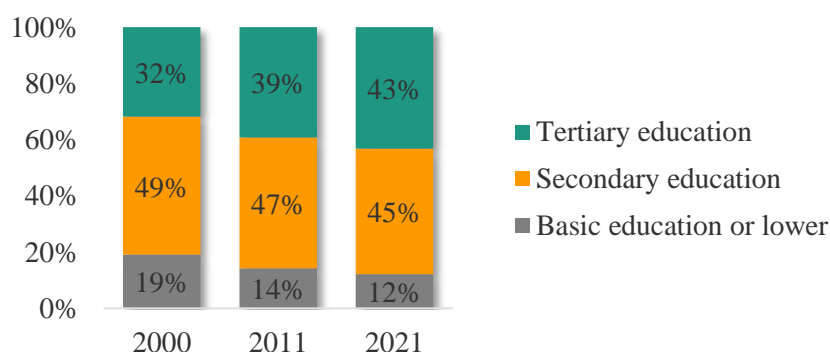


Figure 2.1. Distribution of educational attainment in Estonia
Source: (Statistics Estonia, 2023a), compiled by the author

Figure 2.2 depicts a comparison of the proportion of individuals with tertiary education level among Organisation for Economic Co-operation and Development (OECD) countries. As observed in this figure, Estonia surpasses the OECD average by one percentage point as of the year 2021. Estonia is ranked 19th out of all OECD nations.

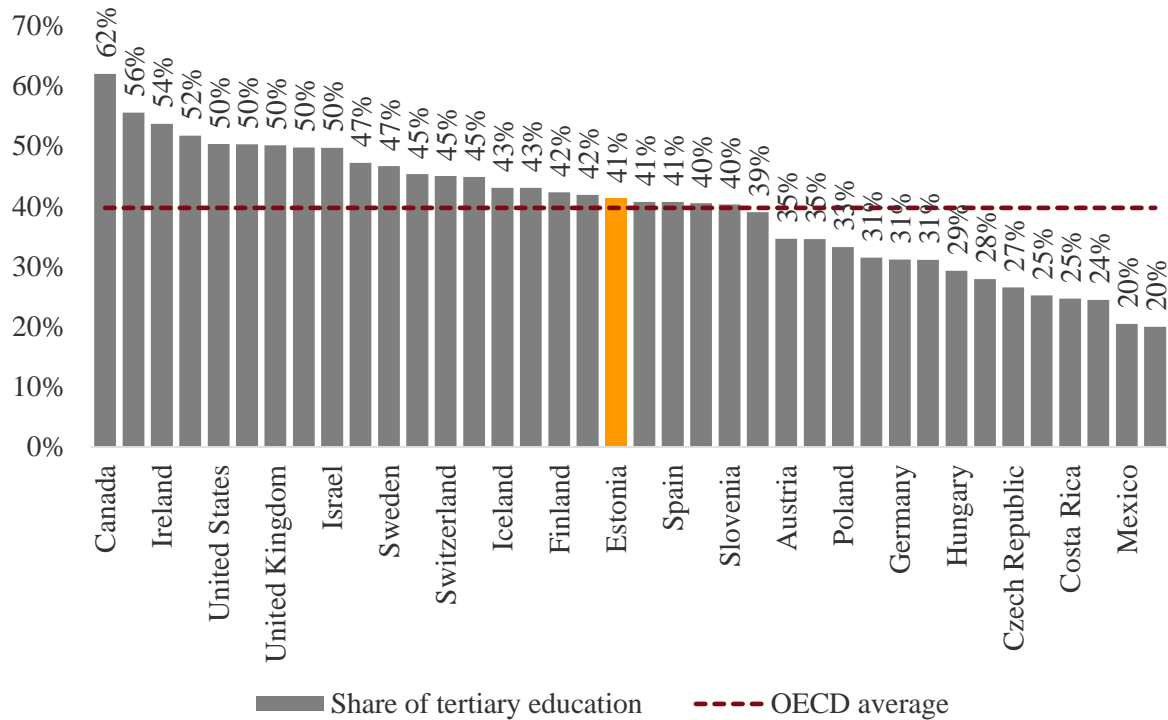


Figure 2.2. Tertiary education in OECD countries in 2021, share of population
 Source: (OECD, 2023), compiled by the author

The field of business, administration, and law are the most preferred majors for new tertiary students in Estonia, with 21% of entrants choosing this field, much like in other OECD countries. Although the demand for digital skills and the employment prospects of Information and communications technology (ICT) graduates is growing, only a small percentage of students entering tertiary education in Estonia pursue ICT programs. 91% of individuals with a tertiary ICT qualification are employed in Estonia, but ICT students comprise only 10% of new entrants to tertiary education, although this is higher than the OECD average of 6%. (OECD, 2022)

Having a higher level of education is commonly tied to greater job opportunities, and Estonia is no exception to this. As of 2021, individuals with tertiary education in Estonia have a 14% higher employment rate compared to those with below upper secondary attainment. This trend has proved especially strong for females. Nearly four out of five (81%) women with tertiary education were

employed in 2021, as opposed to only about half (55%) with less than upper secondary education. For men, the figures were 92% and 80%, respectively. (OECD, 2022)

Not only does educational attainment have an impact on employment prospects, but it also influences wage levels. In 2020, employees in Estonia who held upper secondary or post-secondary non-tertiary education earned 6% more than those with below upper secondary attainment, while individuals with tertiary education earned 37% more than those with below upper secondary attainment. Advanced learning offers significant market advantages during recessions such as the recent COVID-19. In Estonia, between 2019 and 2020, the percentage of unemployed individuals with below upper secondary education increased by 3.1 percentage points. The unemployment rate for individuals with upper secondary education increased by 3.5 percentage points, while for those with tertiary education, the increase was 1.9 percentage points. (OECD, 2022)

The OECD has compiled data for each country on proficiency levels based on the PIAAC data (OECD, table *Educational attainment...*). They compared proficiency levels by educational attainment as a share of population. This information is valuable in assessing the competencies associated with different levels of education. Figures 2.3 and 2.4 present the share of the population in Estonia in 2012, based on their scores in literacy and numeracy assessments, respectively, with level 0 representing the lowest level and level 5 the highest. In Estonia, most individuals who have tertiary-level education demonstrate proficiency levels above level 3. Even though 19% of individuals with tertiary education have the highest skill level, a portion of tertiary-level individuals still have lower skill levels. For example, 7% have only level 0/1 proficiency in literacy, while 6% have the same proficiency in numeracy. Moreover, 28% and 29% of individuals with tertiary education have only level 2 proficiency in literacy and numeracy, respectively. These figures indicate that while individuals with higher levels of education generally have higher skill levels, there is still a notable variation in the skill levels possessed by individuals with tertiary education. Therefore, the relationship between education and skills appears to be relatively weak, suggesting that higher education levels do not always guarantee higher skill levels.

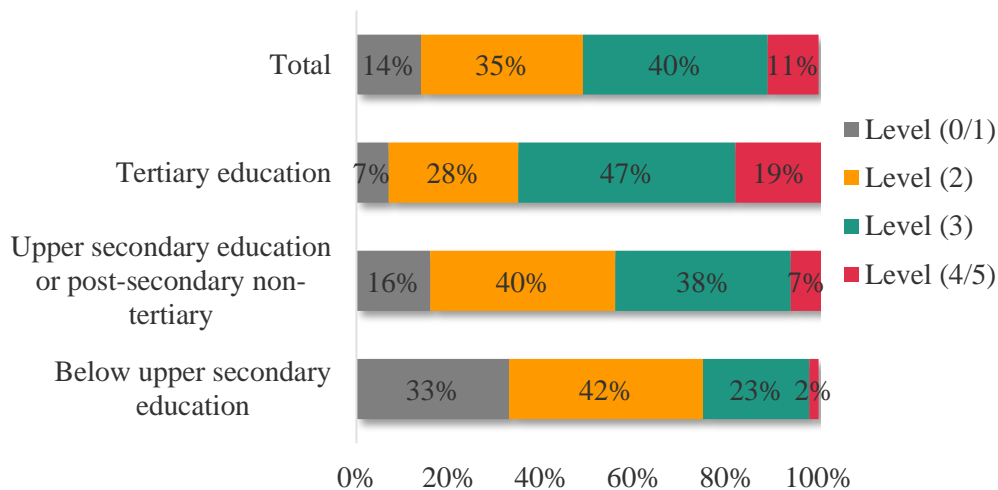


Figure 2.3. Share of population by literacy proficiency levels in Estonia in 2012
 Source: (OECD, table *Educational attainment...*), compiled by the author

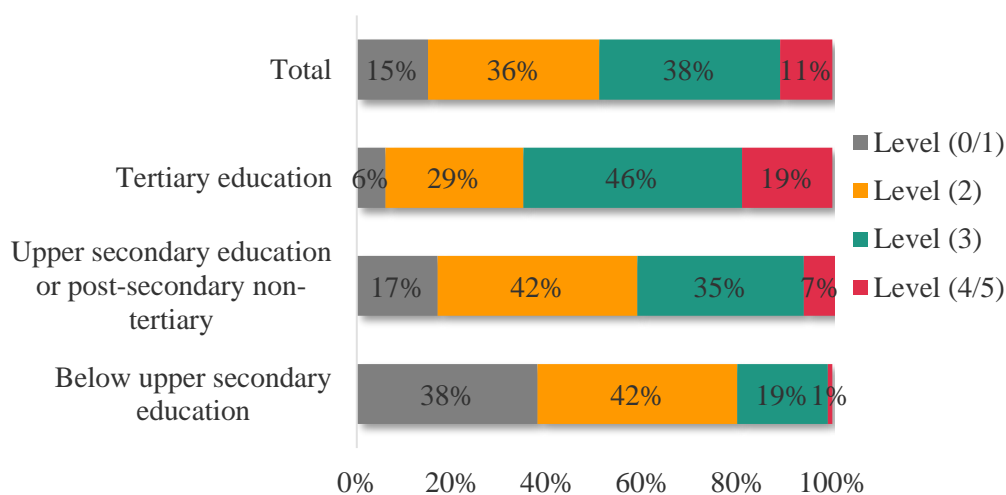


Figure 2.4. Share of population by numeracy proficiency levels in Estonia in 2012
 Source: compiled by the author

In 2019, the OECD published a report evaluating the performance of skills in Estonia (OECD, 2019a). The report notes that while Estonia's average PIAAC scores were above the OECD average in 2012, and Estonia ranks in the top 40% of countries for the strength of its learning culture, there are still areas for improvement. The report highlights significant skills imbalances in the labor market, with a shortage of cognitive and transferable skills and an excess of technical skills. Additionally, labor shortages have been identified in science, technology, engineering, and managerial positions, while sectors such as manufacturing face a surplus. To address these imbalances, the report recommends expanding Estonia's current tertiary attainment rate, which is

around the OECD average, and improving the intensity of skills used in the workplace through the adoption of high-performance workplace practices and strengthening the innovation system.

2.5.3. Empirical studies of mismatches in Estonia

Lamo & Messina (2010) studied educational mismatch and its consequences in Estonia during the years 1997-2003 using The Estonian labor force survey data. They found the incidence of overeducation to be 12,6% and undereducation 2,5%. They also observed large wage penalties associated with educational mismatch (24%). In 2021, the OECD conducted a review of the Estonian labor market and its policies. The report found that overeducation was prevalent among 14% of workers, while 24% were undereducated. Moreover, a horizontal mismatch was identified among 36% of workers.

Discussing the results of the PIAAC study, Halapuu (2015) estimates that the share of overeducated employed individuals in Estonia was the highest among the countries surveyed, at 36.9%. The incidence of undereducation was found to be 12.6%. Halapuu explained that the reason for the high rate of overeducation in Estonia may be due to the older generation receiving their education during a different economic system. This education may not be relevant to the current requirements of the labor market, resulting in a significant number of overeducated individuals. Regression analysis supported this, showing that older people and individuals with higher education were more likely to be overeducated.

Furthermore, Halapuu employed the Allen et al. (2013) method to measure skill use in the workplace, which revealed a 7.4% incidence of skill surplus and a 9.9% incidence of skill deficit in Estonia. This is the only incidence known to the author of this thesis in which skill mismatch has been investigated in the context of Estonia, however in this case, only skill use was measured rather than the skills possessed by individuals, therefore these results should be interpreted with caution. The author also reported that the proportion of individuals with both skill and educational surplus was 3.8%, while the proportion of individuals with skill and educational deficits was only 1.9%.

3. METHODOLOGY AND DATA

This chapter gives an overview of the data used in the analysis as well as the methods used to measure mismatches. It also provides an explanation for why these methods were selected and highlights their limitations. Furthermore, the chapter discusses the variables and estimation methods used in the analysis.

3.1. Data

This paper relied on data gathered from the PIAAC study, which was conducted by the OECD between 2011 and 2012. The PIAAC survey is an extensive global assessment that evaluates the numeracy, literacy, and problem-solving skills of adults aged 16 to 65 years. Respondents participated in computer-assisted personal interviews, as well as pencil-and-paper data collection strategies, and were given assessment tests to directly measure their numerical and literacy skills, as well as their problem-solving abilities in technology-rich environments. The survey also collected a comprehensive set of information on education, work experience, personal characteristics, and other socio-demographic factors through a background questionnaire completed by PIAAC respondents prior to taking the skills assessment. (OECD, 2019b)

For the purposes of this master's thesis, the dataset was limited to Estonian respondents aged 20 to 64 years who self-reported that they were currently employed, resulting in a sample size of 4760 respondents.

