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OVEREDUCATION, EDUCATIONAL MISMATCH AND LABOR MARKET PERFORMANCE

Master's Thesis

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I have written this Master's Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

Table of Content

Abstract

The primary purpose of this thesis is to estimate the potential impact of educational mismatch on labor market performance, with a particular focus on wage dynamics. Using data from the Estonian Labor Force Survey for the period 2010 to 2020, the study employs the mean and mode measurement methods to define the required years of education for the occupations under consideration. The empirical analysis centers on the estimation of wage specifications proposed by Verdugo and Verdugo and Duncan and Hoffman, across genders. Key econometric issues, unobserved ability heterogeneity and potential measurement errors, are addressed through the utilization of panel estimators and instrumental variables. The estimation results for Verdugo and Verdugo's model suggest that overeducated employees earn less than equally educated individuals who work in positions that require their education level. In contrast, undereducated ones earn more than their peers with the same education level and in well-matched jobs. Simultaneously, the outcomes of Duncan and Hoffman's model indicate that there is an earning advantage for overeducated workers compared to those in the same positions but correctly matched, while the opposite holds true for undereducated employees. The influence of gender is also noteworthy, as females consistently have higher returns for the required years of education than males. Overall, the investigation of the main determinants of wages discloses that jobs' educational requirements have an essential impact on wages. The fixed effects instrumental variable estimates support these findings, except for female employees below 35, whose actual education levels matter more for their wages than the job requirements. Finally, the thesis recommends that public authorities should provide proper career counseling to prevent educational mismatch cases from increasing to unnecessarily high levels. This action may potentially protect the labor market and decrease the incidence of educational mismatch.

1. Introduction

The issue of overeducation has been a concern since the mid-20th century, with notable attention in the 1970s. Scholars like Freeman underscored the challenge of educational expansion outpacing demand for skills (Freeman, 1976). Duncan and Hoffman (1981) initiated the empirical evaluation of overeducation and its impact on wages, and since then, it has become significant. Currently, the literature on the subject of educational mismatch is quite resourceful. It has also been widely acknowledged that the increasing trend in the education level of individuals in advanced industrial nations has continued over the recent decades (Barro & Lee, 2001). Notably, a considerable degree of educational mismatch seems to be present in Western labor markets, with estimates suggesting that between 20% and 50% of employees possess more years of schooling than their job necessitates (Bauer, 2002; Marsikova & Urbanek, 2015). The same period coincided with the requirements of jobs experiencing elevation as well. However, the upward pattern for educational attainment was stronger than the growth in job requirements (Åberg, 2003).

Skills mismatch arises when there is a disequilibrium between the skills available and skills demanded by the labor market, including both surplus and deficit scenarios. It's crucial to note that throughout the thesis, the term "educational mismatch" will refer to a scenario where a worker's educational attainment does not align with the educational requirements of the job—a situation described by the term "vertical mismatch". Individuals will be denoted as “overeducated” if their actual education levels are beyond the required level, while the opposite holds for “undereducated” individuals. Experts consider it essential to differentiate vertical and “horizontal mismatch”, the latter meaning a situation where workers opt for jobs that require skills outside the area of their academic background (Kupets, 2016).

Richard B. Freeman's early work "The Overeducated American" (Freeman, 1976) reported a declining rate of return to higher education in the U.S. in the 70s, stressing concerns about the consequences of overeducation on economic outcomes. Simultaneously, Heckman and Krueger pointed out that the economic value of a bachelor’s degree in the 70s descended in the U.S.A (Heckman & Krueger, 2005). The persistence of overeducation as an area of study, from Freeman to contemporary research, emphasizes the importance of the topic in understanding growing labor market dynamics.

Labor mismatch, which encompasses skill and educational mismatch, is expected to yield negative consequences on both individuals and the economy, such as a reduction in productivity and growth (McGowan & Andrews, 2015). If firms face challenges in finding workers whose skills align with new technological developments, then it might make them reluctant to upgrade their capital stock with R&D investments. The negative effects on productivity may also result from incomplete exploitation of the potential of workers. Consequently, the decline in productivity gains is expected to lead to reduced wages and a decrease of overall economic growth, which could potentially exacerbate structural unemployment (Esposito & Scicchitano, 2022; Skott & Auerbach, 2005). McGuinness and Sloane also emphasized the importance of addressing the overeducation issue as it could be one of the supporting factors of decreased welfare at the individual level (McGuinness & Sloane, 2011).

The primary objective of this thesis is to estimate the potential impact of educational mismatch on labor market performance, with a particular focus on wage dynamics. Educational mismatch has been an investigation point in many scholarly works that examine the matter for European Union countries (Davia et al., 2017; Marsikova & Urbanek, 2015; Wincenciak et al., 2022), as understanding this phenomenon's influence on earnings is crucial for developing effective labor market policies. When concentrating on the outcomes of these studies, the Baltic region countries (Estonia, Latvia, and Lithuania) draw the attention for their high mismatch incidence. These economies faced a transition from centrally planned to market-orientated type, which consequently led to alterations in the labor supply structure. One of the driving factors of these supply changes is the growing interest for higher education, especially among young generations (Irena et al., 2008). Post-transition, the labor markets offered better opportunities for individuals with tertiary education. In a broader context, the Baltic countries possess shared economical and historical backgrounds and have commonalities regarding labor market characteristics and educational structures. Within the region, Estonia stands out, as the country has been ranked highly for its levels of overeducation in the labor market by multiple studies. An analysis conducted by the European Commission provided that approximately 35% of the Estonian high-skilled labor force is susceptible to overeducation, placing Estonia among the top countries with overeducation (European Commission, 2015). Halapuu and Valk (2013) obtained supporting results, with an overeducation incidence of 30%. Additionally, the European Centre for the Development of Vocational Training (CEDEFOP) (2015, pp. 33–37) obtained over-qualification rate in the range of 25-30% for the Estonian labor force. Therefore, consideration of Estonia for the thorough analysis to uncover the dynamics of educational mismatch and its impact on wages would be useful not only in the context of Estonia but also would exhibit insights in the context of Baltic region. To the knowledge of the author, there are studies that have examined the subject, however, this thesis analyzes more recent data for updated results, and brings an additional level of empirical clarity by employing various econometric techniques to achieve unbiased outcomes. Furthermore, the study measures the educational mismatch phenomenon through different methods and investigates how its impact on wages performs across gender and age groups. Subsequently, these outcomes are useful to compare the labor market situations and determine where Estonia stands in the region. Overall, the question which is assessed throughout the analysis is the following: To what extent does educational mismatch influence wages in the labor market?

To comprehensively understand the topic and answer the research question, the thesis has the following structure. The next section provides a theoretical background through the analysis of existing literature and further details about the mismatch phenomenon for a thorough understanding. The literature on the topic focuses on two main theories: Career Mobility theory and Human Capital theory. According to the human capital theory (Becker, 1962), the wages individuals earn are closely connected to the amount of effort they invest in their education. In essence, this theory suggests that if there is an oversupply of a certain type of workers in the job market compared to demand, it will lead to a decline in earnings. On the other hand, Career Mobility theory by Sicherman and Galor extends the human capital theory by stating that the impact of schooling on career mobility is stronger in occupations with lower returns to education (Sicherman & Galor, 1990). According to empirical findings, the authors demonstrate that individuals with higher education levels are more inclined to transition to higher-level occupations within a given field.

Section 3 of the thesis covers a detailed description of the data and explains the methodologies used to obtain the necessary variables for the empirical analysis. The data employed is cross-sectional individual-level data from the Estonian Labor Force Survey (LFS) conducted by the Statistical Office of Estonia for the period of 2010-2020. This survey is representative of the population who are permanent Estonian residents aged 15-74, and contains variables related to individuals' education levels, demographic backgrounds, and employment history, which are crucial for the regression analysis. The required years of education for considered occupations, one of the most essential variables for the analysis, are defined by the mean and mode measurement methods. The section concludes with descriptive statistics and the comparison of education-related variables derived under these methods.

The empirical approach section includes a thorough overview of the wage specifications proposed by Verdugo and Verdugo (1989) and Duncan and Hoffman (1981), which are employed for the regression analyses. Moreover, the section discusses testing several models against the mentioned specifications to identify the main sources of impact on wages. One of these models is the human capital model, which assumes that individuals' wages are determined by their education rather than the requirements of a position. At the same time, the other one is the job-competition model, which suggests that wages are mainly determined based on the individuals' job characteristics rather than the characteristics of the individuals themselves. Additionally, the study incorporates panel estimation techniques and instrumental variables to account for potential bias-creating econometric issues.

The main findings from the empirical analysis are discussed in Section 5. The obtained outcomes align with the existing literature, indicating that jobs' educational requirements have an essential impact on wages. The analysis by gender shows that being overeducated brings relatively bigger earning advantage for females than males compared to their peers in the same positions but adequately matched. Simultaneously, when respondents' ages become part of the estimations, the analysis discloses quite intriguing results, especially for female employees below the age of 35. The tested models lead to a conclusion that these individual's wages are mainly determined by their attained level of education rather than the requirements of the job. Additionally, the last sub-section compares the study results with those for the Baltic region countries found in the literature to examine whether there is a regional pattern for mismatch incidence. Finally, Section 6 concludes with reflections on the findings and necessary actions that could be taken to stabilize and potentially decrease cases of mismatch.

Keywords: educational mismatch, overeducation, undereducation, job requirements, actual education.

CERCS: S180 Economics, econometric, economic theory, economic systems, economic policy

2. Theoretical Background Through Existing Literature

The literature commonly utilizes the Human Capital theory and Career Mobility theory for exploring the subject of educational mismatch. The Human Capital theory (Becker, 1962) supports the idea that individuals' investments in their academic background will present themselves positively in terms of economic returns. Importantly, the theory challenges the notion that an excess number of skilled workers results with underutilization of their skills. Instead, it claims that such a scenario instigates a temporary reduction in the relative wages of these skilled workers. The key idea here is that the market dynamically responds to shifts in the equilibrium between the supply and demand for specific skills, thereby influences the earnings workers receive for the education they have acquired. The literature tests this theory by utilizing the human capital model hypothesis, which assumes that individuals' wages are determined by their education levels and other personal features which can influence their productivity level, rather than the requirements of a job they perform.

The Career Mobility theory was modeled by Sicherman and Galor (1990) by building on the framework of Human Capital theory. They empirically revealed that having a high academic degree is essential in assisting individuals to maintain a successful career and reach higher-level positions. Sicherman, in his next article, expands this basis by offering that workers willingly accept temporary overeducation as they believe in the high probability of having advanced career prospects for specific jobs (Sicherman, 1991). The theory states that the wage penalty connected to overeducation is offset by future wage growth arising from promotions. Theoretically, the cases of pay penalties and lower job satisfaction occurring to overeducated individuals are expected to motivate them to search and switch to higher level occupations. This position shift is anticipated to result in a greater rate of wage growth compared to what they earned before making this move. Overall, this section will consider reputable articles that analyze related topics by using the mentioned theoretical approaches. However, the differences in data and regression techniques will lead to various outputs.

