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THE EFFECTS OF SKILLS ON THE GENDER WAGE GAP IN ESTONIA: AN ANALYSIS BASED ON PIAAC DATA

Master thesis

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Majanduse modelleerimise õppetooli juhataja Jaan Masso

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Olen koostanud töö iseseisvalt. Kõik töö koostamisel kasutatud teiste autorite tööd, põhimõttelised seisukohad, kirjandusallikatest ja mujalt pärinevad andmed on viidatud.

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(töö autori allkiri)

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INTRODUCTION

Human life has changed remarkably over the past few decades. Today, people use and rely on technologies and devices that had not even been imagined in 1980. The way they live and work has changed profoundly, and so has the set of skills they need to participate fully in and benefit from the hyper-connected societies and increasingly knowledge-based economics. Thus, it is not surprising that there is a growing interest in research regarding the skills of adults.

Faced with the challenges of increasing demands for a skilled workforce in knowledge-based societies, it was only in the more recent past, that the OECD implemented two comparative studies, the International Adult Literacy Survey (IALS), which was conducted in three periods between 1994 and 1998 and covered 21 countries, and the 2003 Adult Literacy and Lifeskills Survey (ALL) that covered six countries.

With regard to Estonia, the influence of education level on earnings has been studied in earlier research works, but there were no studies focused on labour skills due to limitations in data. The gender wage gap in Estonia has been a popular topic in recent years. The average difference between the earnings men and women is the largest in Europe and it is about 30%. This study will be useful in determining, whether skills play a role in the gender wage gap in Estonia.

This research is based on the last survey, a product of the OECD Programme for the International Assessment of Adult Competences (PIAAC), which focuses on skills – literacy, numeracy and problem solving. The Survey of Adult Skills focuses on how adults develop their skills, how they use them, and what benefits they gain from using them. In this research the author focuses on pay-offs from the skills and compares the results between the male and female labour force.

The aim of the present master thesis is to determine whether there is still an unexplained wage gap between men and women in Estonia when skills are taken into account, relying on the the data provided by the PIAAC survey.

In accordance with the aim of the thesis the following research tasks were settled:

- to clarify the main aspects of the human capital theory;
- to give an overview of human capital measurements;
- to give an overview of explanations for the gender wage gap;
- to present a review of earlier studies of gender wage gap in Estonia and other countries;
- to give an overview of the PIAAC survey and of the data about individuals' skills gathered within it;
- to explain the methodology of the present survey;
- to find out how large is gender wage gap in Estonia when skills are taken into account.

The theoretical chapter of the master thesis will be based on earlier articles, studies, and research papers.

Considering the theoretical background of the topic, the author gives a definition of human capital and reveals the history of human capital evolution. The author is focusing on human capital theory, which is one of the most influential and utilized theories in wage gap research. Human capital theory has its roots in Adam Smith's theory about compensated wage differences and provides tools to analyze wage differences between workers with different education and experience backgrounds.

Key to the theory of human capital is the concept that education is an investment of current resources for future returns, knowledge, and skills, and raises the value of a person's human capital, thereby increasing their employability, income potential, and productivity.

The author also touches the topic of assessing human capital, introducing the main methods: the cost-based approach, the income-based approach, and the educational-stock-based or indicators approach.

To make clear the concept of wage gap, the author provides a brief review of the trends in different countries, including Estonia. In addition causes and explanations according to the supply-side and demand-side theories are revealed. The methods of estimating gender wage gap are also presented in the theoretical part of the thesis.

The Mincer equation (1974) is a cornerstone of empirical economics and it is one of the most commonly used tools in earlier research works based on human capital theory. The original Mincer equation assumes linear effect on earnings for each year of education regardless of the attainment level.

However, most earning functions now include numerous supplementary variables in addition to the schooling and potential experience terms used by Mincer. These include race, gender, regional dummy categorical variables, health status, ethnicity, marital status, children, union membership, city size, and numerous other variables. They serve as exogenous "control variables" which essentially shift the earnings function upward or downward depending on the sign. The coefficients on some, such as gender or race, are often interpreted as discrimination, since they allegedly indicate how earnings levels differ between otherwise similar individuals.

The theories mentioned above have been a popular topic for plenty of studies. In the theoretical part the author also describes empirical results of previous studies which analyse earnings based on human capital. The brief overview of the gender wage gap worldwide and in Estonian labour market is done.