3.2. Educational mismatch indicator

The PIAAC survey asks respondents to indicate their highest attained level of education based on the international ISCED classification. The categories are described in detail in Appendix 1. The PIAAC survey also includes a question that asks respondents to indicate the usual qualifications required to get a job similar to their current job: "If applying today, what would be the usual

qualifications, if any, that someone would need to GET this type of job?”. (OECD, 2016a) These variables offer insight into the supply and demand of qualifications in Estonia (Figure 3.1).

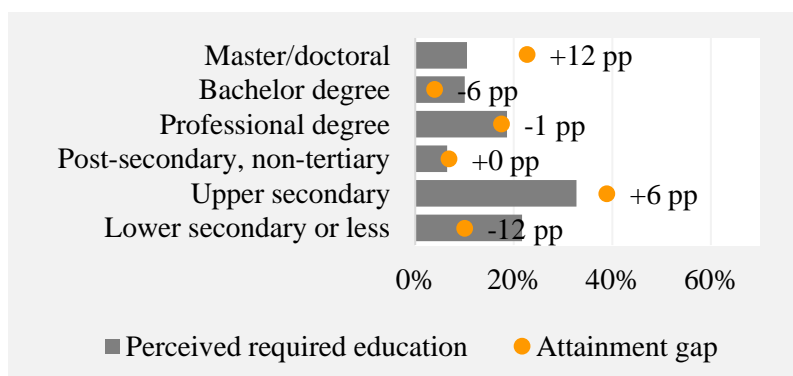


Figure 3.1. The supply and demand of educated workers
 Source: (OECD, 2016b), author’s calculations

The attainment gap measures the difference in percentage points between the actual educational attainment of respondents and the perceived required education. The data reveals that there is a notable surplus of workers with master’s or doctoral degrees (12 pp) and upper secondary education (6 pp) while there is a shortage of workers with a bachelor’s degree (6 pp). Additionally, there are 12 percentage points fewer workers with lower secondary or less education than required, which represents a greater supply of educated workers than jobs with high educational requirements. In such cases, some highly educated workers are compelled to take jobs with lower educational requirements than they possess.

The educational mismatch variables are derived from the highest attained education level variable and the perceived required education variable. If the level of perceived required education is above their own highest education level, then they are considered to be undereducated. If the required level is lower than their own highest education level, then they are overeducated, and if the required level matches their education level, then they are deemed well-matched. Figure 3.2 shows the distribution of variables derived for educational mismatches. In the sample, 38% of Estonians are overeducated and 14% are undereducated.

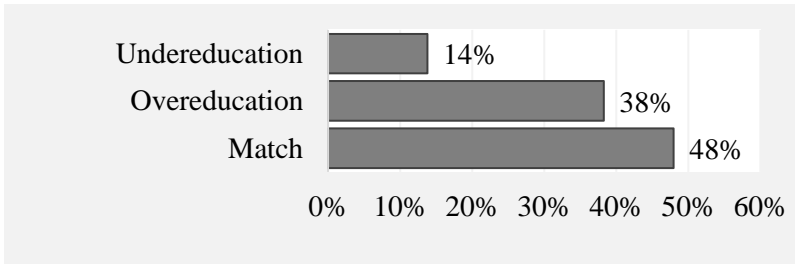


Figure 3.2. The distribution of educational matching variables
Source: (OECD, 2016b), author’s calculations

These results are consistent with the findings of Halapuu (2015), although some differences exist due to varying sample restrictions. In the present study’s sample, only Israel and New Zealand had a higher prevalence of overeducation than Estonia.

3.3. Skills mismatch indicator

The methodology used to measure skill mismatches in this thesis is based on the approach proposed by Perry et al. (2014). Although the PIAAC survey questions on skills are potential indicators of skill mismatches, they are subject to interpretation issues. The survey includes questions, such as "Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?" and "Do you feel that you need further training in order to cope well with your present duties?" (OECD, 2016a). While a "Yes" to the first question but a "No" to the second implies an overskilled status, and vice versa for underskilled, the challenge arises when a respondent answers "Yes" to both. Table 3.1 shows the different answer combinations of these questions and Figure 3.3 demonstrates the distribution of the variables derived from these combinations. Subjectively, 90% of respondents feel that their skills do not match their job.

Table 3.1. The answer combinations of the two skill-related survey questions in PIAAC

		Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?	
		No	Yes
Do you feel that you need further training in order to cope well with your present duties?	No	Skills match	Overskilled
	Yes	Underskilled	Both over- and underskilled

Source: (OECD, 2016b), compiled by the author

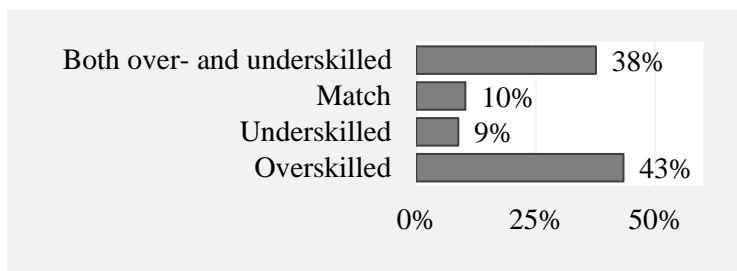


Figure 3.3. The distribution of skill matching variables based on the two skill related survey questions

Source: (OECD, 2016b), author's calculations

Perry et al. (2014) pointed out that in such a situation, the answers may refer to different skill sets. For instance, a respondent may think of their mathematical skills when asked if they can handle more demanding work tasks, but when asked if they require additional training to perform their job duties, they may think of their negotiation skills. Moreover, respondents may believe that they can manage more demanding tasks in general but still feel the need to continuously maintain and develop their skills through training (*Ibid.*). These inconsistencies raise concerns about the validity of using this method to measure skill mismatches. Therefore, a need for a more precise and objective way of measuring skill mismatches is evident.

To overcome these issues, Perry et al. (2014) developed a new measure based on previous research by Pellizzari & Fichen (2013) and Allen et al. (2013). The proficiency score for each occupation was standardized, and ranges were established based on the average skill level for each occupation. The proficiency score for each occupation was standardized and the respondent was defined as "overskilled" if their proficiency score is more than 1.5 standard deviations above the mean, "underskilled" if their proficiency score is less than 1.5 standard deviations below the mean, and "well-matched" if their proficiency score is between 1.5 and -1.5 standard deviations of the mean proficiency score.

A noteworthy improvement on previous methods is using all 10 of the plausible values that were calculated using the IRT (item response theory). As IRT was used, not all respondents were evaluated using the same set of assessment items. To obtain skill information for each respondent and every competency domain, the missing competency scores were imputed. To address the potential for errors due to imputation, 10 plausible values were generated for each respondent and skill domain instead of only one individual proficiency score. Therefore, competency scores in PIAAC are presented as a distribution of competencies, rather than an individual score. (OECD,

2019b). The 10 plausible values were used to calculate skill mismatch variables in this paper, and the average of the resulting statistics was reported. Perry et al. (2014) contended that using only one plausible value or the average of the 10 plausible values fails to capture the uncertainty in a respondent’s skill level in PIAAC.

Although, the PIAAC dataset provides measures of three types of skills, namely literacy skills, numeracy skills, and skills related to problem-solving in technology-rich environments (OECD, 2019b), only numeracy skills are used in this paper for estimating skill mismatches. This is due to the fact that tests for problem-solving in technology-rich environments were only presented to individuals who reported having computer experience, were willing to take the computer-based assessment, and possessed a minimum level of computer ability (*Ibid.*). Additionally, the proficiency levels of literacy and numeracy are highly correlated ($r = 0.814$). The numeracy tests evaluate how well respondents can use mathematical information to solve real-life problems (*Ibid.*). Moreover, since other forms of skills, like job-specific skills or those involving generic skills, are not measured in PIAAC, it is important to acknowledge this limitation and recognize that the results may not reflect the full extent of skill mismatches across different domains.

Figure 3.4 illustrates the distribution of skill matching variables derived using the Perry et al. (2014) methodology. Notably, the results differ significantly from the self-assessed approach. While the subjective assessment demonstrated that 43% of respondents feel they are overskilled, the objective method implies only 5% are actually overskilled. In terms of underskilling, the findings from the subjective and objective approaches are more in line, with the subjective approach indicating 9% are underskilled, and the objective approach suggesting 8% are underskilled.

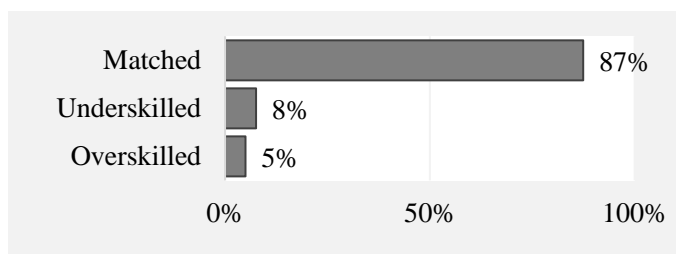


Figure 3.4. The distribution of skill matching variables based on the Perry et al. (2014) methodology

Source: (OECD, 2016b), author’s calculations

Since the subjective method leaves too much open for interpretation and the objective method relies on actual skill level based on proficiency scores, this paper implements the Perry et al. (2014) methodology to measure skill mismatches. However, a limitation of this methodology is that it assumes required skill levels are homogenous across occupations, which is generally not the case. Therefore, it is possible that the results may still be biased. Additionally, it has been suggested that the bandwidth of 1.5 standard deviations is arbitrary, and perhaps other boundaries should be considered (Asai et al., 2020). Perry et al. (2014) argue that these relatively high bandwidths ensure that workers identified as mismatched have skill levels that are indeed notably high or low compared to workers with similar job requirements.

3.4. Variables

In the models used to estimate the determinants of educational and skills mismatches, overeducation, undereducation, overskilling, and underskilling are the dependent variables. Each mismatch variable is represented by a dummy variable.

The model used to estimate the effects of educational and skills mismatches on job satisfaction includes job satisfaction as a dependent variable. Job satisfaction is measured using an ordered categorical variable obtained from the survey question, "All things considered, how satisfied are you with your current job?". The response categories range from 1 "Extremely satisfied" to 5 "Extremely dissatisfied". The model also controls for certain socio-demographic characteristics and job-related attributes. Figure 3.6 shows the distribution of the job satisfaction variable, indicating that the majority of Estonian workers are satisfied with their jobs, with only 20% reporting a lower level of satisfaction than satisfied.

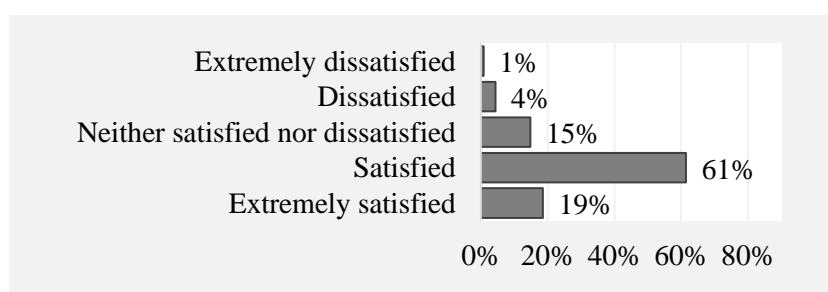


Figure 3.6. The distribution of the job satisfaction variable

Source: (OECD, 2016b), author's calculations

Appendix 1 contains the descriptions of the variables analyzed, and Appendix 2 provides the descriptive statistics for these variables. The frequency distribution for all variables can be found in Appendix 3.

In order to examine the relationships between the main variables of interest, Spearman’s correlation was calculated (Table 3.2). It appears that there is almost no correlation between educational mismatches and skills mismatches.

Table 3.2. Correlation between main variables of interest

	Overeducated	Undereducated	Overskilled	Underskilled	Job satisfaction
Overeducated	1.000	–	–	–	–
Undereducated	-0.269***	1.000	–	–	–
Overskilled	0.016	-0.035**	1.000	–	–
Underskilled	-0.041***	0.058***	-0.065***	1.000	–
Job satisfaction	0.0933***	-0.027*	-0.002	0.024	1.000

Source: (OECD, 2016b), author’s calculations

Note: *** p<0.01, ** p<0.05, * p<0.1

Moreover, as illustrated in Figure 3.5, there is little overlap between educational mismatch and skills mismatch, as only 6% of overeducated workers are also overskilled and 12% of undereducated workers are also underskilled. This implies that qualifications are not reliable indicators of skills mismatch and should not be used as proxies for it.