2.1. Human Capital Model

This topic was trending in the Euro area at the beginning of 2000s as educational mismatch was considered to play a part in the causality of differences in wages across various sectors. Potential impacts on wages and wage growth arising from educational mismatch were investigated by Korpi and Tåhlin (2009) in the case of Sweden. They took into consideration the ORU (over, required, and under the level of education) model with the cross-sectional and panel data spanning from 1974 to 2000 provided by the Swedish Level of Living survey (Levnadsnivåundersökningarna, LNU). The empirical part of the study relied on the career mobility hypothesis, mismatch dissolving over the period and initial wage losses being compensated by expected wage growth, and human capital model hypothesis, wage returns to education being independent of the job's skill requirements when unobserved heterogeneity considered, which will be an important player in our analysis as well. For generating comprehensive results, the study utilized the OLS method and later moved into Fixed Effects (FE) as it is easier to control for unobserved heterogeneity with this method. However, the study's results did not align with the hypotheses considered. The findings demonstrated that overeducation impacts wages. Even when the heterogeneity of individuals' abilities was considered, the difference in returns to education was there. Unlike Korpi and Tåhlin, when Tsai used the fixed effects model on the sample of U.S. individuals, the wage disparities between overeducated and adequately educated employees vanished (Tsai, 2010). Moreover, the analysis didn't reveal any indication that overeducated workers experience higher wage growth compared to others, and it contradicted the career mobility perspective. Alba-Ramirez (1993) found, in the case of Spanish labor market, that overeducation dissolves with employees' ages. The overeducation incidence was 30% for employees in the age group of 35 and above, while it was only around 4% for the cohort above 59. The study also pointed high job mobility as one of the contributing factors to overeducation.

While the educational mismatch has been analyzed quite often, various econometric approaches have been tested to check their potential to explain the outcomes in a detailed manner, with efficient ones being added to the literature. Bauer (2002) examined the wage effects of educational mismatch by using several econometric techniques on German Socioeconomic Panel (GSOEP) data from 1984-1998. The first estimation was conducted using pooled Ordinary Least Squares (OLS) for the wage specification proposed by Verdugo and Verdugo (1989), and the findings matched what have been found in the literature. Accordingly, overeducated employees get paid less than their equally educated counterparts who work in well-matched positions. The opposite situation holds for undereducated employees. These individuals earn more than their peers who possess the same level of education but are adequately matched to their positions. On the other hand, estimation results of the wage specification proposed by Duncan and Hoffman (1981) indicated that individuals get a positive return for each excess year of schooling and a negative return for each deficit year. The human capital model, which presumes equal returns for required, over-, and undereducation years, was rejected. Levels et al. (2014) obtained comparable outcomes for returns to schooling, which were also inconsistent with the model, when analyzing Programme for the International Assessment of Adult Competencies (PIAAC) data across Europe. Bauer retested the hypothesis by considering unobserved heterogeneity through panel estimation techniques to see whether the estimation results would change. In contrast to Korpi and Tåhlin's case, the outcomes altered. The educational mismatch impact on wages became negligible among individuals possessing the same education level. Simultaneously, the returns to required education years became closer to the returns to over- and undereducation. While the hypothesis was still rejected for males, it wasn't challenged for females. Similar outcomes for the hypothesis were provided by Iriondo and Pérez-Amaral (2016); however, their results were specific to the age group under 35.

The share of public expenditure spent on education in the European Union GDP, approximately 5.1% in 2008, drew the attention of public policymakers, too (Eurydice, 2010). This emphasis on education is highlighted by the number of individuals enrolling to obtain tertiary degrees, which became almost three times more during the period 1975-2009 (Eurydice, 2010). In 2010, despite this progress, 20% of individuals who held tertiary degrees were employed in positions that underutilized their skills (Eurydice, 2012). While the studies' concentrations were primarily on investigating the impacts of educational mismatch on a particular country, Iriondo and Pérez-Amaral (2016) examined the topic by covering major euro area countries. Their data was from the European Union Statistics on Income and Living Conditions (EU-SILC) covering

2006 to 2009. Another feature that positions this paper apart from others is its attention to the main econometric problems that literature mostly disregarded. The authors handled the omitted variable (ability) bias by employing panel estimation techniques which accord with Bauer's approach. This action allowed them to control for the impact of these omissions. Also, the bias caused by measurement error concerning educational mismatch was resolved through the use of instrumental variables. The paper revealed important outcomes after a detailed analysis by using various models (OLS, FE, FE with instrumental variables), which contributed to the robustness as well. According to the results of the instrumental variable fixed-effects estimation, the magnitude of the wage penalty experienced by overeducated employees is similar to the return they receive based on their actual schooling. Essentially, the concluding point was that the educational requirements of the job are the determining factor for wages, and having an additional year of education beyond what the job requires yields a negligible return. Moreover, when the analysis considered for ages, wages for cohorts under 35 correlated with the level of schooling possessed, aligning with human capital theory. In contrast, for the cohort over 35, the results altered, and the educational requirements of jobs became a key influencer on wages.

Developed countries encourage individuals to obtain tertiary education, as the jobs requiring such education levels are typically more qualified and better paid (Chevalier, 2000). The main rationale behind this policy from countries' perspective is that an educated labor force drives economic growth. However, these individuals who equipped themselves with high levels of education commenced to have difficulties finding appropriate positions. Maršíková and Urbánek (2015) addressed this matter by following a similar path to Iriondo and Pérez-Amaral (2016) and provided a comparison of educational mismatches across European countries. The authors took into consideration European Social Survey (ESS5) data for the analysis and compared the outcomes with those of the PIAAC survey data analyzed by Levels et al. (2014). Findings from the PIAAC data indicated that overeducated employees earn less than the ones with the same level of education but hired for position necessitate their education levels. The effects of educational mismatch in the ESS5 dataset were explored by employing the ORU model and OLS regression. Based on the outcomes, the returns for each extra year of education beyond the required level were positive, while they were negative for each year of undereducation. Comparison of the authors' analysis of ESS5 data with PIAAC results revealed a lower proportion of adequate matches under ESS5, as the overeducation incidence was higher. The study by Maršíková and Urbánek seemed to have some empirical limitations. Homogeneity among employees, not taking into account potential skill variations, is the foremost one. Chevalier (2000), based on UK graduate data, pointed out the fact that a minimum of 30 to 40% of wage gaps between the overeducated and accurately matched individuals could be accounted for by controlling for unobserved ability.

Overall, the scholarly works reviewed in this section demonstrate that educational mismatch is indeed an essential field of study, particularly across European Union countries. The outcomes obtained from testing of the human capital model were heterogeneous. Literature suggests that overlooking the potential bias-creating econometric issues is the primary reason behind this heterogeneity. These issues comprise not controlling for unobserved ability heterogeneity and potential bias that could arise from measurement errors. Several of the studies explicitly mention these as limitations of their studies. Additionally, some studies analyzed the topic under both ways, and when accounting for these issues, supporting results appeared.

2.2. Career Mobility Theory

Various studies have achieved diverse outcomes through the application of the Career Mobility theory. Firstly, Sicherman's (1991) analysis of U.S. data supported the theory with the results indicating that overeducated workers in the U.S. indeed experience higher turnover rates and improved upward occupational mobility. In a contrasting study, Büchel and Mertens (2004) employed the German Socioeconomic Panel (1984-1997) data in a static model, and the results ran counter to the Career Mobility theory. According to their findings, German overeducated workers are less likely to undergo above-average wage growth or transition to higher occupational levels. Later, Rubb (2006) conducted an analysis, close to Büchel and Mertens' empirical approach, on the U.S. population survey data for the 1994-2000 period. The outcome contradicted Büchel and Mertens' findings by obtaining a higher probability of career advancement and faster wage growth for overeducated employees. The main factor behind these outcomes considered to be country-specific, as the degree of freedom in transitioning between positions varies among these countries.

Does overeducation pay off? This question potentially crosses the minds of individuals on the way to becoming overeducated. Under the German administrative data, Grunau and Pecoraro's recent research found positive outcomes as an answer to that question (Grunau & Pecoraro, 2017). The results supported the Career Mobility theory by highlighting that overeducation facilitates workers' access to managerial positions. Consequently, the promotion of overeducated employees to higher positions brought many benefits for them. In the case of moving to another establishment, these individuals were rewarded even higher. Also, this study divides overeducation into apparent and real ones. In the apparent case, individuals voluntarily accept a position even though their qualifications exceed the requirements, only because they expect career development there. Additionally, the real case is a situation in which overeducated individuals accept the position without expecting any promotion or targeting an advanced new position. The lowest wage growth emerged for this overeducated group of individuals who neither got promoted nor experienced a career growth. Furthermore, Wen and Maani's retest of the theory with Australian longitudinal data reached a contrasting view with results indicating a lower likelihood of career advancement and no sign of wage growth for over-educated workers (Wen & Maani, 2019). These employees experienced even worse wage growth rates when they replaced their current company compared to those who remained in the same establishment for three years. Lastly, the authors noticed an interesting point that undereducated employees, who are usually not the center of attention, are the ones experiencing career improvement.

Educational mismatch, as a labor market friction, not only aggravates wage inequality but also has an influence on unemployment. In order to evaluate whether the mismatched employees in Italy are at a higher risk of falling into an unemployment trap in comparison with the well-matched ones, Esposito and Scicchitano (2022) utilized the career mobility theory framework. Analysis of Italy under this context makes it even more intriguing, as the country is known for high structural unemployment (OECD, 2019). To obtain more details around the subject, the study digs into determining the main factors in both the supply and demand sides that influence both unemployment risk and educational mismatch. For the empirical part, a multinominal probit model was utilized with data merged from the ICP and PLUS surveys for the period 2014-2018. The paper builds up its empirical exploration on the assumption that the labor market provides mismatched employees fewer chances to be competitive. The findings led to the conclusion that career mobility theory's ideas are supported only among the young, overeducated employees with tertiary-education, especially males. This group actively participated in job-search for finding the best match. Additionally, the study unveiled that firm size could be one of the influencing factors to unemployment risk. Namely, this risk elevates in the case of overeducated workers being employed at small firms where career development is uncertain. The limitation of the study is that the time span only considered the recovery phase of Italy, and it could lead to the underestimation of the unemployment risk.

2.3. Details of Mismatch Phenomenon

Scholars were mainly engaged in analyzing the impacts of educational mismatch but the factors leading to it were left to large extent without attention. This research gap underlines the necessity for a comprehensive examination of these factors. One of the recent academic works by Jiang and Guo (2022) addressed the major reasons for education field-job mismatch alongside their impact on labor market performance. The study used a combination of data extracted from administrative records of provincial institutions, comprising information about college graduates for 2019, and provided by a labor market survey. The time span could be mentioned as one of the limitations of the study. Based on the analysis, it was found that the economic return for matched and mismatched employees did not differ noticeably. However, the mismatched employees tend to experience lower levels of job satisfaction, fewer opportunities for development and reduced stability. Jiang and Guo contributed to the literature by distinguishing among various types of mismatches. The authors unveiled that the most favorable labor market outcomes were achieved by employees who were mismatched because of personal interests. These individuals work in positions that match their interests but not the college majors they acquired. Workers who were mismatched due to the non-availability of jobs in their fields and needed more skills to satisfy the requirements of jobs in related fields faced with comparatively worse outcomes. Importantly, the study tackled the endogeneity problem by examining factors linked to both job status and labor market outcomes.