In the empirical part of the master thesis the author introduces the last survey – the Programme for the International Assessment of Adult Competences (PIAAC). This is an international survey conducted in 33 countries but already implemented in 24 countries, and Estonia is among them. The first results from the survey were released on 8 October 2013.

An econometric model of earnings in Estonia is made, focusing on PIAAC data and answering the research question. The author presents descriptive statistics of variables selected for the research grouped by gender. After that, the author will answer the main question of the thesis making various analyses: the OLS regression analysis based on

Mincer equation, and the Oaxaca-Blinder decomposition to find the size of the unexplained wage gap.

1. ASSESSMENT OF HUMAN CAPITAL AND IT'S CONNECTION TO GENDER WAGE GAP

1.1. Overview of Human Capital Theory

Humans, their skills and knowledge, what they use to be successful in society were traditionally in the central place in social and economic sciences. However, because of the industrial revolution, material and technological values were put into first place. Since that period human skills and their influence on social and economic growth and community success were underestimated. Thanks to this fact for a long period of time human skills were considered a quantitative factor of industry.

Recent challenges such as globalization, a knowledge-based economy, and technological evolution have promoted many countries and organizations to seek new ways of maintaining competitive advantage and to increase economic success (Boarini 2012: 10, Kwon 2009: 1). The ability of an economic system to innovate and compete is strictly connected to the accumulation and availability of human capital, which is highly skilled, motivated and innovative (Human Capital 2008: 20). It is hereby necessary to emphasize that the same challenges motivate individuals to discover and improve their own competitive advantages.

Not only the quantity of offered goods and services becomes important, but their quality. To awaken the customer's interest, the producer should not only enlarge the offered assortment, but also think about attractive and innovative goods that are oriented to the customer's needs. Employed people with higher levels of individual competence play a great role in this process. There is no doubt that people are becoming valuable assets and can be recognized within a framework of human capital (Kwon 2009: 1).

There are many definitions of human capital used in the literature, but most of them stress the economic returns of human capital investment. Schultz (1961), for example, defined human capital as “acquired skills and knowledge” to distinguish raw (unskilled) labour from skilled labour; similarly, the Penguin Dictionary of Economics (1984) defined human capital as “the skills, capacities, and abilities possessed by an individual which permit him to earn income”, a definition which emphasizes the improvement of people’s economic situation due to human capital investment. The World Bank (2006) similarly defined human capital as the productive capacity embodied in individuals, with a special focus on its contribution to economic production. (Boarini 2012: 9)

Boldizzoni (2008) states that broadly the concept of human capital is semantically the mixture of human and capital. In the economic perspective, the capital refers to “factors of production used to create goods or services that are not themselves significantly consumed in the production process”. (Kwon 2009: 1). Thereby, human capital is rather associated with intellectual impact, ideas and concept creation, and design, which are essential parts of a finished product.

The sense of an investment for the future is a key characteristic of the human capital theory. McNabb in Nübler (1997: 6) claims that the acquisition of human capital through education and training is an investment in the sense that the individual foregoes current income for increased earning potential in the future. Boarini mentions that human capital investment delivers many other non-economic benefits as well, such as improved health status, enhanced personal well – being, and greater social cohesion (Boarini 2012: 10). For example, from the employer’s point of view investment into human capital means not only a stable salary, but also social security, motivation to lead a healthy life, and organization of cultural events. The employee investing into his or her own human capital receives more opportunities for self-realization along with the salary.

Acknowledging these broader benefits, the OECD gradually extended its definition of human capital. In an OECD report published in 1998, human capital was defined as “the knowledge, skills, competences and other attributes embodied in individuals that are relevant to economic activity” (OECD, 1998). A later report, however, defined human capital as “the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being” (OECD, 2001). (Boarini 2012: 10)

Figure 1 is presented below has been composed in accordance with the broader definition of human capital performed in the 2001 OECD report. The box displays different sources and elements of human capital investment, as well as benefits generated due to it. Terms introduced in the diagram are commonly used in different approaches and methods to measure human capital.