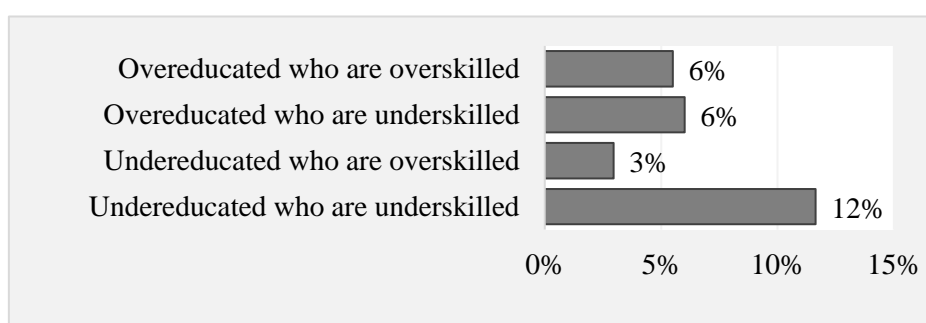


Figure 3.5. Skill mismatches among overeducated and undereducated workers

Source: (OECD, 2016b), author’s calculations

Table 3.2 indicates that overeducation correlates positively with job satisfaction while undereducation shows a negative relationship. However, these correlations are relatively weak. Furthermore, the relationship between job satisfaction and skills mismatches does not appear to be

statistically significant. This suggests that the influence of educational mismatches on job satisfaction is stronger than that of skills mismatches.

3.5. Estimation methods

To determine the factors that contribute to educational and skills mismatches, a logit model is employed due to dependent variables being binary variables. In parameter estimation, the maximum likelihood estimation (MLE) method is used to obtain the most accurate estimates. This model assesses the probability of the binary outcome (dependent variable) as a function of predictor variables, assuming a logistic distribution of the errors. The coefficients represent the log odds of the binary outcome changing by one unit for each unit increase in the predictor variable, *ceteris paribus*. The standard errors are assumed to be heteroscedastic, and robust standard errors are applied. As the logit model only allows determining the direction of the effect of explanatory variables on the dependent variable, marginal effects are also calculated to better understand the impact of independent variables on the dependent variable. (Gujarati, 2003) The model specification is:

$$Y_i = \ln \left[\frac{p(Y=1)}{p(Y=0)} \right] = \beta_0 + \beta_1 X_i + \dots + \varepsilon_i \quad (1)$$

where

Y_i – dependent variable of respondent i , representing the probability of being overeducated, undereducated, overskilled, or underskilled;

β_0 – the intercept;

β_1 – parameter estimate;

X_i – a vector of control variables, including socio-demographic characteristics, skill proficiency, and employment attributes;

ε_i – error term.

An ordered logit model is employed to estimate how educational and skill mismatches affect job satisfaction. Since the job satisfaction variable in the PIAAC dataset is categorical and ordered, with more than two levels, the ordered logit model is the most appropriate. Ordinal logistic regression is used to examine the associations between various factors and distinct categories of a dependent variable. It evaluates the probability of the dependent variable falling within a particular category considering the independent variables, *ceteris paribus*. Marginal effects are calculated

for interpreting the results, assuming heteroscedastic error terms and employing robust standard errors. (Gujarati, 2003) The model specification is:

$$Y_i = \ln[P(Y \leq j)] = \beta_{0j} + \beta_1 X_i + \dots + \beta_k M_i + \varepsilon_i \quad (2)$$

where

Y_i – the cumulative probability of job satisfaction being less than or equal to category j for categories 1 to 5;

β_{0j} – the intercept for each category j ;

X_i – a vector of control variables, including socio-demographic characteristics, and work-related attributes;

M_i – a vector of dummy variables representing overeducation, undereducation, overskilling, and underskilling;

ε_i – error term.

It is important to bear in mind that the estimated parameters should not be considered as causal relationships when interpreting the results. Instead, they show conditional correlations between the dependent and explanatory variables.

4. RESULTS AND DISCUSSION

This chapter discusses the results from the analysis and provides an overview of the robustness check carried out to assess the validity of the results.

4.1. Mismatches

The marginal effects of the regressions are presented in Appendix 4. The results reveal notable gender differences in the likelihood of being mismatched. Specifically, the findings suggest that, relative to women, men are 3.7% less likely to be overeducated, while they are 3% more likely to be undereducated. At the same time, the results indicate that men are 5.2% more likely to be overskilled and 5.7% less likely to be underskilled compared to women.

These results are somewhat unexpected considering the prevailing literature on the subject, which commonly suggests that men are more likely to experience overeducation than women (Groot, 1996; Kiker et al., 1997; Sloane et al., 1999). These differences could be influenced by hiring practices and labor market discrimination. For example, employers may hold unconscious biases or stereotypes about the abilities and suitability of men and women for certain jobs, which could affect their hiring decisions. This could result in women feeling the need to acquire more credentials to be able to compete in positions that accept men based on less "proof" of their skill set. In addition to potential biases in hiring practices, it is important to note that men are often paid more than women, which could also contribute to gender differences in overeducation. In Estonia, there is a significant wage gap where men earn considerably more than women (Statistics Estonia, 2023b). This could result in women seeking higher levels of education to increase their earning potential, leading them to potentially end up in positions that do not require as much education as they have, while men may be in jobs that require less education than they actually have. In fact, there are consistently more highly educated women than men in Estonia (Statistics Estonia, 2022), which supports the author's proposed theory explaining this disparity. In addition, men in Estonia tend to lean more towards vocational education (*Ibid.*), which could account for their higher probability of being overskilled compared to women.

To investigate the potential impact of family responsibilities on these gender differences, interaction terms were introduced into the model. The results, illustrated in Figure 4.1, suggest that men living with a partner are more likely to be undereducated and overskilled than single men or women. The effect on undereducation is greater for men (4.3%) compared to the effect of gender alone, while the effect on overskilling is smaller (2%). These findings suggest that having a partner contributes to men’s mismatches, but not necessarily for women. Men living with a partner might be more likely to weigh the opportunity cost of pursuing higher education against the immediate benefits of entering the workforce and developing specific skills. The pressure to contribute financially to the household may lead men in partnerships to prioritize skill development over further education, resulting in undereducation and a higher likelihood of being overskilled. These findings are in line with Sloane et al. (1999) who also identified men’s financial burden as a contributing factor. Having children, however, does not appear to have a significant impact on educational or skill mismatches.

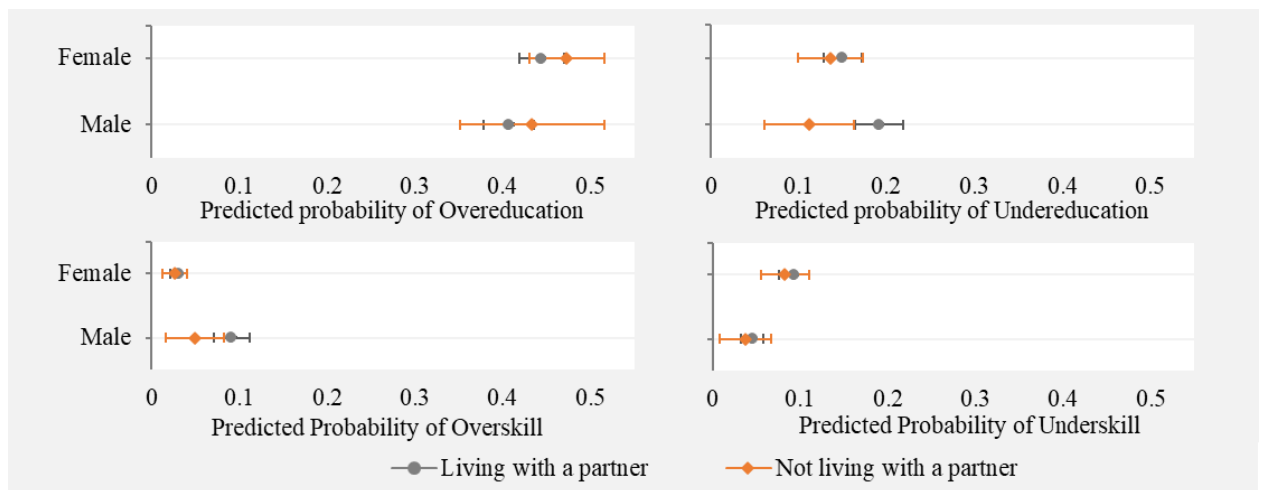


Figure 4.1. The marginal effects of interaction terms between gender and cohabitation status on mismatches

Source: (OECD, 2016b), author’s calculations

The relationship between age and mismatches is presented in Figure 4.2. The analysis reveals a U-shaped pattern between age and overeducation, indicating that the probability of being overeducated initially rises with age until a certain point, after which it starts to decline. This may be explained by the fact that older individuals in Estonia acquired education during the Soviet Era, which may not align with the current job market demands, as suggested by Halapuu (2015). The

relationship between age and undereducation is not as clear. The trend between overskilling and age indicates that older individuals are less likely to be overskilled compared to younger individuals, possibly because they have acquired more job-specific skills and experience which may give them the opportunity to negotiate better job opportunities. Conversely, the positive relationship between underskilled and age implies that older individuals are more likely to be underskilled, potentially due to technological advancements and changing skill requirements in the labor market or an inability to keep up with new knowledge and skill demands.

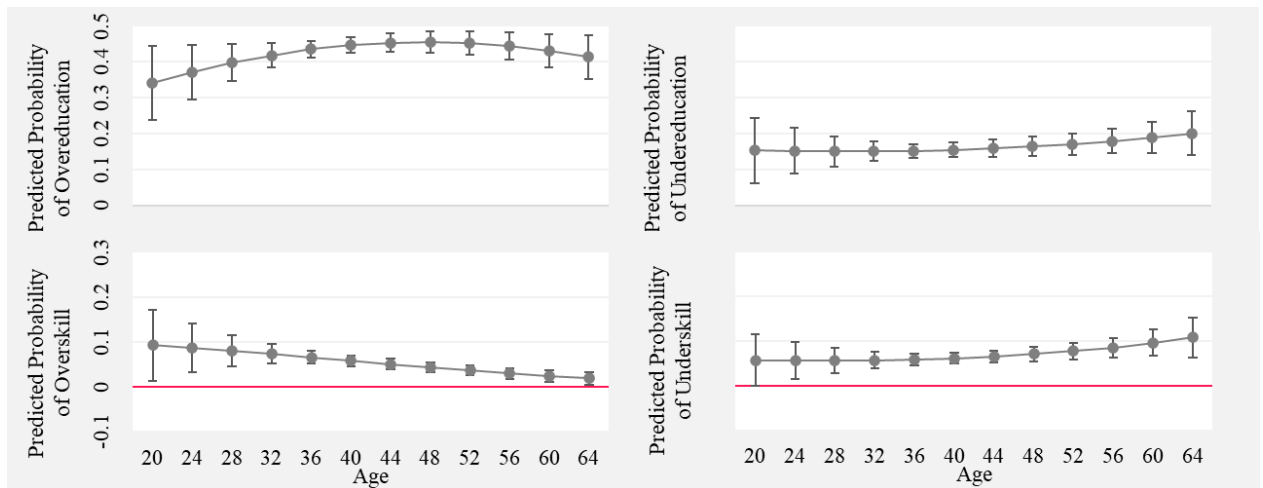


Figure 4.2. The marginal effects of age on mismatches

Source: (OECD, 2016b), author’s calculations

The results suggest that the likelihood of being overeducated as well as overskilled increases with education level, while the effect for undereducation and underskill is the mirror image of that. These results are consistent with most of the literature on the subject (Frenette, 2004; Pellizzari & Fichen, 2013; Wirz & Atukeren, 2004). This could be explained by the supply and demand of educated individuals in the labor market when the demand for highly educated people is lower than the supply, resulting in individuals with higher education accepting jobs that do not match their level of education.

The findings regarding the impact of the field of education on mismatches are inconclusive. While previous literature suggests that individuals with a general education background are more likely to experience educational mismatches compared to those with specialized education in fields (Dolton & Silles, 2008; Frenette, 2004; Green & McIntosh, 2007; Mcguinness, 2003), the results

of this study do not allow for a clear conclusion to be drawn regarding the influence of the field of study.

The general consensus among researchers is that immigrants experience more mismatches in the labor market (Falcke et al., 2020; Green et al., 2007; Joonas et al., 2014; Lindley, 2009). In this study, the effects for overeducation and overskill were not statistically significant, but the results indicated that immigrant workers were 4% more likely to be undereducated and 5% more likely to be underskilled compared to native workers. Pellizzari & Fichten (2013) similarly found that immigrant workers are more likely to be underskilled, with a larger effect size, as they were twice as likely to be underskilled. It is important to note that the immigrant workers in this sample were all born in the Russian Federation and received their education there, with Russian being their primary language spoken at home. Although one might expect larger disparities due to language and cultural differences, the historical context of Estonia being part of the Soviet Union until 1991 and the continued prevalence of the Russian language in Estonia may account for the smaller effect size observed in this study. Nonetheless, barriers for immigrant workers persist, including language proficiency, the transferability of skills, discrimination, and challenges related to credential recognition.

Previous research has indicated that workers at the start of their careers tend to experience more mismatches (Crompton, 2002; Dekker et al., 2002; Frei & Sousa-Poza, 2012; Vahey, 2000). This is largely attributed to the notion that employers value work experience over qualifications. The findings of this study are largely consistent with prior research. As workers gain more experience, they tend to find better-matched jobs, which reduces the likelihood of overeducation. Furthermore, having more work experience seems to decrease the probability of being underskilled which may be due to the accumulation of job-specific skills and knowledge.

The findings indicate that participating in adult training decreases the likelihood of being overeducated. Adult training can help individuals acquire new and updated skills, making them more attractive to employers and better equipped to find well-matched positions. However, adult training can also increase the likelihood of being undereducated, which suggests that it can provide some individuals who lack the necessary qualifications an opportunity to compete for jobs that usually require higher educational credentials.