Rationally, one would expect that as educational mismatch occurs, some individual groups or fields/characteristics may be more inclined to it than others. This notion for the individual groups was analyzed by Alba-Ramirez (1993), whose work states the presence of overeducation in the Spanish labor market, particularly among the group of workers who had recently graduated. Aligning outcomes were obtained by Sevilla and Farias in their recent scholarly work on the Chilean labor market, where overeducation was mainly prevalent among younger generations (Sevilla & Farías, 2020). For the field-specific analysis, Rossen et al. (2019) employed the European Labor Force Survey (2016) data that contains details about graduate employees in the European Union countries. Analysis was conducted using the probit model estimated with Maximum-Likelihood-Method. The authors did not overlook the potential selection bias and used the Heckman method to prevent it. Simultaneously, the study observed significant field-related differences in the occurrence risk of educational mismatch. Graduates' gender even influenced certain fields. The fields with the highest risk of overeducation among male graduates at the European level were Natural sciences, Services, and Agriculture. On the other hand, the risk of overeducation was low for individuals with degrees in engineering, health and welfare, and education. These estimations were consistent across countries considered in the dataset and educational standards. Moreover, gender differences across most of the fields were not statistically significant. However, Services and Natural sciences fields were exceptions with low overeducation risk for females. Males appeared to have the same situation in the fields of Art and Humanities. A noteworthy point is that the positions in fields like engineering, medicine, and law have very specific job requirements; therefore, graduates rarely underutilize their obtained academic degrees (Reimer et al., 2008). These specificities act as guarding shields of corresponding graduates (Ortiz & Kucel, 2008). Rossen et al. also suggested that differences in the ability of labor markets to accommodate recent graduates could contribute to this risk. As a limitation of the study, the omission of some provenly relevant factors for overeducation propensity, such as the academic skills of students prior to starting higher education, should be mentioned (Barone & Ortiz, 2011).

2.4 Educational mismatch in Estonia

The educational mismatch phenomenon has attracted attention because of its impacts on the labor market, and it has also been analyzed in the context of Estonia. After joining the European Union, the country became part of the studies concerning the EU and European Economic Area (EEA). The report by Galasi (2008) analyzed ESS data for the period 2004-2006. Based on the self-evaluation method, overeducation rate for the Estonian labor force was notably high at 78.9%. The rest 8.2% of employees categorized themselves as adequately educated and 12.9% as undereducated. However, Lamo and Messina (2010) found different incidences of educational mismatch when they analyzed the Estonian LFS data for the time span of 1997-2003. The incidence of individuals who categorize themselves as overeducated was 12.6%, with only 2.5% as undereducated.

The PIAAC study in 2012, which included Estonia, ranked the country highly among the participating countries for its levels of overeducation in the labor market. Around 33% of those who took part in the survey were overeducated. Also, the study found that possessing tertiary education plays a significantly positive role in earnings, irrespective of individuals' skills, highlighting the importance of education over skills (Halapuu & Valk, 2013). Furthermore, another analysis was conducted by the European Commission (2015) by focusing on over-qualification among tertiary graduates in the age range of 15-64. The results concluded that approximately 30% of the Estonian labor force is categorized as over-qualified. Based on this report, which employed Eurostat LFS data for 2013, the country stood as one of the top five countries with overeducation. It was also mentioned that the likelihood of positions not demanding tertiary education being occupied by individuals with tertiary education is high. Moreover, the report by the European Centre for the Development of Vocational Training (CEDEFOP) (2015, pp. 33–37) reached comparable outcomes when it concentrated on a sample of the EU countries. The over-qualification rate for the Estonian labor force ranged between 25-30%. Overall, the findings based on the referred studies indicated high levels of overeducation which allows to state educational mismatch as an issue to be considered in the Estonian labor market.

To reiterate, Section 2 has provided an overview of numerous papers that analyze different theories and employ various estimation techniques on the topic of educational mismatch. The results yielded include both similar and opposing ones. The studies that tested the human capital model mainly utilized the ORU model. Before considering unobserved heterogeneity and measurement errors econometrically through the utilization of panel estimation techniques and instrumental variables, the human capital model was often rejected. However, after accounting for these econometric issues, the results started to support the model. The application of career mobility theory also delivered diverse outcomes. The differences in occupational movements of overeducated individuals were connected with country-specific characteristics. In the following subsection, the center of attention extended beyond the impacts of educational mismatch, with some works focusing on the various mismatch types and field-specific analysis of overeducation risk. These details contribute to the understanding of the subject. Additionally, the last subsection concentrates on studies that included the Estonian labor market in their analysis. These studies will play a significant role in comparing the outcomes with those obtained by the thesis.

In conclusion, to analyze the impact of educational mismatch on wages, several of the mentioned models and estimation techniques are employed in the thesis to investigate these theories. A key aspect is to test them using data from the Estonian Labor Force Survey. This step is crucial for gaining insights into the reliability level of these theories in the context of the Estonian labor market. By focusing on the details of the Estonian labor force, the thesis aims to unveil valuable information that adds depth to our understanding of how the theories align with real-world cases of educational mismatch.

3. Data and Required Education

The data and derivation methods of the required education variable are mentioned in this section. It starts with an explanation of various methods for defining the required years of education and notes their advantages and disadvantages. Then, the section continues with a detailed description of the data and the necessary variables for regression analysis. Finally, the comparison of educational mismatch incidence under various methods is discussed.

3.1 Measures of Required Education

The economic phenomenon of “educational mismatch” emerges when an individual’s attained level of education does not align with the requirements of the position that person is performing. It is measured by taking the difference between the individual’s achieved level of schooling and the educational requirement for that specific occupation. A positive difference signals the existence of overeducation. Conversely, negative difference is a sign of undereducation. For adequately educated individuals, the level of education matches the requirements. In order to proceed with all these measurements, the required amount of schooling for particular occupations needs to be estimated. This task could be addressed through several methods. Some studies have utilized a method that relies on external evaluations of educational requirements provided by professional job analysts. Another approach involves defining the necessary level of education based on the self-evaluation of employees. Finally, the last method, which is appropriate for the employed dataset due to the availability of necessary variables, derives the required amount of schooling from realized job matches, and will be utilized in this study.

One of the derivation techniques of the last method by Verdugo and Verdugo (1989) suggests that the required level of education can be defined as a range of one standard deviation around the average schooling level within occupation classifications. If workers’ actual educations position within this range, then they fall into the category of adequately educated. In the case of possessing educational attainment above one standard deviation range for observed occupations, individuals are considered overeducated. Conversely, actual education years below one standard deviation range around the mean schooling place their holders in the undereducated category. However, this approach has been criticized due to insufficient justification for the choice of one standard deviation range. Additionally, Kiker et al. (1997) pointed out that this measure is highly sensitive to technological changes. According to them, this sensitivity could lead to biased results regarding trends in inadequate schooling, as technological evolutions might shift the skill requirements beyond what one standard deviation range can capture.

Subsequently, Kiker et al. presented an evolved technique in which required schooling is measured by using the mode value of individuals’ actual education for the occupations under consideration. In this scenario, individuals are adequately educated if their actual schooling is equal to the mode value for their respective occupations. Simultaneously, overeducation occurs when actual education exceeds the mode value for that occupation, whereas the opposite holds true for undereducated individuals. The primary benefit of utilizing this technique is its reduced sensitivity against technological changes, different from Verdugo and Verdugo’s method. The mode framework can better capture the potential shifts in education and skill requirements occurring due to technological changes. The thesis will use both the mean and mode value measurements in the estimations and provide a comparison of their results.

The method which is based on workers' self-evaluation can be classified into direct and indirect types. In the direct type, employees are asked whether they categorize themselves as overeducated or undereducated for their respective positions. On the other hand, the indirect type encompasses querying individuals about the minimum educational requirements for the job they perform. The data utilized in this thesis includes a direct type of self-assessment of respondents, which will be analyzed empirically. Velden and Smoorenburg (1997) compared the accuracy of this method and the job-analyst approach, with the results being in favor of employees' self-reported education levels. However, this method appears to have some limitations. Questioned individuals might not always have an accurate idea about the required level of education for the job, which could add noise to the estimation and consequently decrease its quality (Cohn & Khan, 1995). Furthermore, it has been observed that individuals tend to overestimate the necessary levels of education or take their actual education as the required level (Hartog & Jonker, 1998). This scenario would lead to an underestimation of overeducation levels, potentially introducing bias into the results.

3.2 Data

This thesis employs cross-sectional individual-level data from the Estonian Labor Force Survey (LFS) conducted by the Statistical Office of Estonia. Individuals included in the sample are permanent residents of Estonia and in the age span of 15-74. The survey is organized quarterly and follows a rotational panel structure. Each individual is surveyed for two quarters and then interviewed again for two more quarters after a break of two quarters in between. Estonian LFS interviews approximately 4000 respondents quarterly and collects thorough information about the participants' demographic background, educational attainment, employment history, and more. These details will be useful in the creation of the necessary variables for the empirical analysis and in the assessment of the wage impact of educational mismatch. The estimation process will utilize a sample that covers the period from 2010 to 2020. This dataset includes 221,280 personal observations for 67,244 distinct individuals. However, as the study mainly focuses on the impact on wages, including only employed male and female individuals whose wage information is not missing would contribute to the precision of the empirical estimations. The sample under these conditions covers 98,121 observations of 37,820 individuals and is the primary one for the descriptive statistics and estimations. Only for the purpose of obtaining more meticulous required years of education from realized matches, the measurement of this variable proceeds with a larger sample that includes all employed individuals by overlooking the condition about the availability of their wage information. When only considered for employment status, the sample size increases to 134,955 personal observations of 45,654 individuals.

The Estonian Labor Force survey incorporates direct type of self-evaluation concept by asking participants about the "Correspondence between a job and education level", and the responses define whether they are adequately educated or mismatched, with options including "1. Yes", "2. No, the job presupposes a more advanced level of education", and "3. No, the job presupposes a lower level of education". Individuals who answered “1” are adequately matched, while “2” and “3” represent those who are undereducated and overeducated, respectively. However, the survey doesn’t ask about specifics such as “How many years of education are required for a position like yours?” or “What is the required level of education for your position?”. This omission prevents the direct definition of the required education levels for occupations and decreases the feasibility of employing the self-assessment method for various models utilized in the analysis of educational mismatch. Overall, Table 1 shows that, based on the dataset employed, out of 45,369 male self-evaluation responses, the share perceiving their actual schooling as more than the necessary level for their jobs is 8.38%, while only 2.96% think that their actual schooling is below the required level. Moreover, 88.66% of the male participants consider themselves adequately educated. Similarly, the fractions based on 52,752 female self-evaluation responses are quite close, with a slight increase to 12.91% in the share of respondents who assume to be overeducated for their positions. For the general sample, the incidences of over- and undereducated individuals under the self-assessment method are 10.81% and 2.36%, respectively. Lamo and Messina (2010) also analyzed the Estonian LFS data covering the period 1997-2003, and the mismatch incidences[1] based on individual’s self-assessment is very comparable to ours, even though the considered time spans are different.

The individuals’ attained years of education haven’t been explicitly provided in the dataset. The survey collects information about the respondents’ highest level of completed education categorized by the International Standard Classification of Education (ISCED) levels. The conversion of these levels into corresponding years will yield the actual education of employees (see Appendix 1). As the utilized data starts from 2010 and updated ISCED (2011) levels have been employed since 2014, I will align the former ISCED (97) levels with the new version for the years 2010 to 2013. Actual education will play a significant role in defining the required education for occupations. The required education years to perform a job adequately will be determined by applying the mean and mode methods on the actual education of employees working in the same occupations, based on the International Classification of Occupations (ISCO-08) to two digits. Consequently, deriving overeducation and undereducation variables based on the mentioned methods will be straightforward. When examining the outliers, there appeared to be several noteworthy ones. From the perspective of wages, among all participants, individuals who are the highest earners and the lowest education level holders, based on the ISCED levels, are excluded. The average education level for individuals with comparable earnings is above “post-secondary” level, while the excluded individuals had “lower-secondary” and lower levels, which could lead to an undervaluation of required education levels. Additionally, excluding occupations with less than 50 observations per year is expected to bring more clarity to the data.