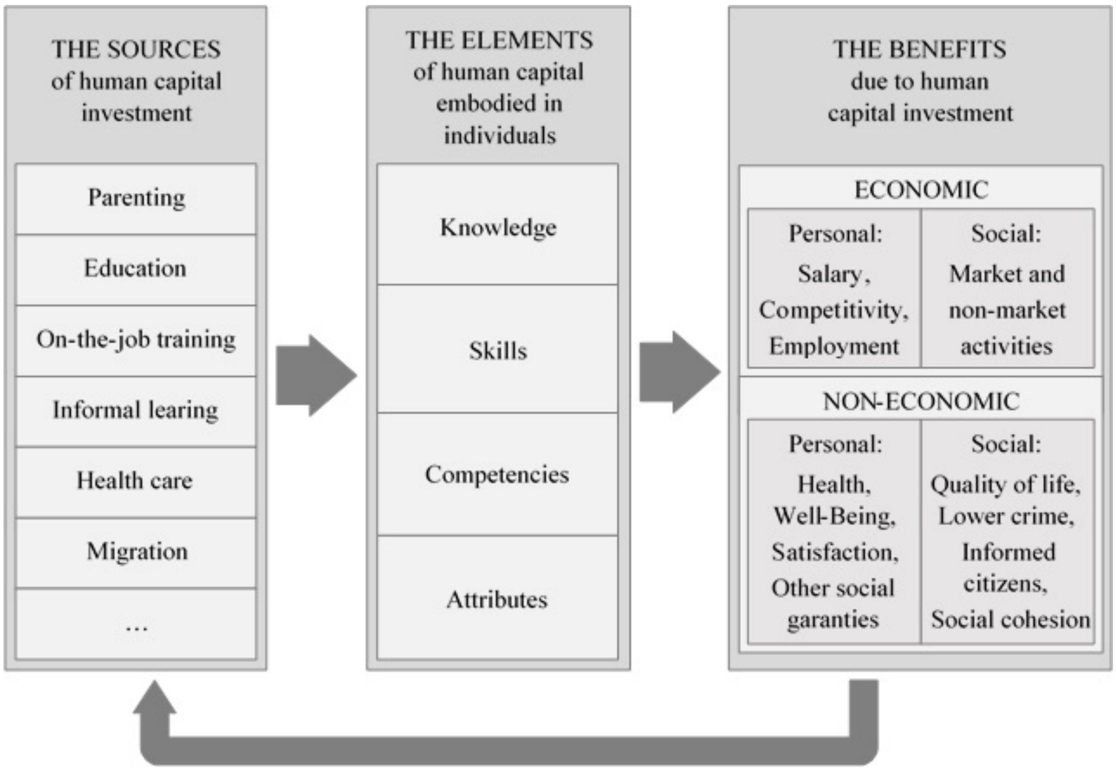

Figure 1. Human capital formation and its' benefits (Boarini 2012:10; author's adjustment).

Above, the author has considered the importantance of human capital todays. But it's also necessary to take a look at the historical background. It is arguable that Sir William Petty (1690) was the first to try to define and measure the concept of the human capital (Folloni 2010: 248). Petty thought that social well - being depends on the kind of activities. He divided them into useless activities and activities that increase individuals' qualifications and disposes them to some kind of performance that has a huge impact on economics. Petty believed that labour was the 'father of wealth' and that a measure of its value should be included in the estimation of national wealth (Folloni 2010: 248).

After Petty there were other significant approaches. The greatest role in human capital measurement is assigned to Adam Smith, who introduced the human capital concept in "The Wealth of Nations" (1776).

Smith has proposed that it would be a misjudgment to consider only the value of machines and not that of individuals in the stock of the wealth of a nation. It is not correct to compare the national income and the wealth of the nation. (Human Capital 2008: 16). The first refers to the sum of all production factors that are material and personal means, and the second is generated with the aid of human capital.

Over one hundred years after Smith, Alfred Marshall (1890) proposed in his definition of the human capital to include all those energies, faculties, and habits that directly contribute to making people industrially efficient. Such production capabilities are also capabilities whose value can be measured only indirectly. (Human Capital 2008: 17) Taking into consideration the views of Smith, Marshall defined capital so broadly that personal wealth could be interpreted as capital (Sweetland 1996: 344).

In the 1960s scientific researchers tried to introduce human capital theory and put it into separate section of economic analysis. Theodore Schultz (1960) studied increasing wealth in the U.S.A. between 1889 and 1957 and found that the human capital stock, which could be acquired through education and literacy, forms the basis of all theories, which seek to explain economic growth. (Human Capital 2008: 17)

In his book on "Human Capital" (1964), Gary S. Becker demonstrated that an investment in training and education to increase one's human capital was as important and measurable as an investment in other forms of capital (The Nobel Foundation, n.d., with reference through McIntyre: 2). Eleven years later Becker (1975) defined "forgone earnings" as those that people relinquish to invest in human capital accumulation (Bowman, p. 25 with reference through McIntyre: 1).