The relationship between firm size and the likelihood of being overeducated appears to be negative. Larger firms tend to offer a wider variety of job positions and opportunities compared to

smaller firms. This increased diversity in job roles may provide better matching opportunities for employees, allowing them to find positions that align with their education level, and thus reducing the likelihood of overeducation. Larger firms are also more likely to have well-established human resource management systems and processes in place to ensure better employee-job matching. Concerning the sector of the firm, the relationship does not appear to be relevant.

Similarly to Pietro & Cutillo (2006), the results in this study indicate that having an indefinite contract increases the likelihood of being overeducated. The sense of job security associated with such contracts may prompt individuals to accept positions that do not require their full education and qualifications, leading to overeducation. At the same time, the results suggest that having an indefinite contract decreases the likelihood of being underskilled. Employers may be more likely to invest in training and development for employees with indefinite contracts, as they expect a longer-term return on their investment. This can lead to better skill matching and a reduced likelihood of underskill. The relationship between working part-time and mismatches, however, is statistically insignificant.

The results regarding industry and occupation seem to point toward the notion that working in industries or occupations that generally require higher education or skills, decreases the likelihood of being overeducated. In industries and occupations with higher skill requirements, the matching process between workers and jobs could more precise due to the specialized nature of the job roles. As a result, employees may be more likely to find positions that align with their education and skill levels. Working in lower skilled occupations decreases the likelihood of being undereducated, as the education requirements are relatively low. No other significant conclusions can be drawn with regard to industry and occupation.

The relationship between numeracy skills and overeducation is negative, suggesting that higher level of skills leads to a lower likelihood of being overeducated. This finding is consistent with previous research that has found a link between higher proficiency scores and a reduced likelihood of experiencing educational mismatch (Green et al., 1999; Green & McIntosh, 2007).

4.2. Job satisfaction

The results from the model that investigates how mismatches affect job satisfaction reveal that when controlling for socio-demographic characteristics and job-related attributes, only overeducation appears to affect job satisfaction with statistical significance (Table 4.2). Full regression is reported in Appendix 5. The results from this study indicate that being overeducated reduces the likelihood of being extremely satisfied with work by 3.1%. Individuals who are overeducated may face a higher opportunity cost as they could have potentially pursued more rewarding careers that align with their qualifications, both financially and intellectually, resulting in lower job satisfaction. Furthermore, overeducated individuals might have higher income expectations due to their higher educational attainment. When their actual earnings do not meet these expectations, it could translate to lower overall job satisfaction. This may also be linked to inefficient job-market signaling, where higher educational qualifications have not led to better job opportunities, which can contribute to a sense of frustration and further reduce job satisfaction.

Table 4.2. Marginal effects of mismatches on job satisfaction

Variable	Extremely satisfied	Satisfied	Neither satisfied nor dissatisfied	Dissatisfied	Extremely dissatisfied
Overeducated	-0.031*** (0.012)	-0.004* (0.002)	0.023** (0.009)	0.010** (0.004)	0.002** (0.001)
Undereducated	0.001 (0.016)	0.000 (0.001)	-0.001 (0.012)	-0.000 (0.005)	0.000 (0.001)
Overskilled	-0.030 (0.020)	-0.007 (0.008)	0.024 (0.018)	0.010 (0.008)	0.002 (0.002)
Underskilled	-0.003 (0.019)	-0.000 (0.002)	0.003 (0.014)	0.001 (0.006)	0.000 (0.001)
Observations	3,101				
Pseudo R2	0.0427				

Source: (OECD, 2016b), author's calculations

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Undereducation and skill mismatches do not appear to significantly affect job satisfaction. These results are in direct contrast to (Allen & van der Velden, 2001; Green & Zhu, 2010; Sloane & Mavromaras, 2014) who also investigated the impact of both educational and skill mismatches on job satisfaction and found that skill mismatch is a better predictor of job satisfaction. However, all the abovementioned studies used a skill mismatch measure that was based on skill use in the workplace. The skill mismatch measure utilized in this study is based on actual skill levels, so the

opposing results might be explained by the different methodologies used in measuring skill mismatches.

The observed lack of effect of overskilling on job satisfaction, as opposed to the significant effect of overeducation, may be due to the different measurement methods used. While overeducation was measured subjectively, overskilling was measured objectively. Additionally, only 47% of workers classified as overskilled using the objective measure considered themselves to be purely overskilled based on survey responses, with 35% indicating that they felt both overskilled and underskilled (Figure 4.3). This may indicate that individuals who perceive themselves as having additional skills beyond what is required for their current job, but also recognize the need for further training, are not necessarily dissatisfied with their work.

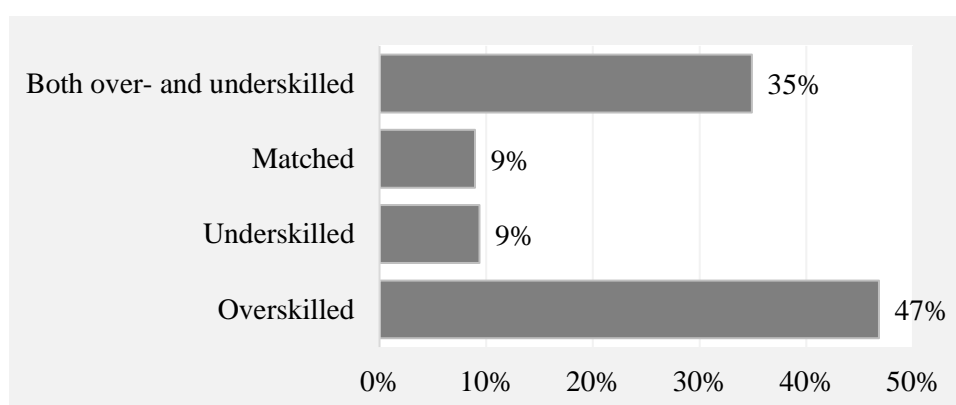


Figure 4.3. Skill mismatches based on survey questions

Source: (OECD, 2016b), author's calculations

Additionally, workers who are overskilled, or underskilled might be more adaptable in the workplace, developing strategies to compensate for their mismatches, which could mitigate the negative impact of mismatches on job satisfaction. Some individuals may view their mismatched job as a temporary situation, which provides them with opportunities to gain experience and additional skills. This perspective could help to reduce the negative effects of mismatches on job satisfaction.

It is also important to acknowledge that this model does not capture all the personal and work-related heterogeneity that could affect job satisfaction, such as social aspects of the workplace, a person's character and their coping capabilities, and the overall organizational culture. Workers who are overskilled or underskilled may prioritize different aspects of their jobs, such as job

security, work-life balance, or workplace relationships, which could outweigh the dissatisfaction caused by the mismatch. Furthermore, non-cognitive factors like personality traits, soft skills, and social networks may play a more significant role in job satisfaction for individuals experiencing skills mismatches, which could explain the lack of significant effects observed in the model.

CONCLUSION

The main goal of this master's thesis was to assess the relationship between educational and skills mismatches in the Estonian labor market and their effects on job satisfaction. The research is centered around two fundamental questions:

1. What factors contribute to educational and skills mismatches, and how do they differ for each type of mismatch?
2. To what degree do educational and skills mismatches impact job satisfaction, and which one is more influential?

The PIAAC dataset was utilized to address the research questions posed in this study. Educational mismatches were measured using the subjective method, which involved comparing an individual's attained education level with their self-assessed required level of education for their job. Skills mismatches were assessed using the Perry et al. (2014) methodology, which examined standardized numeracy scores of individuals and deviations from the mean, with a 1.5 deviation threshold for determining mismatched individuals. Binary variables for mismatches were derived, and logistic regressions were employed to investigate the factors influencing mismatches. To answer the second research question, the survey question which asked about how satisfied an individual feels at their job was used as a dependent variable, and ordinal logistic regression was employed.

When interpreting the results of this master's thesis, it is crucial to recognize that no single method for measuring mismatches is universally applicable, and different methods may yield varying results. The main limitation of using the subjective method to measure educational mismatches is the potential for workers to overstate their job requirements, possibly leading to biased results. Concerning skill mismatches, the limitations include the lack of consideration for occupational heterogeneity and the sole reliance on numeracy skills, which do not capture the full extent of skill mismatches across various skill domains. In addition, the cut-off points of 1.5 deviations used in the methodology are arbitrary, and there is no clear evidence indicating the most accurate boundaries to use.

The findings of this master's thesis reveal that several socio-demographic factors influence mismatches, including gender, age, partnership status, and immigration status. Educational attributes, such as the highest level of education attained, field of study, and participation in adult training, also impact mismatches, as do job-related attributes like work experience, firm size, type of contract, industry, and occupation. Furthermore, an individual's skill level has some bearing on educational mismatch. However, these variables affect educational and skills mismatches differently, with no common trend. Consequently, it is not appropriate to assume that educational mismatches can serve as a proxy for skills mismatches. When discussing mismatches in the labor market, it is more informative and accurate to assess educational and skills mismatches separately without the assumption that they are related to one another.

Regarding the influence of mismatches on job satisfaction, the results indicate that only overeducation has a significant impact, suggesting that educational mismatches are more influential than skills mismatches. However, the prevailing literature posits that skills mismatches have a greater impact on job satisfaction. On the one hand, the contrasting results could stem from the different methods utilized in measuring mismatches. On the other hand, in the sample used in this paper, some individuals deemed overskilled subjectively felt they possessed more skills than their job required, yet simultaneously believed they needed additional training to manage their job demands effectively. Such a situation might not necessarily lead to job dissatisfaction. The model employed in this study does not account for various personal and work-related attributes, which could affect job satisfaction and potentially offset dissatisfaction arising from mismatches.

These results suggest that a more refined model, possibly incorporating subjective assessments and objective methods for measuring skills mismatches is needed in order to investigate these effects more precisely. Furthermore, this study solely estimated the impact of mismatches on overall job satisfaction, leaving open the possibility that mismatches could affect various aspects of job satisfaction differently. A more comprehensive model could consider additional variables such as social aspects of the workplace, individual's personality and coping capabilities, and organizational culture, although the challenge is that these attributes are very difficult to measure. A deeper understanding of these relationships might provide valuable insights for policymakers and employers to develop strategies to address educational and skill mismatches in the labor market and enhance overall job satisfaction.

KOKKUVÕTE

HARIDUSE JA TÖÖ VÕI OSKUSTE JA TÖÖ MITTEVASTAVUS: MIS ON EESTI TÖÖTAJATE SEAS TÖÖRAHULOLU JAOKS OLULISEM?

Gerda Fatal

Käesoleva magistr töö põhieesmärk oli hinnata hariduse ja oskuste mittevastavuse seost Eesti tööturul ning nende mõju tööga rahulolule. Töö keskendub kahele põhilisele uurimisküsimusele:

1. Millised tegurid põhjustavad hariduse ja oskuste mittevastavust ning kuidas need erinevad igat tüüpi mittevastavuse korral?
2. Millisel määral mõjutavad hariduse ja oskuste mittevastavused tööga rahulolu ja kumma mõju on suurem?

Töös püstitatud uurimisküsimuste lahendamiseks kasutati PIAAC andmestikku. Valimisse kuulusid Eestis töötavad isikud vanuses 20 kuni 64 aastat. Hariduse mittevastavust mõõdeti kasutades subjektiivset meetodit, mis hõlmas isiku kõrgeima omandatud haridustaseme võrdlemist tema hinnangul tööks vajalikuks peetud haridustasemega. Oskuste mittevastavust hinnati kasutades Perry et al. (2014) meetodikat, mille käigus uuriti isikute standardiseeritud matemaatilise kirjaoskuse tulemusi ning nende kõrvalekaldeid keskmisest, kasutades 1,5 standardhälve piiri, et selgitada välja isikud, kelle oskused ei vastanud vajalikule tasemele. Mittevastavuste esindamiseks tuletati binaarsed muutujad ja neid mõjutavate tegurite hindamiseks kasutati logistilist regressiooni. Teisele uurimisküsimusele vastamiseks kasutati järjestatud logistilist regressiooni, kus sõltuvaks muutujaks oli tunnus, mis tuletati uuringu küsimusest, kus küsiti inimestelt kuivõrd rahul on nad oma tööga.

Antud magistr töö tulemuste tõlgendamisel on oluline tõdeda, et ükski mittevastavuste mõõtmiseks kasutatav meetod ei ole üheselt rakendatav ning erinevad meetodid võivad anda erinevaid tulemusi. Peamine piirang hariduse mittevastavuste mõõtmiseks kasutatud subjektiivse meetodi puhul on töötajate kalduvus ülehinnata oma töö nõudeid, mis võib viia kallutatud

tulemusteni. Oskuste mittevastavuse mõõtmiseks valitud meetodi piiravateks asjaoludeks on tõsiasi, et see ei arvesta ametialaste eripäradega ja et see tugineb ainult matemaatilisele kirjaoskusele, mis ei hõlma oskuste mittevastavuse täielikku ulatust erinevate oskuste raames. Lisaks on antud metoodikas kasutatud 1,5 standardhälbe piirid meelevaldsed ja puuduvad selged tõestatud piirid, mis oleksid täpsemad.