Table 1 provides further information about the means and standard deviations of the variables, following the abovementioned transformations of variables and mitigation of possible bias-creating factors, which will play a key role in the empirical analysis. The mean method results indicate that the majority of employed respondents are adequately educated. Among males, 15,79% are estimated to be overeducated and 21.27% are estimated to be undereducated.

[1] The authors highlighted that among individuals, 12.6% consider themselves overeducated and 2.5% undereducated. (Lamo & Messina, 2010)

Table 1. Summary statistics.

	Male	Female	Overall
Log (real hourly gross wage)	1.959 (0.82)	1.693 (0.81)	1.816 (0.82)
Years of actual schooling	12.758 (2.42)	13.718 (2.31)	13.27 (2.41)
Self-evaluation method:			
Overeducated (%)	8.38	12.91	10.81
Undereducated (%)	2.96	1.84	2.36
Mean method:			
Years of required schooling	12.901 (1.28)	13.614 (1.35)	13.285 (1.36)
Years of overeducation	0.473 (1.17)	0.460 (1.13)	0.466 (1.15)
Years of undereducation	0.643 (1.29)	0.436 (1.12)	0.532 (1.21)
Overeducated (%)	15.79	15.96	15.88
Undereducated (%)	21.27	14.11	17.42
Mode method:			
Years of required schooling	12.588 (1.41)	13.097 (1.69)	12.862 (1.59)
Years of overeducation	0.806 (1.50)	1.081 (1.55)	0.954 (1.53)
Years of undereducation	0.637 (1.31)	0.460 (1.10)	0.542 (1.20)
Overeducated (%)	26.16	38.33	32.70
Undereducated (%)	20.73	16.93	18.68
Number of observations	45 369	52 752	98 121

( ): Standard deviations. Source: Estonian LFS data. Author's elaboration based on Estonian LFS data.

Moreover, overeducated female individuals comprise 15.96%, while the 14.11% are falling into the undereducated category. When taking into consideration the mean values for the mean method from Table 1, the data indicates a mean of around 0.473 years of more schooling than necessitated by the occupations for males, and 0.46 years for females. The numbers for the case of undereducated males and females are 0.643 and 0.436 years, respectively. Table 1 also exhibits that the average years of actual schooling are higher for females than for males, with a difference of approximately 1.5 years. The mean value of 13.27 years of actual education, based on the whole sample, roughly corresponds to additional two years beyond secondary education.

The mode method results exhibit differences from the rest in some points. It is evident from Table 1 that the share of overeducated males increases to 26.16%, and for females, it rises to 38.33%. Furthermore, a key difference from the mean method is observed in the mean values of overeducation years. This value increases to 0.806 years for males and 1.081 years for females. The mean values for the whole sample under the mode method are in line with the ones estimated using PIAAC (2013) data by Levels et al.(2014). The statistics, based on 21 countries, showed an average of 0.89 years for overeducation and 0.51 years for undereducation. It is also noteworthy that when comparing the fractions for the mode method with the self-assessment method, there is a notable reduction in the share of adequately educated respondents, dropping from 85-90% to the range of 45-55%. These findings align with the idea suggested by Cohn and Khan (1995) regarding not all respondents having accurate information about the required level of education for their occupations which is causing biased results.

All-in-all, it contributes to our understanding of the data to examine the correspondence level among classifications obtained by the mean and mode value methods. Table 2 provides the percentages for this comparison. The diagonal of the table represents the cases where observations under the mode and mean methods fall into the same category. In total, 75.6% of the observations are in the same category under both models.

Table 2. Educational mismatch results based on the mean and mode methods (%).

	Mode method			
	Adequately educated	Overeducated	Undereducated	Row total
Mean method				
Adequately educated	45.45	16.82	4.43	66.7
Overeducated	0	15.89	0	15.89
Undereducated	3.16	0	14.25	17.41
Column total	48.61	32.71	18.68	100

Source: Estonian LFS data. Author’s elaboration.

4. Empirical Approach

As has been constantly mentioned throughout the study, the main objective of the thesis is to analyze the impact of educational mismatches on wages. The literature has addressed the matter by utilizing two specifications. The first model, proposed by Verdugo and Verdugo (1989), is defined as follows:

(1) $lnW_{it} = \alpha_0 + \alpha_1 E_{it} + \alpha_2 O_{it} + \alpha_3 U_{it} + X_{it}\gamma + \varepsilon_{it}$,

where lnW_{it} represents the log of gross hourly wages of individual i in year t. Individuals' actual education years are denoted by E_{it}. O_{it} and U_{it} are the dummy variables which have a value of 1 if the individual is overeducated or undereducated, respectively, and 0 for the other cases. The additional explanatory variables, including marital status dummy, age, age squared, industry dummies, year-quarter dummies, firm size dummies, regional dummies, and full-time job dummy, are contained in the X_{it} vector along with their corresponding coefficients in vector γ. Finally, ε_{it} represents the error term. Firm size is categorized based on the number of individuals employed in the company. The time dummies account for the effects of any time-specific factors. While the literature often takes the experience of individuals as an explanatory variable, measurement of this variable for the employed dataset led to the generation of a huge number of missing values. Therefore, the age variable is utilized to indirectly control and be a proxy for it. This case could be noted as a limitation of the data.

Equation (1) compares overeducated and undereducated employees with employees who have the same level of actual education but are correctly matched for their positions. Under the scenario where actual education levels are the determinant of wages, overeducation (α_2) and undereducation (α_3) coefficients are expected to be zero. Moreover, if the wage determinant is the required education level for positions, then additional years of education beyond the required amount to perform the job would be unproductive. This case would even lead to overeducated employees earning less than equally educated individuals whose positions require their education level. Conversely, earnings for undereducated employees would be higher than for those with the same education levels but in perfectly suited jobs.

On the other hand, the classic wage specification which perfectly fits the purpose of the study and is utilized by most of the literature is the one proposed by Duncan and Hoffman (Duncan & Hoffman, 1981). According to Duncan and Hoffman, actual years of schooling attained (E_{it}) are disaggregated into required years of education by the position (E_{it}^{r}), years of overeducation (E_{it}^{o}), and years of undereducation (E_{it}^{u}) as expressed by the following expression:

(2) $E_{it} = E_{it}^{r} + E_{it}^{o} - E_{it}^{u}$ where,

(3) $E_{it}^{o} = \begin{cases} E_{it} - E_{it}^{r}, & if \;\; E_{it} > E_{it}^{r} \\ 0, & if \;\; E_{it} \leq E_{it}^{r} \end{cases}$

, and

$$(4)\ E_{it}^{u} = \begin{cases} E_{it}^{r} - E_{it}, & if\ \ E_{it} < E_{it}^{r} \\ 0, & if\ \ E_{it} \geq E_{it}^{r} \end{cases}$$

These equations exhibit that the acquired years of education are equal to the required years of education for correctly matched individuals, as the years of overeducation and undereducation for them are equal to zero.

By incorporating these expressions into the Mincer wage equation (Mincer, 1974), Duncan and Hoffman's model is obtained:

$$(5)\ lnW_{it} = \beta_0 + \beta_1 E_{it}^{r} + \beta_2 E_{it}^{o} + \beta_3 E_{it}^{u} + X_{it}\gamma + \varepsilon_{it}$$

where the return to the required years of education is β_1. The β_2 coefficient indicates the change in employees' wages for each year of over-schooling in comparison with individuals working in the same occupations but well-matched education-wise. In the same manner, β_3 denotes the variation in employees' wages for each year of educational deficit compared to individuals in the same positions but correctly matched.

Most studies in the literature that have conducted cross-sectional wage regression have obtained consistent results for equation (5) (Rubb, 2003). The returns to individuals for schooling beyond the required level are positive (β_2 > 0). However, when comparing with returns to required level schooling, they are smaller (β_1 > β_2 > 0). On the other hand, the returns for under-schooling are negative (β_3 < 0). Under the current scenario, overeducated employees earn higher salaries than those who are working in the same positions with adequately matched education. But, individuals with the same education level as overeducated workers and in the well-matched positions get even higher wages. The opposite pattern applies to undereducated employees. Their salaries are higher than the salaries of the employees with the same education level and in well-matched positions, yet lower than those in the same occupation but correctly matched.

These empirical outcomes contradict the human capital model. The model emerges when the coefficients of Duncan and Hoffman's model (5) are satisfying β_1 = β_2 = -β_3 condition. The equality of coefficients indicates that the individuals' wages are determined by their education and other personal features which impact their productivity level, rather than the requirements of a position. Moreover, after incorporating the coefficients corresponding with the requirements of the human capital model into the equation (5), the standard human capital earnings equation is revealed:

$$(6)\ lnW_{it} = \gamma_0 + \gamma_1 E_{it} + \varepsilon_{it}$$

An alternative to the human capital model is the job-competition model developed by Thurow (1975). According to this model, wages are mainly determined based on the individuals' job characteristics rather than the characteristics of the individuals themselves. This occurs when the overeducation (β_2) and undereducation (β_3) coefficients equal to zero in the equation (5) (β_2 = β_3 = 0), and wages are determined by the required education levels (β_1) of jobs. Furthermore, the career mobility theory modeled by Sicherman and Galor (1990) can't be tested due to the design of the Estonian LFS data. This theory requires repeated observations of the same individuals over time to examine whether occupational mobility is temporary or has lasting influences. However, the survey adds new respondents continuously, which consequently only allows for the analysis of short-term effects of career movement.

The concept of unobserved heterogeneity provides a background for the explanation of the estimated coefficients that contradicted the human capital model. Without controlling for unobserved heterogeneity, the estimation results for each year of undereducation and overeducation are expected to be biased. If we consider a scenario where overeducated individuals possess fewer unobserved abilities and undereducated ones more unobserved abilities compared to those correctly matched and in the same positions, then the returns for each year of over-schooling would be underestimated, while the returns for each deficit year would be overestimated. Therefore, it is anticipated that controlling for unobserved heterogeneity would mitigate the differences among the absolute values of returns to years of required, over-, and under-schooling. As mentioned earlier, the results of the study by Chevalier supported the fact that controlling for unobserved ability could explain at least 30-40% of wage differences between overeducated and well-matched individuals (Chevalier, 2000). The thesis utilizes panel estimators (Fixed Effects and Random Effects) to examine the influence of unobserved heterogeneity. To make the panel estimation feasible, a panel identifier is incorporated into the data to distinguish individuals over time. This identifier is formed by concatenating unique household values with member numbers, thus enables differentiation among respondents from the same household.

The general estimations with the standard fixed effects model are appropriate for equations (1) and (6) as the model accounts for unobserved heterogeneity and achieves the objective. However, Duncan and Hoffman's wage specification is suitable for decomposing the error term ε_{it} and control for ability explicitly. Accordingly, equation (5) can be written as follows:

$$(7)\quad lnW_{it} = \beta_0 + \beta_1 E_{it}^{r} + \beta_2 E_{it}^{o} + \beta_3 E_{it}^{u} + X_{it}\gamma + (\alpha_i + \varepsilon_{it})$$

with α_i being an indicator of ability. It is an individual component and doesn't vary over time. Under the case that there is a positive correlation between the ability component and under-schooling years and a negative one with over-schooling years, OLS estimation would be biased and lead to a reduced absolute magnitude of the coefficients β_2 and β_3. The utilization of panel estimation techniques will play a key role in addressing the impact sourcing from the omitted variables and obtaining unbiased estimates. In the thesis, the technique is implemented in the format by estimating the deviations from the mean of each respondent. For proceeding with the estimation, primarily, the mean wage of each respondent across time will be computed as:

$$(8)\quad ln\bar{W}_{it} = \beta_0 + \beta_1 \bar{E}_{it}^{r} + \beta_2 \bar{E}_{it}^{o} + \beta_3 \bar{E}_{it}^{u} + \bar{X}_{it}\gamma + (\alpha_i + \bar{\varepsilon}_{it})$$

where $\bar{X}_{it}$ calculates the mean for the time-variant and numerical explanatory variables. Subtraction of equation (8) from equation (7) will provide the deviation from the mean of each respondent. It is evident from the following that

(9) $lnW_{it} - ln\overline{W}_{it} = \beta_1(E^r_{it} - \bar{E}^r_i) + \beta_2(E^o_{it} - \bar{E}^o_i) + \beta_3(E^u_{it} - \bar{E}^u_i) + (X_{it} - \bar{X}_i)\,\gamma +$
$+ (\varepsilon_{it} - \bar{\varepsilon}_i)$

the time-invariant ability indicator α_i disappears. Hereby, the estimation results become unbiased. Moreover, this fixed-effects estimator precludes the estimation of the effects of variables that do not change over time within each respondent, as it relies on the within-individual information. The main factor preventing the Verdugo and Verdugo model (1989) from being estimated with the deviation-from-mean form of the fixed effects model is its usage of dummy variables for mismatched individuals, which are not appropriate for computing deviations.

Another point that the literature warns us to take cautiously is the potential bias that could arise from errors when measuring educational mismatch (Leuven & Oosterbeek, 2011). This thesis employs both the mean and mode measurement methods for the year-wise exploration of educational mismatch. Based on Tables 3 and 4, the correlation between these methods in the context of mismatch years is strong but not perfect. The results signal potential circumstances of measurement errors to some degree.

Table 3. Correlation between log wages and overeducation years based on the mean and mode methods (%).

Variables	Log (real hourly gross wage)	Mean-Overeducation	Mode-Overeducation
Log (real hourly gross wage)	1.0000	-	-
Mean-Overeducation	0.0511	1.0000	-
Mode-Overeducation	0.0624	0.7778	1.0000

Source: Estonian LFS data. Author's elaboration.

Table 4. Correlation between log wages and undereducation years based on the mean and mode methods (%).

Variables	Log (real hourly gross wage)	Mean-Undereducation	Mode-Undereducation
Log (real hourly gross wage)	1.0000	-	-
Mean-Undereducation	-0.0471	1.0000	-
Mode-Undereducation	0.0265	0.8651	1.0000

Source: Estonian LFS data. Author's elaboration.

To address the measurement error bias, the study also uses fixed effects regression with instrumental variables for the estimation of equation (9). In line with the existing literature, the required, over-, and undereducation variables derived under the mean method are instrumented with the respective variables calculated based on the mode method (Iriondo & Pérez-Amaral, 2016; Robst, 1994). While there is a small correlation between the educational mismatch measures and the dependent variable, the pairwise correlation of instruments is notably strong, mattering for their validity the most. Although these instruments are commonly used in studies analyzing similar matters (Iriondo & Pérez-Amaral, 2016; Korpi & Tåhlin, 2009), their quality will be examined under the first stage within regression to ensure clarity regarding their selection. The related outcomes will be provided in the next section.

5. Results

This section will present the results of the analysis based on the models proposed by Verdugo and Verdugo, as well as Duncan and Hoffman. These models are estimated for several sub-samples, like gender and age groups, under different measurement methods. This approach is supported by the literature (Bauer, 2002; Iriondo & Pérez-Amaral, 2016) and is expected to bring clarity about whether gender and age are influencing factors in the evaluation of the earnings impact of educational mismatch. Additionally, the last subsection of the thesis will examine, based on the existing literature, the educational mismatch situation from the perspective of Baltic region countries, and Estonia's place there.

5.1. Verdugo and Verdugo model

Table 5 provides information about the estimation results of equation (1). As the descriptive statistics for the self-evaluation method exhibited controversial results, it was expected that the estimation results for this method would also differ from the others. The results for the Ordinary Least Squares (OLS) model show that for male employees, overeducated ones earn 30.25% less, while undereducated ones 14.80% more compared to male employees with the same level of education but correctly matched to their positions. The outcomes for females are similar to those for males. The only notable change is that undereducated females earn 7.46% more than females with identical education levels who are in adequately matched jobs.

Under the mean method measurement of the OLS model, the differences in earnings between adequately matched and overeducated males and females drop to approximately 21% and 26%, respectively. On the other hand, the gains for undereducated males compared to similar males with jobs fully matching their education level increases to 26.80%. This number rises to 38.18% for undereducated females. When using the mode method, the earning disadvantage for overeducated males decreases from 21.15% to 15% relative to the mean method. This drop is observed for overeducated females, too, from 25.60% to 18.83%. Likewise, the earning advantages for undereducated males and females decrease. Undereducated males receive 18.05% more, and females 24.12% more than their peers with well-matched jobs. Taking into consideration the estimation results of the OLS model, it is possible to say that these outcomes align with the existing literature as overeducated employees earn less and undereducated employees earn more than those equally educated but working in correctly matched positions. The earning penalties observed here show a close resemblance to the outcomes obtained by Lamo and Messina (2008) based on Estonian LFS data for the period of 1997 to 2003. The authors found penalties of 24% pertaining to overeducation.

After incorporating panel estimators, the coefficients for mismatched individuals experience a decrease (see Table 5). Estimations of the dummy variables for both overeducated and undereducated employees act according to the predicted behavior under both random and fixed effects models. Generally, the random effects model reduces the earning gap for mismatched individuals under all the methods compared to the OLS model. Moreover, the fixed effects model performs in a similar way by decreasing this gap even further, especially under the mode method.

The absolute values of earning penalties and advantages for both sub-samples become comparable. The earning disadvantage for overeducated females drops to 8.34%, while for males, it drops to 4.05%. Simultaneously, wage differences between undereducated and well-matched male employees decrease to 3.60%. The same trend follows for undereducated females, with a drop to 6.10%. Even though the panel estimators do not entirely eliminate the influence of job characteristics, accounting for unobserved heterogeneity plays an essential role in obtaining better outcomes. Overall, the estimation results indicate that neither overeducation nor undereducation coefficients are zero, pointing to the educational requirements of jobs being a main determinant of wages.

Table 5. Verdugo and Verdugo model.

	OLS			Random effects			Fixed effects		
	SE	Mean	Mode	SE	Mean	Mode	SE	Mean	Mode
Male									
Actual schooling	0.0668*** (0.001)	0.1131*** (0.002)	0.1001*** (0.002)	0.0615*** (0.002)	0.0926*** (0.003)	0.0835*** (0.003)	0.0423*** (0.007)	0.0543*** (0.008)	0.0503*** (0.008)
Overeducated	-0.3025*** (0.008)	-0.2115*** (0.008)	-0.1500*** (0.007)	-0.2379*** (0.013)	-0.1404*** (0.012)	-0.0976*** (0.011)	-0.1329*** (0.026)	-0.0691*** (0.019)	-0.0405** (0.019)
Undereducated	0.1480*** (0.014)	0.2680*** (0.007)	0.1805*** (0.007)	0.0824*** (0.021)	0.1758*** (0.011)	0.1176*** (0.010)	0.0123 (0.037)	0.0530*** (0.019)	0.0360* (0.019)
R^2	0.6493	0.6507	0.6456	0.6482	0.6487	0.6441	0.6282	0.6262	0.6238
Female									
Actual schooling	0.0872*** (0.001)	0.1435*** (0.001)	0.1301*** (0.001)	0.0814*** (0.002)	0.1225*** (0.002)	0.1124*** (0.002)	0.0575*** (0.005)	0.0810*** (0.006)	0.0747*** (0.006)
Overeducated	-0.3119*** (0.006)	-0.2560*** (0.007)	-0.1883*** (0.005)	-0.2676*** (0.010)	-0.1977*** (0.009)	-0.1417*** (0.008)	-0.2031*** (0.022)	-0.1419*** (0.015)	-0.0834*** (0.013)
Undereducated	0.0746*** (0.015)	0.3818*** (0.007)	0.2412*** (0.006)	0.0401* (0.021)	0.2567*** (0.010)	0.1564*** (0.008)	-0.0157 (0.034)	0.0991*** (0.016)	0.0610*** (0.014)
R^2	0.7164	0.7221	0.7192	0.7155	0.7197	0.7169	0.6998	0.6989	0.6971

SE – self-evaluation method. ( ): Standard errors (robust for OLS, clustered for RE and FE models). *** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level. For the RE and FE models R^2 is the overall R^2. All regressions include abovementioned explanatory variables. Source: Estonian LFS data for 2010-2020. Author's elaboration.

The employed variables have been tested for multicollinearity through the Variance Inflation Factor (VIF), and no indication of it appears[2]. The related outcomes have been mentioned in Appendix 3. To provide clarity regarding which estimation results to rely on more, I have conducted several econometric tests. The Breusch and Pagan Lagrange Multiplier test is employed

[2] Only the age and age squared variables have multicollinearity. It is an expected outcome due to the quadratic relationship between the variables. This situation is not influential on the validity of the results, and there is no collinearity among the other independent variables.

for checking the presence of random effects (Breusch & Pagan, 1980), and it has been statistically significant at the 1% level for all the specifications considered in the analysis (Appendix 4). These results allow to decide in favor of the random effects model over OLS. Furthermore, the utilization of the Hausman test contributes to the selection process between random effects and fixed effects models (Hausman, 1978). The outcomes in Appendix 5 are in favor of the fixed effects model, as the hypothesis supporting the random effects model is rejected under all specifications. Therefore, fixed effect estimates which are considerably lower than those of the other models could be considered essential.

5.2. Duncan and Hoffman model

The analysis conducted based on Duncan and Hoffman's model will be the main discussion point of this subsection. The estimation results for equations (5) and (6) are presented in Table 6. Simultaneously, this table reports the outcomes of the tests for the human capital model with a hypothesis that considers the same returns for each required, over-, and undereducation year and for the job competition model with a hypothesis that presumes only required education is awarded. These hypotheses are examined by investigating the necessary requirements for the corresponding coefficients.

The OLS model estimation results align with the results found in the literature. As evident from Table 6, returns to the actual level of education years are smaller than the returns to required schooling for both sub-samples and methods. The coefficients based on the mean method are similar for males and females, with each deficit year of schooling yielding a punishment of 3.36% for males and 3.01% for females. In addition, the wage advantage for males for each year of overeducation is 3.09%, whereas it is 4.31% for females. Furthermore, the returns to overeducated males for each additional year of schooling under the mode method increase to 5.77%. For the female sub-sample, the returns increase to 7.22% for each additional year beyond the required level, compared to the individuals in the same position but correctly matched. These OLS model coefficients, especially for the required years of education, exhibit a degree of resemblance to what Marsikova and Urbanek (2015) obtained for Estonia[3] based on the European Social Survey data. However, there are discrepancies in the returns for overeducation. This variation could source from their study's reliance on only one method of overeducation measure which might limit the ability to check for potential biases.

Similar to the Verdugo and Verdugo model's case, the thesis checks for multicollinearity among variables using VIF and conducts both the Breusch and Pagan Lagrange Multiplier test and Hausman test to evaluate the appropriateness of the employed models. VIF doesn't show any high level of multicollinearity[4], evident from Appendix 3. The Lagrange Multiplier test is statistically significant in all cases, indicating the existence of random effects and supporting the random effects model against the OLS model (Appendix 4). Additionally, the results of the Hausman test guide in favor of the fixed effects model rather than random effects, as shown in Appendix 5.