Käesoleva magistritöö tulemused näitavad, et mittevastavusi mõjutavad mitmed sotsiaaldemograafilised tegurid, sealhulgas sugu, vanus, partnerluse staatus ja sisserände staatus. Haridusega seotud tunnused, nagu kõrgeim omandatud haridustase, õppevaldkond ja täiskasvanute koolitusest oosavõtt, ning tööga seotud omadused, nagu töökogemus, ettevõtte suurus, tegevusala ja amet mõjutavad samuti mittevastavusi. Lisaks, isiku oskuste tase on teatud määral seotud hariduse mittevastavusega. Siiski mõjutavad need muutujad hariduse ja oskuste mittevastavusi erinevalt, puudub ühine trend. Seetõttu ei ole asjakohane eeldada, et hariduse mittevastavust võiks kasutada oskuste mittevastavuse asendusnäitajana. Tööturu mittevastavustest rääkides on informatiivsem ja täpsem hinnata hariduse ja oskuste mittevastavusi eraldi, eeldamata, et need on omavahel seotud.

Mis puudutab mittevastavuste mõju tööga rahulolule, siis näitavad tulemused, et ainult üleharitusel on oluline mõju tööga rahulolule, mis viitab sellele, et hariduse mittevastavus omab suuremat mõju tööga rahulolule kui oskuste mittevastavus. Valdav kirjandus antud teemal väidab aga, et oskuste mittevastavused avaldavad tööga rahulolule suuremat mõju. Ühest küljest võivad erinevad tulemused tuleneda sellest, et mittevastavuste mõõtmiseks on kasutatud erinevaid meetodeid. Teisalt, osad oskuste ülekaaluga isikud antud valimis tundsid, et neil on küll rohkem oskusi kui nende töö nõuab, kuid samal ajal ka, et nad vajavad oma tööülesannetega toimetulekuks täiendavat koolitust. Selline olukord ei pruugi tingimata viia tööga rahulolematuseeni. Käesolevas töös kasutatud mudel ei arvesta mitmete isiklike ja tööga seotud omadustega, nagu töökoha sotsiaalsed aspektid, indiviidi iseloom ja toimetulekuvõime ning organisatsioonikultuur, mis võiksid samuti mõjutada tööga rahulolu ja potentsiaalselt kompenseerida mittevastavusest tulenevat rahulolematust.

Need tulemused viitavad asjaolule, et vaja oleks töötada välja täiustatud mudel, näiteks ühildades subjektiivseid hinnanguid ja objektiivseid meetodeid oskuste mittevastavuse mõõtmiseks, mis võimaldaks uurida neid mõjusid täpsemalt. Käesolevas töös hinnati üksnes mittevastavuse mõju üldisele tööga rahulolule, jättes lahtiseks võimaluse, et mittevastavused võivad mõjutada tööga

rahulolu erinevaid aspekte erinevalt. Ulatuslikum ja täpsem mudel võiks võtta arvesse täiendavaid muutujaid, nagu töökoha sotsiaalsed tegurid, individuaalsed toimetulekuvõimed ja organisatsioonikultuuri kirjeldavad muutujad, kuigi selle puhul osutuks väljakutseks nende omaduste mõõtmise keerukus. Kirjeldatud seoste sügavam mõistmine võiks pakkuda poliitikakujundajatele ja tööandjatele väärtuslikke teadmisi, et kujundada välja strateegiaid hariduse ja oskuste mittevastavuste lahendamiseks tööturul ja üldise rahulolu suurendamiseks.

LIST OF REFERENCES

- Alba-Ramírez, A. (1993). Mismatch in the Spanish Labor Market: Overeducation? *The Journal of Human Resources*, 28(2), 259–278. <https://doi.org/10.2307/146203>
- Allen, J., Levels, M., & van der Velden, R. (2013). Skill mismatch and skill use in developed countries: Evidence from the PIAAC study. *ROA-RM-2013/17*.
- Allen, J., & van der Velden, R. (2001). Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search. *Oxford Economic Papers*, 53(3), 434–452. <https://doi.org/10.1093/oep/53.3.434>
- Asai, K., Breda, T., Rain, A., Romanello, L., & Sangnier, M. (2020). *Education, skills and skill mismatch. A review and some new evidence based on the PIAAC survey* (p. 114 p.) [Report, Institut des politiques publiques (IPP)]. <https://shs.hal.science/halshs-02514746>
- Battu, H., Belfield, C. R., & Sloane, P. J. (2000). How Well Can We Measure Graduate Over-Education and Its Effects? *National Institute Economic Review*, 171, 82–93.
- Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education* (3rd ed.). University of Chicago Press.
- Becker, G. S. (1994). *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education, Third Edition*. The University of Chicago Press. <https://www.nber.org/books-and-chapters/human-capital-theoretical-and-empirical-analysis-special-reference-education-third-edition>
- Belfield, C. R., & Harris, R. D. F. (2002). How well do theories of job matching explain variations in job satisfaction across education levels? Evidence for UK graduates. *Applied Economics*, 34(5), 535–548. <https://doi.org/10.1080/00036840110041895>

- Boto-García, D., & Escalonilla, M. (2022). University education, mismatched jobs: Are there gender differences in the drivers of overeducation? *Economia Politica*, *39*(3), 861–902. <https://doi.org/10.1007/s40888-022-00270-y>
- Büchel, F. (2002). The effects of overeducation on productivity in Germany—The firms' viewpoint. *Economics of Education Review*, *21*(3), 263–275. [https://doi.org/10.1016/S0272-7757\(01\)00020-6](https://doi.org/10.1016/S0272-7757(01)00020-6)
- Büchel, F., & Mertens, A. (2004). Overeducation, undereducation, and the theory of career mobility. *Applied Economics*, *36*(8), 803–816. <https://doi.org/10.1080/0003684042000229532>
- Büchel, F., & Pollmann-Schult, M. (2004). Overeducation and human capital endowments. *International Journal of Manpower*, *25*(2), 150–166. <https://doi.org/10.1108/01437720410535963>
- Castagnetti, C., Rosti, L., & Töpfer, M. (2018). Overeducation and the gender pay gap in Italy. *International Journal of Manpower*, *39*(5), 710–730. <https://doi.org/10.1108/IJM-12-2016-0235>
- Cedefop (Ed.). (2010). *The skill matching challenge: Analysing skill mismatch and policy implications*. Publications Office of the European Union.
- Chevalier, A. (2003). Measuring Over-Education. *Economica*, *70*(279), 509–531.
- Chevalier, A., & Lindley, J. (2009). Overeducation and the Skills of UK Graduates. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, *172*(2), 307–337.
- Cohn, E., & Khan, S. P. (1995). The wage effects of overschooling revisited. *Labour Economics*, *2*(1), 67–76. [https://doi.org/10.1016/0927-5371\(95\)80008-L](https://doi.org/10.1016/0927-5371(95)80008-L)
- Crompton, S. (2002). I still feel overqualified for my job. *Canadian Social Trends*, *67*, 23.

- Dekker, R., de Grip, A., & Heijke, H. (2002). The effects of training and overeducation on career mobility in a segmented labour market. *International Journal of Manpower*, 23(2), 106–125. <https://doi.org/10.1108/01437720210428379>
- Di Pietro, G., & Urwin, P. (2006). Education and skills mismatch in the Italian graduate labour market. *Applied Economics*, 38(1), 79–93. <https://doi.org/10.1080/00036840500215303>
- Dolton, P. J., & Silles, M. A. (2008). The effects of over-education on earnings in the graduate labour market. *Economics of Education Review*, 27(2), 125–139. <https://doi.org/10.1016/j.econedurev.2006.08.008>
- Dolton, P., & Vignoles, A. (2000). The incidence and effects of overeducation in the U.K. graduate labour market. *Economics of Education Review*, 19(2), 179–198. [https://doi.org/10.1016/S0272-7757\(97\)00036-8](https://doi.org/10.1016/S0272-7757(97)00036-8)
- Duncan, G. J., & Hoffman, S. D. (1981). The incidence and wage effects of overeducation. *Economics of Education Review*, 1(1), 75–86. [https://doi.org/10.1016/0272-7757\(81\)90028-5](https://doi.org/10.1016/0272-7757(81)90028-5)
- Estonian Ministry of Education and Research. (n.d.). *Education | Ministry of Education and Research*. Retrieved February 22, 2023, from <https://www.hm.ee/korgharidus-jateadus/korgharidus/oppimine>
- Estonian Ministry of Education and Research. (2014). *The Estonian Lifelong Learning Strategy 2020*. <https://uil.unesco.org/i/doc/lifelong-learning/policies/estonia-lifelong-learning-strategy-2020.pdf>
- Estonian Qualifications Authority. (n.d.). *OSKA*. OSKA. Retrieved February 16, 2023, from <https://oska.kutsekoda.ee/en/>
- Falcke, S., Meng, C., & Nollen, R. (2020). Educational mismatches for second generation migrants. An analysis of applied science graduates in the Netherlands. *Journal of Ethnic*

and Migration Studies, 46(15), 3235–3251.

<https://doi.org/10.1080/1369183X.2020.1738211>

- Fleming, C. M., & Kler, P. (2008). I'm too clever for this job: A bivariate probit analysis on overeducation and job satisfaction in Australia. *Applied Economics*, 40(9), 1123–1138. <https://doi.org/10.1080/00036840600771254>
- Freeman, R. B. (1978). Job Satisfaction as an Economic Variable. *The American Economic Review*, 68(2), 135–141.
- Frei, C., & Sousa-Poza, A. (2012). Overqualification: Permanent or Transitory? *Applied Economics*, 44, 1837–1847. <https://doi.org/10.1080/00036846.2011.554380>
- Frenette, M. (2004). The overqualified Canadian graduate: The role of the academic program in the incidence, persistence, and economic returns to overqualification. *Economics of Education Review*, 23(1), 29–45. [https://doi.org/10.1016/S0272-7757\(03\)00043-8](https://doi.org/10.1016/S0272-7757(03)00043-8)
- Green, C., Kler, P., & Leeves, G. (2007). Immigrant overeducation: Evidence from recent arrivals to Australia. *Economics of Education Review*, 26(4), 420–432. <https://doi.org/10.1016/j.econedurev.2006.02.005>
- Green, F., MacIntosh, S., Vignoles, A., & McIntosh, S. (1999). “Overeducation” and skills: Clarifying the concepts. *London, England: Centre for Economic Performance*.
- Green, F., & McIntosh, S. (2007). Is there a genuine under-utilization of skills amongst the over-qualified? *Applied Economics*, 39(4), 427–439. <https://doi.org/10.1080/00036840500427700>
- Green, F., & Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford Economic Papers*, 62(4), 740–763. <https://doi.org/10.1093/oep/gpq002>
- Groot, W. (1993). Overeducation and the returns to enterprise-related schooling. *Economics of Education Review*, 12(4), 299–309. [https://doi.org/10.1016/0272-7757\(93\)90064-N](https://doi.org/10.1016/0272-7757(93)90064-N)

- Groot, W. (1996). The incidence of, and returns to overeducation in the UK. *Applied Economics*, 28(10), 1345–1350. <https://doi.org/10.1080/000368496327895>
- Groot, W., & van den Brink, H. M. (1997). Allocation and the Returns to Over-education in the UK. *Education Economics*, 5(2), 169–183. <https://doi.org/10.1080/09645299700000014>
- Groot, W., & van den Brink, H. M. (2000a). Skill mismatches in the Dutch labor market. *International Journal of Manpower*, 21(8), 584–595. <https://doi.org/10.1108/01437720010379493>
- Groot, W., & van den Brink, H. M. (2000b). Overeducation in the labor market: A meta-analysis. *Economics of Education Review*, 19(2), 149–158. [https://doi.org/10.1016/S0272-7757\(99\)00057-6](https://doi.org/10.1016/S0272-7757(99)00057-6)
- Grunau, P., & Pecoraro, M. (2017). Educational mismatch and promotions to managerial positions: A test of the career mobility theory. *Applied Economics*, 49(12), 1226–1240. <https://doi.org/10.1080/00036846.2016.1213369>
- Gujarati, D. N. (2003). *Basic econometrics* (4th ed). McGraw Hill.
- Halapuu, V. (2015). *Oskuste ja hariduse mittevastavuse mõõtmise Eestis PIAACi andmete baasil*. <https://dspace.ut.ee/handle/10062/46966>
- Hartog, J. (2000). Over-education and earnings: Where are we, where should we go? *Economics of Education Review*, 19(2), 131–147. [https://doi.org/10.1016/S0272-7757\(99\)00050-3](https://doi.org/10.1016/S0272-7757(99)00050-3)
- Hartog, J., & Oosterbeek, H. (1988). Education, allocation and earnings in the Netherlands: Overschooling? *Economics of Education Review*, 7(2), 185–194. [https://doi.org/10.1016/0272-7757\(88\)90043-X](https://doi.org/10.1016/0272-7757(88)90043-X)
- Hersch, J. (1991). Education Match and Job Match. *The Review of Economics and Statistics*, 73(1), 140–144. <https://doi.org/10.2307/2109696>
- Hersch, J. (1995). Optimal 'mismatch' and promotions. *Economic Inquiry*, 33(4), 611. <https://doi.org/10.1111/j.1465-7295.1995.tb01884.x>