[3] The authors observed returns of 15.5% for required years of education, 10.6% for overeducation, and -8.7% for undereducation. However, the estimation for undereducation was not statistically significant.

[4] There is an expected multicollinearity between the age and age squared variables, due to the quadratic relationship between them. This situation does not affect the results' validity.

Table 6. Duncan and Hoffman model.

	OLS		Random effects		Fixed effects	
	Mean	Mode	Mean	Mode	Mean	Mode
Male						
Actual schooling	0.0630*** (0.001)		0.0583*** (0.002)		0.0397*** (0.007)	
R^2	0.6380		0.6373		0.3319	
Years of required schooling	0.1592*** (0.002)	0.1107*** (0.002)	0.1286*** (0.003)	0.0901*** (0.003)	0.0658*** (0.009)	0.0541*** (0.008)
Years of overeducated	0.0309*** (0.002)	0.0577*** (0.002)	0.0338*** (0.003)	0.0561*** (0.003)	0.0194*** (0.007)	0.0375*** (0.008)
Years of undereducated	-0.0336*** (0.002)	-0.0417*** (0.002)	-0.0377*** (0.003)	-0.0454*** (0.003)	-0.0328*** (0.007)	-0.0389*** (0.008)
R^2	0.6586	0.6468	0.6565	0.6451	0.3413	0.3413
$H_0: \beta_1 = \beta_2 = -\beta_3$	(F) 1413.57***	567.19***	(chi^2) 626.08***	263.67***	(F) 16.38***	9.26***
$H_0: \beta_2 = \beta_3 = 0$	(F) 334.28***	971.00***	(chi^2) 317.84***	668.40***	(F) 12.38***	15.54***
Female						
Actual schooling	0.0853*** (0.001)		0.0794*** (0.002)		0.0558*** (0.005)	
R^2	0.7000		0.6993		0.3443	
Years of required schooling	0.2073*** (0.002)	0.1443*** (0.001)	0.1755*** (0.003)	0.1225*** (0.002)	0.0998*** (0.006)	0.0789*** (0.006)
Years of overeducated	0.0431*** (0.002)	0.0722*** (0.001)	0.0413*** (0.003)	0.0711*** (0.002)	0.0173*** (0.005)	0.0520*** (0.006)
Years of undereducated	-0.0301*** (0.002)	-0.0437*** (0.002)	-0.0392*** (0.003)	-0.0529*** (0.003)	-0.0364*** (0.005)	-0.0478*** (0.006)
R^2	0.7442	0.7225	0.7418	0.7201	0.3640	0.3620
$H_0: \beta_1 = \beta_2 = -\beta_3$	(F) 4201.79***	1915.10***	(chi^2) 2221.54***	903.38***	(F) 90.72***	44.18***
$H_0: \beta_2 = \beta_3 = 0$	(F) 521.99***	1939.27***	(chi^2) 572.46***	1723.94***	(F) 27.26***	56.74***

( ): Standard errors (robust for OLS, clustered for RE and FE models). *** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level. For the RE and FE models R^2 is the overall R^2. Regressions include abovementioned explanatory variables. Source: Estonian LFS data for 2010-2020. Author's elaboration.

Overall, the mean method produces results which are quite similar across the OLS and random effects models. Wages rise by around 3-4% for each year of overeducation and fall by around 3% for each year of undereducation in both sub-samples. This pattern is observed in the mode method as well. The returns for overeducation years are in the range of 5-7%, while the penalties for deficit years are in the range of 4-5%. On the other hand, the estimation outcomes under the fixed effects model reveal a different scenario, particularly regarding overeducation. Even though the returns for undereducation are consistent with those of the considered models, each additional year of education yields a return of approximately 2% for all workers under the mean method, which is smaller than the other models' respective outcomes. Moreover, similar behavior is experienced under the mode method, with the model providing overeducation returns of 3.75% for males and 5.2% for females.

While the rises and penalties in wages are approximately in the same range for all models under all the considered methods, the returns for required education differ. The impact of gender is also visible, with females consistently having higher returns for the required years of education than males. Among all the model estimations, the returns for each additional year of education required to be well-suited for a position are closest to the returns for over and undereducation under the fixed effects model. This impact of the model was anticipated based on the findings of earlier studies but in a bigger magnitude. The main factor behind this performance could be the low within-sample variation of the education variables. The reduction and convergence of coefficients under the fixed effects model were also observed in the analysis conducted by Tsai (2010). Although unobserved heterogeneity is controlled through the utilization of panel estimation techniques and is expected to remove the differences among the absolute values of returns to years of required, over-, and under-schooling, the variance among these classifications is still there. Korpi and Tåhlin's analysis of Swedish Level of Living Survey data provided similar results (Korpi & Tåhlin, 2009). The findings demonstrated that overeducation is an influencing factor on wages.

The outcomes of the hypothesis tests examined in the study are reported in Table 6. The human capital model hypothesis, which assumes equal rewards for years of required, over, and undereducation, is rejected for all model specifications. This implies that educational requirements by employers for positions have a significant influence on wages. This interpretation is further supported when observing the coefficients, as the returns for required education are consistently higher than those for attained schooling. When tested with the hypothesis considering zero coefficients on over- and undereducation, the job competition model is also rejected for all model specifications. Bauer's analysis represented similar conclusions based on German Socio-Economic Panel data (Bauer, 2002). However, in his study, the fixed effects model led to the human capital hypothesis for females under both mean and mode methods not being rejected.

The analysis proceeds with the consideration of potential bias which could emerge from measurement errors, with equation (9) being estimated for the fixed effects instrumental variable model. Prior to estimation, Table 7 provides the assessment of instrumental variables based on the outcomes of the first-stage within regression. The table exhibits that the instruments for the mean measures for required, over-, and under-schooling variables are the mode measures of their respective variables, and equation (9) is tested for these measures. Reported values include the F-statistic, which checks the quality of instruments by assessing the joint significance of them for each endogenous variable. Ideally, this statistic should surpass 10, indicating the strong predictive capacity of the instruments for the endogenous variable. All the obtained statistic values exceed 10, meaning that the selected instruments are relevant.

Table 7. Instrumental variable relevance based on the first-stage within regression outcomes – Equation (9).

Model Specification	Variable (years)	Instrument	F-test (Robust)	Prob > F
Mean	Over-schooling	Mode	8895.55	0.00
Mean	Under-schooling	Mode	20887.1	0.00
Mean	Required schooling	Mode	23743.1	0.00

Source: Estonian LFS data for 2010-2020. Author's elaboration.

After the assessment of instrumental variables, the estimations continue with the fixed effects instrumental variable model by gender and age, as reported in Table 8. The coefficients for required, over-, and undereducation by gender under this model experience an increase in their absolute values compared to those under the fixed effects model measured by the mean method. A notable difference emerges for overeducated employees, apparent from the first column, as the return for each additional year of education beyond the required level becomes 3.69% for males and 6.15% for females. These results support the existence of attenuation bias to some degree, particularly for overeducated employees. Consistent with the previous models, the returns for the required years of education are greater than returns for mismatched years, leading to the conclusion that job requirements have a significant influence on wages. When focusing on the testing of the human capital model and the job competition model, the outcomes lead to the rejection of both for gender sub-samples.

However, when considering age groups, some remarkable changes occur. For the age group above 35, the main conclusions reached so far are confirmed for both genders. On the other hand, for female employees under 35, the human capital model is not rejected, while the job competition model is rejected. This pattern means that the wages of females under 35 are mainly determined by their attained level of education rather than the requirements of the job. It can be interpreted that in the first stage of employment for females, wages depend on their education, but over the period, the second stage comes and the job requirements take over actual education's place. This shift in the wage determinant supports the fact that actual education is a valid measure of female employees' productivity only in the early stages of their journeys in the labor market. Iriondo and Perez-Amaral (2016) arrived at matching conclusions regarding the wage determinant based on age groups when they utilized a similar econometric approach to analyze EU-SILC data.

Table 8. Fixed effects regressions with instrumental variables (FEIV) for Equation (8).

	Fixed Effects with Instrumental Variables		
	General	Age ≤ 35	Age > 35
Male			
Years of required schooling	0.0813*** (0.012)	0.0193 (0.017)	0.0735*** (0.016)
Years of overeducated	0.0369*** (0.011)	-0.0106 (0.014)	0.0442*** (0.014)
Years of undereducated	-0.0401*** (0.009)	-0.0282*** (0.011)	-0.0272** (0.012)
R^2	0.3416	0.2859	0.3595
$H_0: \beta_1 = \beta_2 = -\beta_3$	(chi^2) 21.49***	(chi^2) 6.10**	(chi^2) 10.24***
$H_0: \beta_2 = \beta_3 = 0$	(chi^2) 27.50***	(chi^2) 8.20**	(chi^2) 12.93***
Female			
Years of required schooling	0.1055*** (0.007)	0.0497*** (0.014)	0.1051*** (0.009)
Years of overeducated	0.0615*** (0.009)	0.0425** (0.018)	0.0532*** (0.010)
Years of undereducated	-0.0475*** (0.007)	-0.0236* (0.014)	-0.0470*** (0.008)
R^2	0.3637	0.2709	0.3828
$H_0: \beta_1 = \beta_2 = -\beta_3$	(chi^2) 64.30***	(chi^2) 2.70	(chi^2) 60.34***
$H_0: \beta_2 = \beta_3 = 0$	(chi^2) 94.89***	(chi^2) 8.65**	(chi^2) 54.75***

( ): Standard errors (clustered). *** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level. R^2 is the overall R^2. Regressions include abovementioned explanatory variables. Source: Estonian LFS data for 2010-2020. Author's elaboration.