- Iaffaldano, M., & Muchinsky, P. (1985). *Job Satisfaction and Job Performance. A Meta-Analysis*. 97, 251–273. <https://doi.org/10.1037/0033-2909.97.2.251>
- Jākobsone, M. (2022). *Estonia—Education Strategy 2021-2035 | Digital Skills and Jobs Platform*. <https://digital-skills-jobs.europa.eu/en/actions/national-initiatives/national-strategies/estonia-education-strategy-2021-2035>
- Johnson, G. J., & Johnson, W. R. (2000). Perceived Overqualification and Dimensions of Job Satisfaction: A Longitudinal Analysis. *The Journal of Psychology*, 134(5), 537–555. <https://doi.org/10.1080/00223980009598235>
- Joona, P. A., Gupta, N. D., & Wadensjö, E. (2014). Overeducation among immigrants in Sweden: Incidence, wage effects and state dependence. *IZA Journal of Migration*, 3(1), 9. <https://doi.org/10.1186/2193-9039-3-9>
- Judge, T. A., Thoresen, C. J., Bono, J. E., & Patton, G. K. (2001). The job satisfaction–job performance relationship: A qualitative and quantitative review. *Psychological Bulletin*, 127, 376–407. <https://doi.org/10.1037/0033-2909.127.3.376>
- Kiker, B. F., Santos, M. C., & de Oliveira, M. M. (1997). Overeducation and undereducation: Evidence for Portugal. *Economics of Education Review*, 16(2), 111–125. [https://doi.org/10.1016/S0272-7757\(96\)00040-4](https://doi.org/10.1016/S0272-7757(96)00040-4)
- Krahn, H., & Lowe, G. S. (1998). Literacy Utilization in Canadian Workplaces. *Statistics Canada, Catalogue No. 89-552-MIE, No. 4*. <https://www150.statcan.gc.ca/n1/pub/89-552-m/89-552-m1998004-eng.pdf>
- Lamo, A., & Messina, J. (2010). Formal education, mismatch and wages after transition: Assessing the impact of unobserved heterogeneity using matching estimators. *Economics of Education Review*, 29(6), 1086–1099. <https://doi.org/10.1016/j.econedurev.2010.06.002>
- Leuven, E., & Oosterbeek, H. (2011). *Overeducation and mismatch in the labor market* (Working Paper No. 5523). IZA Discussion Papers. <https://www.econstor.eu/handle/10419/51653>

- Lindley, J. (2009). The over-education of UK immigrants and minority ethnic groups: Evidence from the Labour Force Survey. *Economics of Education Review*, 28(1), 80–89. <https://doi.org/10.1016/j.econedurev.2007.11.003>
- Mavromaras, K., McGuinness, S., & Fok, Y. K. (2009). Assessing the Incidence and Wage Effects of Overskilling in the Australian Labour Market. *Economic Record*, 85(268), 60–72. <https://doi.org/10.1111/j.1475-4932.2008.00529.x>
- Mavromaras, K., McGuinness, S., O’Leary, N., Sloane, P., & Wei, Z. (2013). Job Mismatches and Labour Market Outcomes: Panel Evidence on University Graduates. *Economic Record*, 89(286), 382–395. <https://doi.org/10.1111/1475-4932.12054>
- McGuinness, S. (2003). Graduate overeducation as a sheepskin effect: Evidence from Northern Ireland. *Applied Economics*, 35(5), 597–608. <https://doi.org/10.1080/0003684022000029284>
- McGuinness, S. (2006). Overeducation in the Labour Market. *Journal of Economic Surveys*, 20(3), 387–418. <https://doi.org/10.1111/j.0950-0804.2006.00284.x>
- McGuinness, S., & Bennett, J. (2007). Overeducation in the graduate labour market: A quantile regression approach. *Economics of Education Review*, 26(5), 521–531. <https://doi.org/10.1016/j.econedurev.2005.12.003>
- McGuinness, S., Pouliakas, K., & Redmond, P. (2018). Skills Mismatch: Concepts, Measurement and Policy Approaches. *Journal of Economic Surveys*, 32(4), 985–1015. <https://doi.org/10.1111/joes.12254>
- McGuinness, S., & Sloane, P. J. (2011). Labour market mismatch among UK graduates: An analysis using REFLEX data. *Economics of Education Review*, 30(1), 130–145. <https://doi.org/10.1016/j.econedurev.2010.07.006>

- McGuinness, S., & Wooden, M. (2009). Overskilling, Job Insecurity, and Career Mobility. *Industrial Relations: A Journal of Economy and Society*, 48(2), 265–286. <https://doi.org/10.1111/j.1468-232X.2009.00557.x>
- Naguib, C., Baruffini, M., & Maggi, R. (2019). Do wages and job satisfaction really depend on educational mismatch? Evidence from an international sample of master graduates. *Education + Training*, 61(2), 201–221. <https://doi.org/10.1108/ET-06-2018-0137>
- OECD. (n.d.). *OECD Statistics, table Educational attainment and labour market outcomes by skills*. Retrieved February 15, 2023, from <https://stats.oecd.org/>
- OECD. (1996). *Lifelong Learning for All*. <https://www.voced.edu.au/content/ngv%3A25305>
- OECD. (2013). *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*. OECD. <https://doi.org/10.1787/9789264204256-en>
- OECD. (2016a). International Codebook, PIAAC. Paris: OECD Publishing. <https://www.oecd.org/skills/piaac/data/>
- OECD. (2016b). *Programme for the International Assessment of Adult Competencies (PIAAC). Estonia* Public Use File (Version: Prgestp1.csv*)*. Paris: OECD Publishing.
- OECD. (2019a). *OECD Skills Strategy 2019—Estonia*. <https://www.oecd.org/estonia/Skills-Strategy-Estonia-EN.pdf>
- OECD. (2019b). *Technical Report of the Survey of Adult Skills (PIAAC) (3rd Edition)*. <https://www.oecd.org/skills/piaac/data/>
- OECD. (2020). *Increasing Adult Learning Participation: Learning from Successful Reforms*. OECD. <https://doi.org/10.1787/cf5d9c21-en>
- OECD. (2021). *Improving the Provision of Active Labour Market Policies in Estonia*. OECD. <https://doi.org/10.1787/31f72c5b-en>

- OECD. (2022). *Education at a Glance 2022: OECD Indicators*. Organisation for Economic Co-operation and Development. https://www.oecd-ilibrary.org/education/education-at-a-glance-2022_3197152b-en
- OECD. (2023). *Adult education level*. TheOECD. <http://data.oecd.org/eduatt/adult-education-level.htm>
- Pellizzari, M., & Fichen, A. (2013). *A New Measure of Skills Mismatch: Theory and Evidence from the Survey of Adult Skills (PIAAC)* (OECD Social, Employment and Migration Working Papers No. 153; OECD Social, Employment and Migration Working Papers, Vol. 153). <https://doi.org/10.1787/5k3tpt04lcnt-en>
- Perry, A., Wiederhold, S., & Ackermann-Piek, D. (2014). How Can Skill Mismatch be Measured? New Approaches with PIAAC. *Methods, data*, 38 Pages. <https://doi.org/10.12758/MDA.2014.006>
- Pietro, G. D., & Cutillo, A. (2006). University Quality and Labour Market Outcomes in Italy. *LABOUR: Review of Labour Economics & Industrial Relations*, 20(1), 37–62. <https://doi.org/10.1111/j.1467-9914.2006.00333.x>
- Quintini, G. (2011). *Over-Qualified or Under-Skilled: A Review of Existing Literature* (OECD Social, Employment and Migration Working Papers No. 121; OECD Social, Employment and Migration Working Papers, Vol. 121). <https://doi.org/10.1787/5kg58j9d7b6d-en>
- Robst, J. (2007). Education and job match: The relatedness of college major and work. *Economics of Education Review*, 26(4), 397–407. <https://doi.org/10.1016/j.econedurev.2006.08.003>
- Robst, J. (2008). Overeducation and College Major: Expanding the Definition of Mismatch Between Schooling and Jobs*. *The Manchester School*, 76(4), 349–368. <https://doi.org/10.1111/j.1467-9957.2008.01064.x>
- Rosen, S. (1972). Learning and Experience in the Labor Market. *The Journal of Human Resources*, 7(3), 326–342. <https://doi.org/10.2307/145087>

- Rumberger, R. W. (1987). The Impact of Surplus Schooling on Productivity and Earnings. *The Journal of Human Resources*, 22(1), 24–50. <https://doi.org/10.2307/145865>
- Santiago-Vela, A., & Hall, A. (2022). Distinguishing challenging and overchallenging jobs: Cognitive and affective skills mismatches and their impact on job satisfaction. *Research in Comparative and International Education*, 17454999221116486. <https://doi.org/10.1177/17454999221116486>
- Santiago-Vela, A., & Mergener, A. (2022). Gender overeducation gap in the digital age: Can spatial flexibility through working from home close the gap? *Social Science Research*, 106, 102727. <https://doi.org/10.1016/j.ssresearch.2022.102727>
- Sattinger, M. (1993). Assignment Models of the Distribution of Earnings. *Journal of Economic Literature*, 31(2), 831–880.
- Sicherman, N. (1991). “Overeducation” in the Labor Market. *Journal of Labor Economics*, 9(2), 101–122.
- Sicherman, N., & Galor, O. (1990). A Theory of Career Mobility. *Journal of Political Economy*, 98(1), 169–192.
- Sloane, P. J., Battu, H., & Seaman, P. T. (1999). Overeducation, undereducation and the British labour market. *Applied Economics*, 31(11), 1437–1453. <https://doi.org/10.1080/000368499323319>
- Sloane, P., & Mavromaras, K. (2014). Overeducation, skill mismatches, and labor market outcomes for college graduates. *IZA World of Labor*. <https://doi.org/10.15185/izawol.88>
- Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, 87(3), 355. <https://doi.org/10.2307/1882010>
- Statistics Estonia. (2022, August 3). *Eesti naised on endiselt Euroopa ühed kõrgemalt haritumad / Statistikaamet*. <https://www.stat.ee/et/uudised/eesti-naised-endiselt-euroopa-uhed-korgemalt-haritumad>

- Statistics Estonia. (2023a). *Haridus / Statistikaamet*. <https://rahvaloendus.ee/et/tulemused/haridus>
- Statistics Estonia. (2023b). *Palgalõhe / Statistikaamet*. <https://www.stat.ee/et/find-statistics/statistics-theme/work-life/wages-and-salaries-and-labour-costs/palgalohe>
- Thurow, L. C. (1975). *Generating Inequality*. Basic Books.
- Tsang, M. C. (1987). The impact of underutilization of education on productivity: A case study of the U.S. Bell companies. *Economics of Education Review*, 6(3), 239–254. [https://doi.org/10.1016/0272-7757\(87\)90003-3](https://doi.org/10.1016/0272-7757(87)90003-3)
- Tsang, M. C., & Levin, H. M. (1985). The economics of overeducation. *Economics of Education Review*, 4(2), 93–104. [https://doi.org/10.1016/0272-7757\(85\)90051-2](https://doi.org/10.1016/0272-7757(85)90051-2)
- Tsang, M. C., Rumberger, R. W., & Levin, H. M. (1991). The Impact of Surplus Schooling on Worker Productivity. *Industrial Relations: A Journal of Economy and Society*, 30(2), 209–228. <https://doi.org/10.1111/j.1468-232X.1991.tb00786.x>
- Vahey, S. P. (2000). The great Canadian training robbery: Evidence on the returns to educational mismatch. *Economics of Education Review*, 19(2), 219–227. [https://doi.org/10.1016/S0272-7757\(98\)00029-6](https://doi.org/10.1016/S0272-7757(98)00029-6)
- Verdugo, R. R., & Verdugo, N. T. (1989). The Impact of Surplus Schooling on Earnings: Some Additional Findings. *The Journal of Human Resources*, 24(4), 629–643. <https://doi.org/10.2307/145998>
- Verhaest, D., & Omey, E. (2006). The Impact of Overeducation and Its Measurement. *Social Indicators Research*, 77(3), 419–448.
- Verhaest, D., & Omey, E. (2010). The determinants of overeducation: Different measures, different outcomes? *International Journal of Manpower*, 31(6), 608–625. <https://doi.org/10.1108/01437721011073337>
- Verhofstadt, E., & Omey, E. (2003). *The impact of education on job satisfaction in the first job*.