5.3 Perspective of the Baltic States

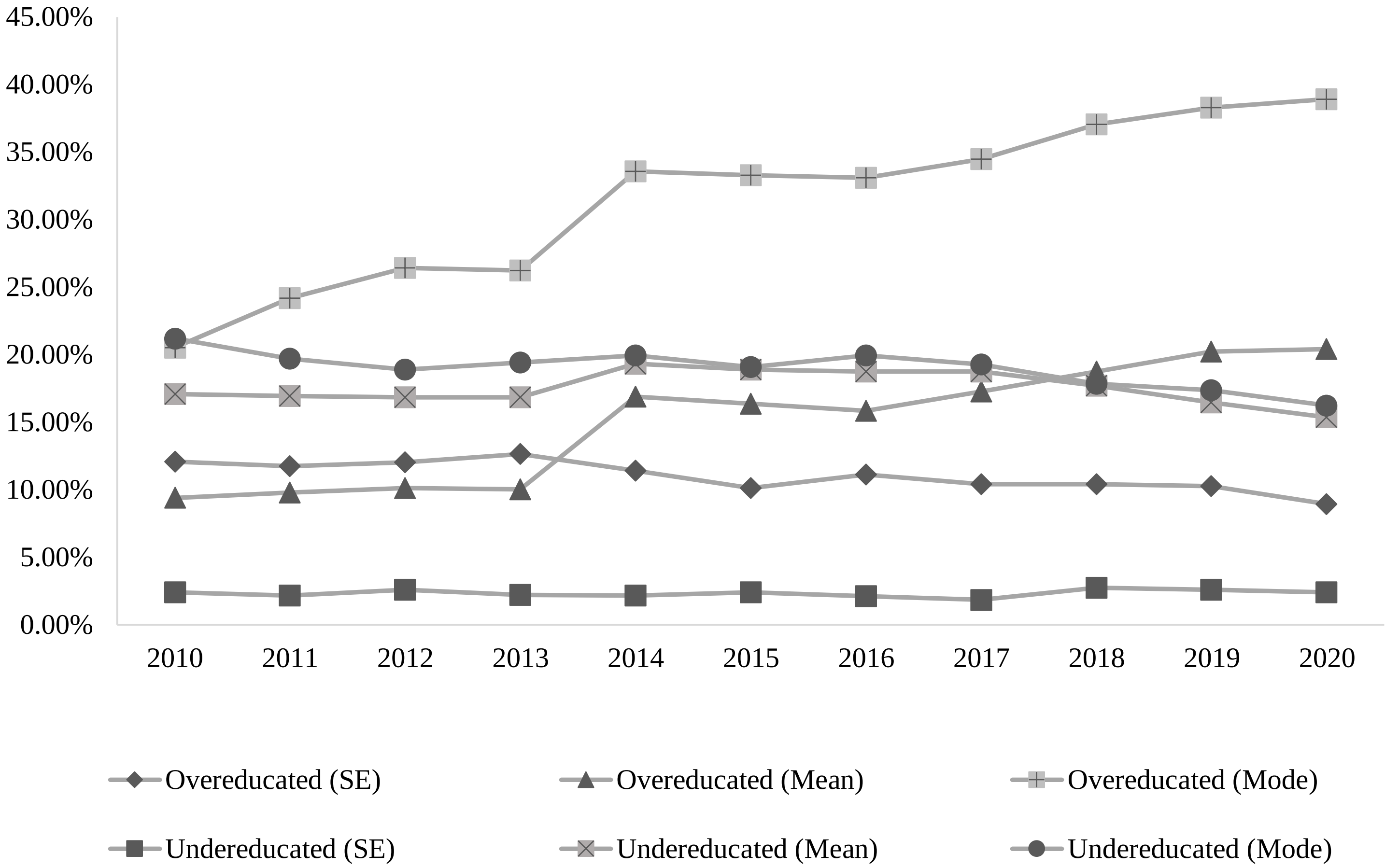
Baltic region countries joined the European Union together in 2004. Several studies have conducted analyses to evaluate whether this event altered how individuals' education is rewarded or not. Wincenciak's meta-analysis shed light on the topic (Wincenciak et al., 2022). The average returns for schooling experienced an increase after 8 out of 12 countries included in the meta-sample became members of the union. Although this outcome was unexpected due to the increased migration of low-skilled individuals post-accession, more favorable labor market conditions and economic environment contributed to the realization of this impact. Regarding the country-specific outcomes of the study, Lithuania rewarded education the highest compared to the other countries within region.

The obtained estimations of returns for years of required, over- and under-schooling in the thesis, especially after controlling for unobserved heterogeneity and measurement errors, became considerably smaller than what has been found by Marsikova and Urbanek based on the analysis of 21 European Union countries (Marsikova & Urbanek, 2015) (see Appendix 2). The authors of that study did not account for unobserved heterogeneity, which increases the likelihood of biased outcomes. Additionally, when paying attention to the countries within the Baltic region, Lithuania demonstrated returns comparable to Estonia for the years of education necessary to perform jobs under consideration optimally. However, the compensation for excess years of education was higher for Estonia. This discrepancy may stem from the employers' evaluations of individuals with high levels of education and the alignment of overeducation levels with industry needs per country.

From the perspective of educational mismatch incidence, the results obtained in the thesis follow a pattern aligning with the literature. Davia et al. (2017) analyzed the primary factors leading to fluctuations in spatial rates of overeducation and provided average overeducation rates for countries included in the European Union Survey on Income and Living Conditions data for the period 2004-2009. The outcomes for Estonia state that 17.1% of males and 22.1% of females are overeducated. The thesis found similar performance for males under the mean method, while the percentage for females was lower. This difference can be associated with variations in the time span of employed datasets. Moreover, drawing attention to the Baltic region countries, Lithuania exceeded Estonia and Latvia by having a higher incidence of overeducated males. The key contributor of it was discovered to be an excess supply of educated labor. Concurrently, Latvia exhibited the lowest occurrence of overeducation in the region for both genders.

Figure 1 exhibits the incidences of educational mismatch obtained in the thesis over the considered period. It is apparent that the mean and mode methods' results follow a similar practice, with relatively smaller outcomes under the mean method. On the other hand, the rates based on the self-evaluation method are smaller in magnitude and more stable over time compared to the other methods. At the same time, when utilizing the Estonian LFS data, analogous rates were reached by Lamo and Messina (2010). However, Galasi's analysis with the ESS data provided a quite higher incidence of individuals referring to themselves as overeducated (Galasi, 2008). This situation could emerge due to the differences between the surveys and participants. Overall, even though Estonia is placed among the top countries with overeducation based on several analysis(European Commission, 2015; Halapuu & Valk, 2013), the returns for these additional years of education are not the highest ones. Evidently, the observed scholarly works did not achieve a common conclusion about the compensation of mismatched individuals, with some of them ranking Lithuania higher as a better rewarder, while others favoring Estonia. Therefore, it opens the spot for further analysis to reach more precise results.

Figure 1. Educational mismatch rates over the time span of 2010-2020.



SE – self-evaluation method. Source: Estonian LFS data for 2010-2020. Author’s elaboration.

6. Conclusions

The primary investigation point of the thesis is to empirically evaluate the impact of educational mismatch on wages using data from the Estonian Labor Force Survey. It also tests whether the incorporation of panel estimation techniques for controlling unobserved individual heterogeneity and the usage of instrumental variables to account for bias from measurement errors lead to consistent outcomes reported by the literature or not. The empirical analysis is conducted using three distinct indicators of educational mismatch. The first indicator directly defines mismatched individuals in the data by relying on their self-evaluation. However, these variables are introduced as dummy variables and, therefore, can only be used for Verdugo and Verdugo's model. The other indicators derive the required education years by utilizing the mean and mode methods. The mean method calculates the mean of respondents' actual education levels based on ISCO-08 occupation levels to two digits and appoints required education as one standard deviation range around the mean. The mode method follows a similar path by setting the required education as the mode value of participants' education for the occupations under consideration. While existing literature mainly utilizes the mean and mode methods, integration of self-evaluation values and comprehensive analysis based on these three measurement indicators can be viewed as a feature that classifies this analysis apart from others.

The estimation outcomes for the OLS model under both Verdugo and Verdugo's and Duncan and Hoffman's models align with the results of scholarly works that have considered the same matter. When comparing educationally mismatched employees to those with the same level of education but correctly matched to their jobs, it becomes evident that there is an earnings penalty for overeducated individuals and a rise for undereducated ones. Moreover, the analysis of the standard human capital earnings equation assists in assessing the returns to actual education, which appear to be lower than the required education returns. The observed differences in earnings for mismatched employees compared to those in the same positions but adequately matched imply that possessing excess or deficit years of schooling has certain consequences. The returns for each excess year of education are positive, while they are negative for each deficit year. Additionally, the examined hypothesis tests for the human capital model, which assumes equal rewards for the years of required, over- and undereducation, and the job-competition model, which considers zero coefficients on over- and undereducation, are rejected.

The scholarly works investigating educational mismatch have been mainly criticized for empirically overlooking the unobserved ability heterogeneity and the potential bias that might be sourcing from measurement errors of mismatch variables. The empirical part of the thesis addresses the mentioned econometric issues through the utilization of panel estimators and instrumental variables. Under both random effects and fixed effects models, the estimated returns experience a general drop in their values. The differences in wages between mismatched employees and adequately matched ones become smaller for both male and female sub-samples. Despite the whole stated impacts, the hypothesis tests for the human capital model and the job-competition model are still rejected. Econometric tests examining the model quality favor the fixed effects model. The empirical analysis carries on with the fixed effects instrumental variables model, which allows for consideration of both econometric issues simultaneously. The outcomes for gender and above 35 age group sub-samples confirm what has been found so far. Each additional year of education beyond necessitated brings a positive return, while each deficit year brings a negative one, and they are smaller compared to the returns of required years. Also, the wage advantage is relatively higher for women than men. The most remarkable change is observed for female employees below the age of 35. The results of tested models concluded that these individuals' wages are mainly determined by their attained level of education rather than the requirements of the job.

Generally, the estimations lead to the findings that the returns for an additional year of required education are greater than the returns for an additional year of education beyond the required level for a job. This suggests that the requirements of a job have a significant impact on wages. Based on the reviewed scholarly works, this result holds in the context of several European Union countries. On the other hand, the returns for the required education level have consistently been higher for females than males. This indicates that the wage influence of job requirements is more powerful for females, particularly over the age of 35.

The returns for required and attained years of education exceed the absolute value of returns for deficit years. Thereby, from the standpoint of individuals, investment in educational background will be profitable as long as they secure jobs that fully utilize their education. However, in the event of high mismatch incidence, being employed in a correctly matched position could be challenging. The levels of educational mismatch incidence should always be under the consideration of public authorities. Countries can determine benchmark levels based on their labor market situation. If it goes above that level, there are several actions that would help improve the situation if implemented. Individuals need to be informed about the labor market demand of the career path they are willing to pursue. Educational and governmental institutions can achieve this through proper career counseling and guidance. It may potentially lead to a reduction in cases of educational mismatch (Quintini, 2011). Furthermore, high rates of educational mismatch obtained based on the measurement methods utilizing realized job matches might imply that not all positions have an accurate required level of education, suggesting room for improvement. To address the issue, employers should review and adjust the necessary educational levels for the positions to the levels that qualify for optimal performance. This action can lead to the advancement in the selection of correct employees and potentially positively impact the productivity of companies and, consequently, the labor market.

The literature emphasizes the significance of distinguishing between education levels and skills for mismatch-related analysis. Unfortunately, the data employed in the study from the Estonian LFS doesn't contain variables related to respondents' skill levels. Therefore, further analysis of the subject by utilizing various data sources and incorporating the skill phenomenon along with education would contribute to the field.

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Appendices

Appendix 1. Conversion of the International Standard Classification of Education (ISCED) (97) and (2011) levels into years.

ISCED 97 levels	Corresponding years
ISCED level 1 – Primary	6
ISCED level 2 – Lower Secondary	9
ISCED level 3 – Secondary	12
ISCED level 4 – Post Secondary non-Tertiary	14
ISCED level 5 – Tertiary	15
ISCED level 6 – Second and higher stages of Tertiary	21

Source: (OECD, 1999)

ISCED 2011 levels	Corresponding years
ISCED level 1 – Primary	6
ISCED level 2 – Lower Secondary	9
ISCED level 3 – Upper Secondary	12
ISCED level 4 – Post Secondary non-Tertiary	14
ISCED level 5 – Short-cycle Tertiary	14
ISCED level 6 – Bachelor’s	15
ISCED level 7 – Master’s	17
ISCED level 8 – Doctoral	21

Source: (OECD, 2015)

Appendix 2. Fixed Effects and Fixed effects with Instrumental Variables regressions for the whole sample.

	Fixed Effects (Mean method)	Fixed Effects (Mode method)	Fixed Effects with Instrumental Variables
Years of required schooling	0.0917^{***} (0.005)	0.0734^{***} (0.004)	0.1023^{***} (0.006)
Years of overeducated	0.0177^{***} (0.005)	0.0446^{***} (0.005)	0.0465^{***} (0.007)
Years of undereducated	-0.0336^{***} (0.005)	-0.0426^{***} (0.005)	-0.0397^{***} (0.006)
R^2	0.3515	0.3514	0.3514
$H_0: \beta_1 = \beta_2 = -\beta_3$	(chi^2) 107.27^{***}	(chi^2) 68.35^{***}	(chi^2) 115.69^{***}
$H_0: \beta_2 = \beta_3 = 0$	(chi^2) 32.73^{***}	(chi^2) 65.31^{***}	(chi^2) 90.68^{***}

( ): Standard errors (clustered). *** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level. R^2 is the overall R^2. Regressions include abovementioned explanatory variables. Source: Estonian LFS data for 2010-2020. Author's elaboration.