- Vieira, J. A. C. (2005). Skill mismatches and job satisfaction. *Economics Letters*, 89(1), 39–47.
<https://doi.org/10.1016/j.econlet.2005.05.009>
- Vila, L. E., Garcia-Aracil, A., & Mora, J.-G. (2007). The Distribution of Job Satisfaction among Young European Graduates: Does the Choice of Study Field Matter? *The Journal of Higher Education*, 78(1), 97–118.
- Vroom, V. H. (1964). *Work and Motivation*. John Wiley S- Sons, Inc.
- Wen, L., & Maani, S. A. (2019). Job mismatches and career mobility. *Applied Economics*, 51(10), 1010–1024. <https://doi.org/10.1080/00036846.2018.1524569>
- Wirz, A., & Atukeren, E. (2004). Overeducation in the Swiss Labour Market: Does Anything Go Wrong? *KOF Working Papers*, 85. <https://doi.org/10.3929/ethz-a-004721092>

APPENDICES

Appendix 1. List of variables used in the analysis

Variable	Description	Coding
Dependent variables		
Overeducated	Based on highest obtained education level and respondent's perceived qualification level required to get the job	1 – undereducated 0 – not undereducated
Undereducated		1 – undereducated 0 – not undereducated
Overskilled	Based on standardized measures computed for proficiency level in numeracy for each occupation	1 – overskilled 0 – not overskilled
Underskilled		1 – underskilled 0 – not underskilled
Job satisfaction	Based on the self-assessed level of job satisfaction	1 – extremely satisfied 2 – satisfied 3 – neither satisfied nor dissatisfied 4 – dissatisfied 5 – extremely dissatisfied
Control variables		
Gender	Respondent's gender	1 – male 0 – female
Age	Respondent's age	Continuous, ages 20-64
Cohabitation status	Respondent living with a spouse or a partner	1 – Is living with a spouse or a partner 0 – Is not living with a spouse or a partner
Children	Whether the respondent has children or not	1 – has children 0 – doesn't have children
Highest education	Highest level of formal education obtained, based on international ISCED classification	1 – lower secondary or less (ISCED 1,2, 3C short or less) 2 – upper secondary (ISCED 3A-B, C long) 3 – post-secondary, non-tertiary (ISCED 4A-B-C) 4 – professional degree (ISCED 5B) 5 – bachelor degree (ISCED 5A) 6 – master/research degree (ISCED 5A/6). Note: The 5 th classification pertains to a bachelor's degree obtained through the 3+2 education system, while the 6 th classification includes the master's and doctoral degrees, along with the previous 4+2 education system's bachelor's degree and Soviet-era diploma-based specialist training, which are now considered equivalent to a master's degree.

Appendix 1 continued

Field of study	Respondent's highest qualification's field of study	1 – General programmes 2 – Teacher training and education science 3 – Humanities, languages and arts 4 – Social sciences, business and law 5 – Science, mathematics and computing 6 – Engineering, manufacturing and construction 7 – Agriculture and veterinary 8 – Health and welfare 9 – Services
Immigration status	Whether the respondent was born in Estonia or elsewhere	1 – Not born in country 0 – Born in country
Earnings	Respondent's monthly earnings including bonuses	Logarithm
Work experience	Respondent's work experience in years	1 – less than 4 years 2 – 4-5 years 3 – 6-15 years 4 – more than 15 years
AET	Whether respondent participated in formal or non-formal adult education/training in the 12 months preceding the survey	1 – participated 0 – did not participate
Economic sector	Economic sector the respondent works in	1 – private sector 0 – public sector
Firm size	Amount of people working for the respondent's employer	1 – 1 to 10 people 2 – 11 to 50 people 3 – 51 to 250 people 4 – 251 to 1000 people 5 – More than 1000 people
Type of contract	The type of contract the respondent has in their current job	1 – indefinite contract 0 – fixed-term contract
Employment status	Whether respondent work part-time or full-time	1 – part-time 0 – full-time

Appendix 1 continued

Industry	Industry classification of respondent's job at 1-digit level (ISIC rev 4), aggregated	<ul style="list-style-type: none"> 1 – Agriculture, forestry and fishing 2 – Manufacturing, mining and quarrying and other industrial activities 3 – Construction 4 – Wholesale and retail trade; repair of motor vehicles and motorcycles 5 – Transportation and storage 6 – Accommodation and food service activities 7 – Information and communication 8 – Financial, insurance and real estate activities 9 – Professional, scientific and technical activities 10 – Administrative, service & leisure activities 11 – Public administration and defense; compulsory social security 12 – Education 13 – Human health and social work activities
Occupation	Occupational classification of respondent's job at 1-digit level (ISCO 2008)	<ul style="list-style-type: none"> 1 – Legislators, senior officials and managers 2 – Professionals 3 – Technicians and associate professionals 4 – Clerks 5 – Service workers and shop and market sales workers 6 – Skilled agricultural and fishery workers 7 – Craft and related trades workers 8 – Plant and machine operators and assemblers 9 – Elementary occupations
Health	The respondent's current health state	<ul style="list-style-type: none"> 1 – Excellent 2 – Very good 3 – Good 4 – Fair 5 – Poor
Numeracy score levels	Numeracy proficiency scores divided into levels suggested by (OECD, 2019b)	<ul style="list-style-type: none"> 1 – Below level 1 (0 to 175) 2 – Level 1 (176 to 225) 3 – Level 2 (226 to 275) 4 – Level 3 (276 to 325) 5 – Level 4 (326 to 375) 6 – Level 5 (376 to 500)
Job autonomy	Representing respondent's autonomy at their current job	Standardized variable of 4 job autonomy variables, where a higher value means more autonomy and a lower value less autonomy

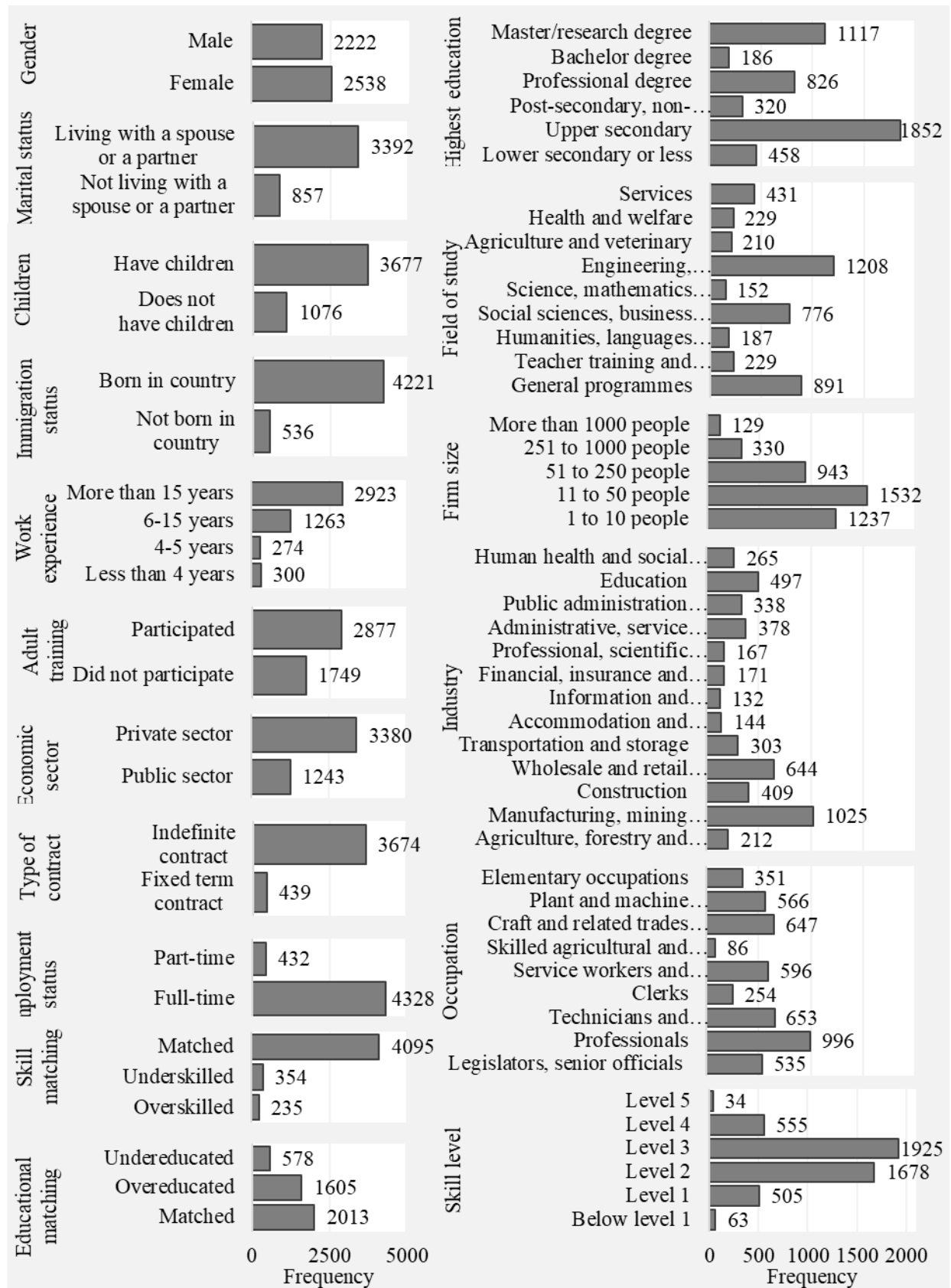
Source: (OECD, 2016a)

Appendix 2. Descriptive statistics

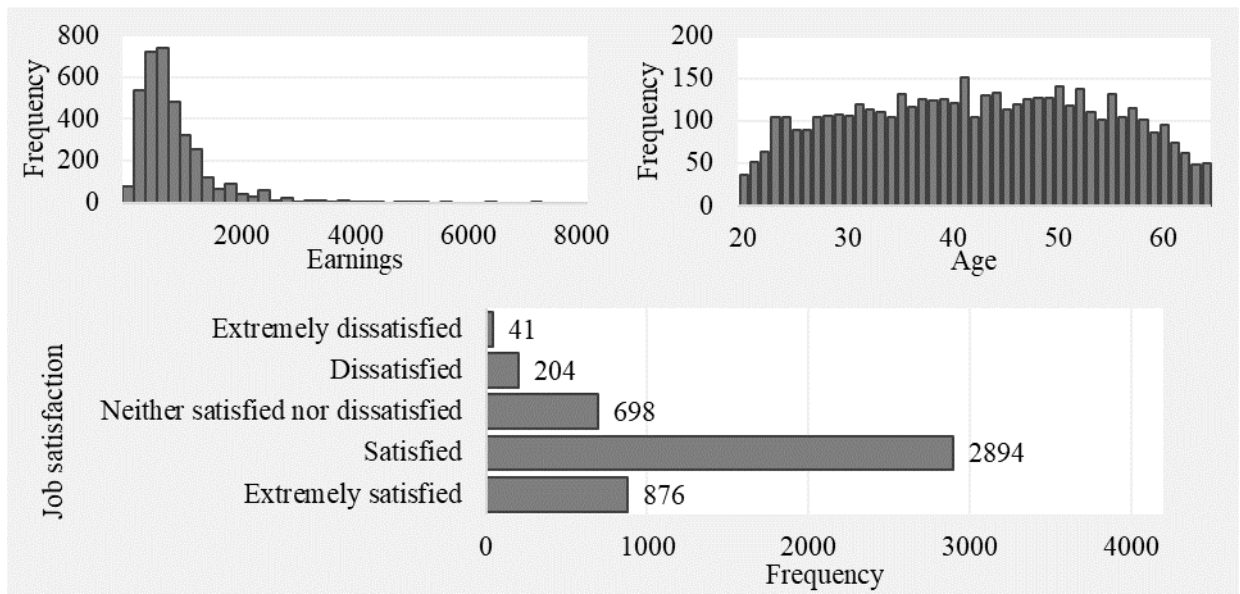
Variable	Nbr of obs	Mean	Std. dev	Min	Max
Dependent variables					
Overeducated	4,760	0.337	0.473	0	1
Undereducated	4,760	0.121	0.327	0	1
Overskilled	4,760	0.049	0.217	0	1
Underskilled	4,760	0.074	0.262	0	1
Job satisfaction	4,713	2.075	0.762	0	5
Control variables					
Gender	4,760	0.467	0.499	0	1
Age (min 20, max 64)	4,760	42.098	11.672	20	64
Cohabitation status	4,249	0.798	0.401	0	1
Children	4,753	0.774	0.419	0	1
Highest education	4,759	3.374	1.754	1	6
Field of study	4,313	4.684	2.567	1	9
Immigration status	4,757	0.887	0.316	0	1
Earnings	3,644	907.623	688.141	34.667	7222.222
Work experience	4,760	3.430	0.859	1	4
AET	4,626	0.622	0.485	0	1
Economic sector	4,623	0.731	0.443	0	1
Firm size	4,171	2.181	1.042	1	5
Type of contract	4,113	0.893	0.309	0	1
Employment status	4,760	0.091	0.287	0	1
Industry	4,685	6.221	4.021	1	13
Occupation	4,684	4.529	2.644	1	9
Health	4,751	3.005	0.938	1	5
Numeracy score 1	4,760	277.445	43.228	91.219	421.214
Numeracy score 2	4,760	277.310	43.051	92.348	406.201
Numeracy score 3	4,760	278.102	43.388	92.057	430.697
Numeracy score 4	4,760	277.616	43.238	68.809	434.065
Numeracy score 5	4,760	277.745	43.630	70.826	439.428
Numeracy score 6	4,760	277.359	43.773	105.892	443.964
Numeracy score 7	4,760	277.462	43.647	72.759	440.552
Numeracy score 8	4,760	277.522	43.973	92.915	463.847
Numeracy score 9	4,760	277.131	43.780	59.504	417.34
Numeracy score 10	4,760	277.556	43.409	98.245	433.506
Job autonomy	4,717	-0.000	1.000	-2.376	1.909

Source: (OECD, 2016b), author's calculations

Appendix 3. Frequency distribution of control variables



Appendix 3 continued



Source: (OECD, 2016b), author's calculations

Appendix 4. Marginal effects with mismatches as dependent variables

Variable	Overeducation	Undereducation	Overskill	Underskill
Gender (reference: female)				
Male = 1	-0.037*	0.030*	0.052***	-0.047***
	(0.021)	(0.018)	(0.011)	(0.012)
Age	0.0015	0.001	-0.002**	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Cohabitation status (reference: not living with a partner or a spouse)				
Living with a partner or a spouse	-0.028	0.043**	0.020**	0.010
	(0.024)	(0.017)	(0.010)	(0.011)
Having children (reference: no children)				
Has children	-0.003	0.015	-0.011	0.002
	(0.027)	(0.023)	(0.013)	(0.017)
Highest education (reference: upper secondary)				
Lower secondary or less	–	0.209***	–	0.189***
	–	(0.062)	–	(0.066)
Post-secondary, non-tertiary	0.292***	-0.033	0.030*	-0.022
	(0.029)	(0.028)	(0.017)	(0.022)
Professional degree	0.283***	-0.164***	0.024*	-0.037**
	(0.020)	(0.018)	(0.012)	(0.018)
Bachelor degree	0.475***	-0.210***	0.067**	-0.048**
	(0.036)	(0.017)	(0.032)	(0.024)
Master/research degree	0.569***	–	0.120***	-0.078***
	(0.017)	–	(0.022)	(0.015)
Field of study (reference: general programmes)				
Teacher training and education science	0.030	-0.077**	-0.050*	0.062**
	(0.044)	(0.037)	(0.030)	(0.030)
Humanities, languages and arts	-0.084*	0.058	-0.046	-0.017
	(0.044)	(0.067)	(0.028)	(0.023)
Social sciences, business and law	0.039	-0.020	-0.049**	0.011
	(0.032)	(0.029)	(0.022)	(0.017)
Science, mathematics and computing	0.039	0.046	0.012	-0.041*
	(0.047)	(0.067)	(0.035)	(0.023)
Engineering, manufacturing and construction	0.024	-0.031	-0.049**	0.0036
	(0.028)	(0.021)	(0.020)	(0.013)
Agriculture and veterinary	0.094**	-0.074**	-0.052**	-0.011
	(0.042)	(0.033)	(0.025)	(0.020)
Health and welfare	-0.060	-0.039	-0.027	0.060
	(0.052)	(0.040)	(0.037)	(0.038)
Services	0.037	-0.038	-0.062***	0.005
	(0.034)	(0.027)	(0.021)	(0.019)
Immigration status (reference: born in country)				
Not born in country	-0.026	0.040*	-0.001	0.052***
	(0.027)	(0.024)	(0.014)	(0.017)

Appendix 4 continued

Work experience (reference: less than 4 years)				
4-5 years	-0.127**	0.0098	-0.021	-0.063*
	(0.054)	(0.043)	(0.022)	(0.038)
6-15 years	-0.073	0.0021	-0.025	-0.039
	(0.049)	(0.039)	(0.022)	(0.034)
More than 15 years	-0.117**	0.018	-0.0041	-0.028
	(0.059)	(0.046)	(0.028)	(0.041)
AET (reference: did not participate)				
Participated	-0.105***	0.070***	0.011	-0.012
	(0.019)	(0.016)	(0.009)	(0.011)
Economic sector (reference: public sector)				
Private sector	0.040	-0.019	-0.004	-0.004
	(0.031)	(0.029)	(0.013)	(0.016)
Firm size (reference: 0 to 10 people)				
11 to 50 people	-0.034	0.015	-0.002	0.009
	(0.021)	(0.017)	(0.010)	(0.012)
51 to 250 people	-0.067***	0.027	0.018	0.021
	(0.024)	(0.021)	(0.012)	(0.014)
251 to 1000 people	-0.091***	-0.001	0.010	-0.025
	(0.032)	(0.030)	(0.016)	(0.016)
More than 1000 people	-0.045	-0.025	0.012	0.039
	(0.049)	(0.042)	(0.022)	(0.035)
Type of contract (reference: fixed term contract)				
Indefinite contract	0.070***	-0.044	-0.0026	-0.045**
	(0.026)	(0.027)	(0.014)	(0.020)
Employment status (reference: full-time)				
Part-time	0.051	-0.025	-0.006	-0.010
	(0.033)	(0.030)	(0.016)	(0.017)
Industry (reference: manufacturing, mining and quarrying and other industrial activities)				
Agriculture, forestry and fishing	-0.024	0.061	0.004	0.013
	(0.055)	(0.052)	(0.031)	(0.034)
Construction	-0.019	-0.012	-0.017	-0.010
	(0.037)	(0.027)	(0.017)	(0.022)
Wholesale and retail trade; repair of motor vehicles and motorcycles	-0.084***	-0.017	-0.004	-0.020
	(0.032)	(0.025)	(0.015)	(0.017)
Transportation and storage	-0.097***	-0.011	0.003	0.010
	(0.036)	(0.029)	(0.017)	(0.024)
Accommodation and food service activities	-0.074	0.015	-0.014	0.016
	(0.056)	(0.044)	(0.025)	(0.035)
Information and communication	0.033	-0.054*	0.052	-0.065***
	(0.053)	(0.033)	(0.034)	(0.019)
Financial, insurance and real estate activities	-0.078	0.025	0.045	-0.037
	(0.048)	(0.052)	(0.033)	(0.024)
Professional, scientific and technical activities	-0.132**	-0.003	0.008	-0.045*
	(0.052)	(0.056)	(0.025)	(0.026)

Appendix 4 continued

Administrative, service & leisure activities	-0.054 (0.043)	-0.019 (0.034)	-0.005 (0.019)	-0.015 (0.023)
Public administration and defense; compulsory social security	-0.084* (0.044)	-0.004 (0.038)	-0.019 (0.017)	-0.007 (0.027)
Education	-0.119*** (0.043)	0.096** (0.049)	-0.027* (0.016)	0.002 (0.025)
Human health and social work activities	-0.173*** (0.048)	0.074 (0.051)	-0.006 (0.025)	-0.025 (0.025)
Occupation (reference: legislators, senior officials and managers)				
Professionals	0.001 (0.023)	0.107** (0.051)	-0.017* (0.011)	-0.053** (0.026)
Technicians and associate professionals	0.111*** (0.028)	-0.118*** (0.045)	-0.007 (0.013)	-0.049* (0.029)
Clerks	0.225*** (0.037)	-0.151*** (0.050)	0.029 (0.025)	-0.083*** (0.031)
Service workers and shop and market sales workers	0.333*** (0.030)	-0.282*** (0.040)	0.096*** (0.028)	-0.101*** (0.027)
Skilled agricultural and fishery workers	0.393*** (0.082)	-0.211** (0.090)	0.031 (0.068)	-0.073 (0.052)
Craft and related trades workers	0.319*** (0.032)	-0.223*** (0.044)	-0.001 (0.015)	-0.076** (0.031)
Plant and machine operators and assemblers	0.434*** (0.029)	-0.294*** (0.040)	0.028 (0.020)	-0.103*** (0.028)
Elementary occupations	0.575*** (0.032)	-0.333*** (0.039)	0.061* (0.034)	-0.109*** (0.028)
Numeracy score	-0.001** (0.000)	0.000 (0.000)	– –	– –
Observations	3,011	2,291	3,011	3,066
Pseudo R2	0.229	0.217	0.141	0.119

Source: (OECD, 2016b), author's calculations

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 5. Marginal effects with job satisfaction as dependent variable

Variable	Extremely satisfied	Satisfied	Neither satisfied nor dissatisfied	Dissatisfied	Extremely dissatisfied
Gender (reference: female)					
Male = 1	-0.042*** (0.012)	-0.005** (0.002)	0.031*** (0.009)	0.013*** (0.004)	0.003*** (0.001)
Age	0.001 (0.001)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Cohabitation status (reference: not living with a partner or a spouse)					
Living with a partner or a spouse	0.030** (0.013)	0.005 (0.004)	-0.023** (0.011)	-0.010** (0.005)	-0.002** (0.001)
Having children (reference: no children)					
Has children	0.006 (0.017)	0.001 (0.002)	-0.004 (0.013)	-0.002 (0.005)	-0.000 (0.001)
Highest education (reference: upper secondary)					
Lower secondary or less	0.008 (0.020)	0.000 (0.001)	-0.006 (0.014)	-0.002 (0.005)	-0.001 (0.001)
Post-secondary, non-tertiary	-0.044*** (0.017)	-0.012 (0.008)	0.036** (0.015)	0.016** (0.007)	0.004** (0.002)
Professional degree	0.002 (0.016)	0.000 (0.001)	-0.002 (0.011)	-0.001 (0.005)	-0.000 (0.001)
Bachelor degree	0.002 (0.032)	0.000 (0.001)	-0.002 (0.022)	-0.001 (0.009)	-0.000 (0.002)
Master/research degree	-0.014 (0.017)	-0.002 (0.002)	0.010 (0.012)	0.004 (0.005)	0.001 (0.001)
Immigration status (reference: born in country)					
Not born in country	-0.019 (0.017)	-0.003 (0.004)	0.015 (0.014)	0.006 (0.006)	0.001 (0.001)
Earnings (ln)	0.056*** (0.011)	0.005** (0.003)	-0.041*** (0.008)	-0.017*** (0.004)	-0.004*** (0.001)
Economic sector (reference: public sector)					
Private sector	-0.039*** (0.013)	-0.001 (0.002)	0.027*** (0.008)	0.011*** (0.004)	0.002*** (0.001)
Firm size (reference: 0 to 10 people)					
11 to 50 people	-0.019 (0.014)	-0.000 (0.001)	0.013 (0.009)	0.005 (0.004)	0.001 (0.001)
51 to 250 people	-0.030* (0.015)	-0.002 (0.002)	0.021* (0.011)	0.009* (0.005)	0.002* (0.001)
251 to 1000 people	-0.047** (0.019)	-0.007 (0.006)	0.036** (0.015)	0.015** (0.007)	0.003** (0.002)
More than 1000 people	-0.002 (0.037)	0.000 (0.002)	0.001 (0.024)	0.001 (0.009)	0.000 (0.002)
Type of contract (reference: fixed term contract)					
Indefinite contract	0.021 (0.017)	0.004 (0.005)	-0.017 (0.014)	-0.007 (0.006)	-0.002 (0.001)

Appendix 5 continued

Employment status (reference: full-time)					
Part-time	0.047*	-0.003	-0.030*	-0.012**	-0.003*
	(0.028)	(0.006)	(0.016)	(0.006)	(0.001)
Job autonomy	0.054***	0.005**	-0.039***	-0.016***	-0.004***
	(0.006)	(0.002)	(0.005)	(0.002)	(0.001)
Health (reference: excellent)					
Very good	-0.086**	0.028*	0.041***	0.014***	0.003***
	(0.035)	(0.016)	(0.014)	(0.005)	(0.001)
Good	-0.115***	0.028*	0.061***	0.022***	0.004***
	(0.034)	(0.016)	(0.013)	(0.005)	(0.001)
Fair	-0.140***	0.022	0.082***	0.030***	0.006***
	(0.035)	(0.016)	(0.015)	(0.006)	(0.002)
Poor	-0.159***	0.011	0.100***	0.039**	0.008**
	(0.044)	(0.025)	(0.033)	(0.015)	(0.004)
Overeducated	-0.031***	-0.004*	0.023**	0.010**	0.002**
	(0.012)	(0.002)	(0.009)	(0.004)	(0.001)
Undereducated	0.001	0.000	-0.001	-0.000	0.000
	(0.016)	(0.001)	(0.012)	(0.005)	(0.001)
Overskilled	-0.030	-0.007	0.024	0.010	0.002
	(0.020)	(0.008)	(0.018)	(0.008)	(0.002)
Underskilled	-0.003	-0.000	0.003	0.001	0.000
	(0.019)	(0.002)	(0.014)	(0.006)	(0.001)
Observations	3,101				
Pseudo R2	0.0427				

Source: (OECD, 2016b), author's calculations

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 6. Non-exclusive licence

A non-exclusive licence for reproduction and publication of a graduation thesis¹

I Gerda Fatal

1. Grant Tallinn University of Technology free licence (non-exclusive licence) for my thesis „Education-job mismatch or skills-job mismatch in Estonia: what matters more for job satisfaction?“,

supervised by Heili Hein,

1.1 to be reproduced for the purposes of preservation and electronic publication of the graduation thesis, incl. to be entered in the digital collection of the library of Tallinn University of Technology until expiry of the term of copyright;

1.2 to be published via the web of Tallinn University of Technology, incl. to be entered in the digital collection of the library of Tallinn University of Technology until expiry of the term of copyright.

2. I am aware that the author also retains the rights specified in clause 1 of the non-exclusive licence.

3. I confirm that granting the non-exclusive licence does not infringe other persons' intellectual property rights, the rights arising from the Personal Data Protection Act or rights arising from other legislation.

08.05.2023

¹ The non-exclusive licence is not valid during the validity of access restriction indicated in the student's application for restriction on access to the graduation thesis that has been signed by the school's dean, except in case of the university's right to reproduce the thesis for preservation purposes only. If a graduation thesis is based on the joint creative activity of two or more persons and the co-author(s) has/have not granted, by the set deadline, the student defending his/her graduation thesis consent to reproduce and publish the graduation thesis in compliance with clauses 1.1 and 1.2 of the non-exclusive licence, the non-exclusive license shall not be valid for the period