Appendix 3. Multicollinearity (VIF) results.

Multicollinearity results for Verdugo and Verdugo model.

Self-evaluation method

Variable	VIF	1/VIF
age	49.99	0.020003
agesq	49.23	0.020314
otherservi~d	6.68	0.149614
wholesale_~d	6.24	0.160266
industry_d	5.51	0.181613
finance_re~d	3.36	0.297908
constructi~d	2.90	0.345012
d_2020	2.72	0.367620
d_2019	2.67	0.374388
d_2018	2.65	0.378050
d_2017	2.15	0.464885
d_2015	2.12	0.472210
d_2014	2.11	0.473317
d_2013	2.06	0.485223
d_2012	2.04	0.491365
d_2016	2.01	0.496682
d_2011	1.93	0.518498
size2_3	1.82	0.549508
size4_5	1.81	0.552818
tallin_d	1.66	0.601745
urban_d	1.48	0.675934
size7_8	1.35	0.742061
size6_6	1.35	0.742874
actual_edu~n	1.26	0.794049
male_dummy	1.23	0.815674
f_harju	1.18	0.844860
f_tartu	1.17	0.856811
f_idaviru	1.14	0.873461
married	1.13	0.881594
fulltime_d	1.13	0.886689
f_parnu	1.07	0.933116
f_saare	1.06	0.945551
overeducated	1.04	0.957584
undereduc~ed	1.02	0.983061
Mean VIF	4.95	

Mean method

Variable	VIF	1/VIF
age	49.97	0.020013
agesq	49.19	0.020330
otherservi~d	6.81	0.146831
wholesale_~d	6.25	0.160025
industry_d	5.51	0.181581
finance_re~d	3.37	0.296326
constructi~d	2.90	0.345156
actual_edu~n	2.79	0.358143
d_2020	2.72	0.367223
d_2019	2.68	0.373746
d_2018	2.65	0.377340
d_2017	2.15	0.464234
d_2015	2.12	0.471668
d_2014	2.12	0.472577
d_2013	2.06	0.485221
d_2012	2.04	0.491360
d_2016	2.02	0.496098
d_2011	1.93	0.518507
size2_3	1.82	0.549598
size4_5	1.81	0.552695
under~ndummy	1.66	0.600919
tallin_d	1.66	0.601641
overe~ndummy	1.58	0.632464
urban_d	1.48	0.675940
size7_8	1.35	0.742126
size6_6	1.35	0.742899
male_dummy	1.23	0.815457
f_harju	1.18	0.844855
f_tartu	1.17	0.856533
f_idaviru	1.14	0.873606
married	1.13	0.882267
fulltime_d	1.12	0.894192
f_parnu	1.07	0.933375
f_saare	1.06	0.947065
Mean VIF	5.03	

Mode method

Variable	VIF	1/VIF
age	50.00	0.020000
agesq	49.19	0.020328
otherservi~d	6.72	0.148900
wholesale_~d	6.25	0.160044
industry_d	5.51	0.181444
finance_re~d	3.36	0.297542
constructi~d	2.90	0.344792
d_2020	2.72	0.367008
d_2019	2.68	0.373575
d_2018	2.65	0.377292
actual_edu~n	2.49	0.402281
d_2017	2.16	0.463976
d_2015	2.12	0.471435
d_2014	2.12	0.472176
d_2013	2.06	0.484886
d_2012	2.04	0.491053
d_2016	2.02	0.495885
d_2011	1.93	0.518345
size2_3	1.82	0.549552
size4_5	1.81	0.552540
overe~edummy	1.78	0.562639
tallin_d	1.66	0.602103
urban_d	1.48	0.676053
under~edummy	1.38	0.724500
size7_8	1.35	0.741320
size6_6	1.35	0.742582
male_dummy	1.22	0.818029
f_harju	1.18	0.845076
f_tartu	1.17	0.856120
f_idaviru	1.14	0.873456
married	1.13	0.882854
fulltime_d	1.12	0.894089
f_parnu	1.07	0.933374
f_saare	1.06	0.946953
Mean VIF	5.02	

Multicollinearity results for Duncan and Hoffman model.

Mean method

Variable	VIF	1/VIF
age	50.02	0.019990
agesq	49.30	0.020283
otherservi~d	6.93	0.144335
wholesale_~d	6.27	0.159586
industry_d	5.51	0.181523
finance_re~d	3.40	0.293726
constructi~d	2.90	0.345112
d_2020	2.72	0.367911
d_2019	2.67	0.374404
d_2018	2.64	0.378109
d_2017	2.15	0.464672
d_2015	2.12	0.472022
d_2014	2.12	0.472779
d_2013	2.06	0.485172
d_2012	2.04	0.491365
d_2016	2.01	0.496625
d_2011	1.93	0.518494
size2_3	1.82	0.549561
size4_5	1.81	0.552968
tallin_d	1.66	0.600826
urban_d	1.48	0.675881
requireded~n	1.42	0.702016
size7_8	1.35	0.742329
size6_6	1.35	0.743123
male_dummy	1.23	0.811455
f_harju	1.18	0.844532
f_tartu	1.17	0.856576
f_idaviru	1.14	0.873439
married	1.13	0.881659
fulltime_d	1.12	0.893727
undereduca~n	1.08	0.929439
overeducat~n	1.07	0.932469
f_parnu	1.07	0.933361
f_saare	1.06	0.946903
Mean VIF	4.97	

Mode method

Variable	VIF	1/VIF
age	50.05	0.019980
agesq	49.25	0.020303
otherservi~d	6.74	0.148376
wholesale_~d	6.25	0.159907
industry_d	5.51	0.181339
finance_re~d	3.36	0.297209
constructi~d	2.90	0.344635
d_2020	2.72	0.367224
d_2019	2.68	0.373725
d_2018	2.65	0.377452
d_2017	2.15	0.464137
d_2015	2.12	0.471511
d_2014	2.12	0.472303
d_2013	2.06	0.484951
d_2012	2.04	0.491096
d_2016	2.02	0.496110
d_2011	1.93	0.518343
size2_3	1.82	0.549459
size4_5	1.81	0.552291
tallin_d	1.66	0.601714
urban_d	1.48	0.676037
size7_8	1.35	0.741624
size6_6	1.35	0.742545
requireded~e	1.34	0.747385
male_dummy	1.22	0.818565
f_harju	1.18	0.845020
overeducat~e	1.18	0.846287
undereduca~e	1.17	0.852540
f_tartu	1.17	0.856264
f_idaviru	1.14	0.873556
married	1.13	0.882900
fulltime_d	1.12	0.894045
f_parnu	1.07	0.933396
f_saare	1.06	0.946957
Mean VIF	4.97	

Appendix 4. Breusch and Pagan Lagrange Multiplier test for the Random Effects models.

	Verdugo and Verdugo model			Duncan and Hoffman model	
	Self-evaluation	Mean	Mode	Mean	Mode
Male (chibar2)	18105.84***	17859.01***	18332.10***	17310.42***	18287.75***
Female (chibar2)	19406.10***	18340.17***	18786.11***	16095.22***	18471.46***

*** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level.
Source: Estonian LFS data for 2010-2020. Author's elaboration.

Appendix 5. The Hausman test for Fixed Effects-Random Effects model selection.

	Verdugo and Verdugo model			Duncan and Hoffman model	
	Self-evaluation	Mean	Mode	Mean	Mode
Male (chi^2)	449.28***	593.09***	503.61***	361.88***	309.48***
Female (chi^2)	451.21***	817.37***	782.75***	303.58***	292.50***

*** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level.
Source: Estonian LFS data for 2010-2020. Author's elaboration.

Resümee

ÜLEHARITUS, HARIDUSE MITTEVASTAVUS JA TÖÖTURU TULEMUSLIKKUS

Käesoleva väitekirja esmane eesmärk on hinnata hariduse ametikohal nõutavale mittevastavuse võimalikku mõju tööturu tulemuslikkusele, keskendudes eelkõige palkasid kujundavatele teguritele. Kasutades Eesti tööjõu-uuringu andmeid ajavahemiku 2010-2020 kohta, kasutatakse uuringus vaadeldavate ametite jaoks nõutavate haridusaastate mõõtmiseks keskmise ja moodi meetodit, st antud konkreetsel ametialal vajaliku haridustaseme (mõõdetuna koolis käidud aastatega) lähendina kasutatakse antud ametialal töötavate inimeste keskmist haridustaset või kõige sagedamini esinevat haridustaset. Empiirilise analüüsi keskmes on Verdugo ja Verdugo (1989) ning Duncan ja Hoffman (1981) pakutud palkade spetsifikatsioonide hindamine, mida tehakse eraldi meeste ja naiste kaupa. Kirjanduses esinevaid peamisi ökonomeetrilisi probleeme, nagu mittevaadeldavate võimete heterogeensus ja võimalikud mõõtmisvead, käsitletakse paneelandmete mudelite ja instrumentmuutujate meetodite kasutamise abil. Empiirikas kasutatud erinevate ökonomeetrilisi mudelite kvaliteeti kontrollivad testid soosivad fikseeritud mõjude mudelit. Lisaks kasutatakse töös moodi meetodil tuletatud nõutaval tasemel hariduse, üle- ja alaharituse muutujaid, ning viimaste instrumentidena vastavate muutujate hinnanguid arvutatuna antud ametiala keskmise haridustaseme alusel.

Verdugo ja Verdugo mudeli hindamistulemused näitavad, et üleharitud töötajad teenivad vähem kui vaadeldavate karateristikute (nt vanus) mõttes sarnased nõutaval tasemel haritud isikud, kes töötavad nende haridustasemele vastavatel ametikohtadel. Seevastu antud ametikoha mõttes alaharitud inimesed teenivad rohkem kui sama haridustasemega ja haridustasemega hästi sobivatel töökohtadel töötavad eakaaslased. Samal ajal väidavad Duncani ja Hoffmani mudeli tulemused, et üleharitud töötajatel on sissetuleku eelis võrreldes samadel ametikohtadel, kuid haridustasemega õigesti sobitatud ametikohtadel töötavate töötajatega, samas kui alaharitud töötajate puhul on olukord vastupidine. Tähelepanuväärne on selle seose sooline aspekt, nimelt on naistel ametialal nõutavate haridusaastate tulumäärad järjepidevalt kõrgemad kui meestel.

Palga suurust määravate peamiste tegurite uurimine näitab niisiis, et ametikohtade haridusnõuded mõjutavad oluliselt palka. Fikseeritud efektidega instrumentmuutujate hinnangud toetavad neid järeldusi, välja arvatud alla 35aastaste naiste puhul, kelle tegelik haridustase mõjutab nende palka rohkem kui töökohal nõutav haridustase. Lõpetuseks soovitatakse magistritöös, et töötajatele peaks olema kättesaadav nõuetekohane karjäärinõustamine, vältimaks haridusliku mittevastavuse juhtumite suurenemist tarbetult suureks. See meede võib potentsiaalselt kaitsta tööturgu ja vähendada haridustaseme mittevastavust ametikohtade nõuetele. Lisaks sellele võib analüüsis täheldatud kõrge haridusliku mittevastavuse määr tähendada, et kõikidel ametikohtadel ei ole nõutav haridustase täpselt mõõdetud ning tööandjad peaksid vastavad tasemed üle vaatama ja neid kohandama, et saavutada oma töötajaskonnalt paremaid tulemusi.

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