According to historical review and the definition proposed by OECD, the author finds that the key words connected with human capital are investment, skills and competencies possessed by individuals, social welfare, and sustainable growth of economy. Acquisition of human capital is necessary for a person who becomes more successful in his career and life on the whole, as well as for economic society due to promoting higher competitiveness and innovative findings.

1.2. Assessment of Human Capital and the Gender Wage Gap

Almost fifty-five years ago when Schultz (1961a) (re) introduced the concept of human capital, it was controversial wheather humans should be classified as “capital”. In general, capital is often defined as a set of resources that are required to produce goods and services and to receive profits.

Today, human capital has become a common piece of jargon not only in academic circles but also among politicians, business people, and the media. The importance of human capital is also understood by official statistical agencies charged with measuring basic economic phenomena (Le *et al.* 2005: 2). Along with financial capital human capital becomes one of the essential components of economic growth and international competitiveness. This means that as in the case of physical capital it is necessary to determine the stock of the human capital and to take into account the factors that may influence its value. Measuring human capital can serve a number of purposes, e.g. to better understand what drives economic growth, to assess the long-term sustainability of a country’s development path, and to measure the output and productivity of the education sector.

Le *et al.* (2005) identifies three major approaches to measuring human capital: the cost-based approach, the income-based approach, and the educational-stock-based or indicators approach. Below are briefly considered the main points of widely used human capital measurement approaches.

A very common approach to measuring the stock of human capital is the cost-of-production method originated by Engel (1883), who estimated human capital based on child-rearing costs to their parents. This approach estimates human capital based on the assumption that the depreciated value of the dollar amount spent on those items defined as investments in human capital is equal to the stock of human capital. (Le *et al.* 2005: 2)

Kendrick (1976) and Eisner (1985, 1989) were among the seminal examples of providing an estimate of the resources invested in the education and other human capital-related sectors and activities, which can be very useful for cost-benefit analyses. Kendrick divided human capital investments into tangible and intangible. The tangible component consists of those costs required to produce the physical human being, including child-rearing costs to the age of 14. Intangible investments are the costs to enhance the quality or productivity of labour, like expenditures on health and safety, mobility, education and training, plus the opportunity costs of students attending school. (Christian 2011: 2; Le *et al.* 2005: 4-5)

The income-based approach measures the stock of human capital by summing the total discounted values of all the future income streams that all individuals belonging to the population in question expect to earn throughout their lifetime. This method is said to be 'forward-looking' (prospective) because it focuses on expected returns to investment, as opposed to the 'backward-looking' (retrospective) method whose focus is on the historical costs of production. (Le *et al.* 2005: 9)

Unlike the "conventional" approaches that measure capital by cost or by yield, the education-based approach estimates human capital by measuring such education output indicators as literacy rates, enrolment rates, dropout rates, repetition rates, average years of schooling in the population, and test scores. The rationale for this method is that these indicators are closely related to investment in education and that (investment in) education is a key element in human capital formation. Educational measures are therefore proxies for, not direct measures of, human capital. Of course, human capital encompasses more dimensions, but education is arguably the most important component. Indeed, for individuals, education can enhance well-being not only by opening up broader economic opportunities, but also through non-market benefits such as improvements in health, nutrition, fertility, upbringing of children, opportunity for self-fulfillment, enjoyment and development of individual capabilities (Haveman and Wolfe, 1984). At the macro level, education plays a central role in economic, institutional and social development, and technological progress. (*Ibid*: 18)

Different approaches have their own advantages and disadvantages. Depending upon the purpose, it is expedient to use one of these approaches either individually or jointly with others. Also worldwide surveys for testing people's actual skills (literacy, numeracy, problem solving) have come popular in last decades. This process helps to unify the data among different countries and makes international analysis possible. This began in the 1990s with the IALS (International Adult Literacy Survey) survey, and there was also an ALL (Adult Literacy and Lifeskills) survey for some developed countries and the newest survey results were received in 2013 with PIACC (Programme for the International Assessment of Adult Competencies).

Due to the data collected within the framework of different international surveys, it is possible to trace the variety of the skills performed by men and women and to estimate their investments in education. As previously shown, these factors influence the value of human capital, i.e. men and women may earn different salaries. The problem of gender wage gap is a topic of an enormous number of research papers and discussions, leading to a search for explanations.

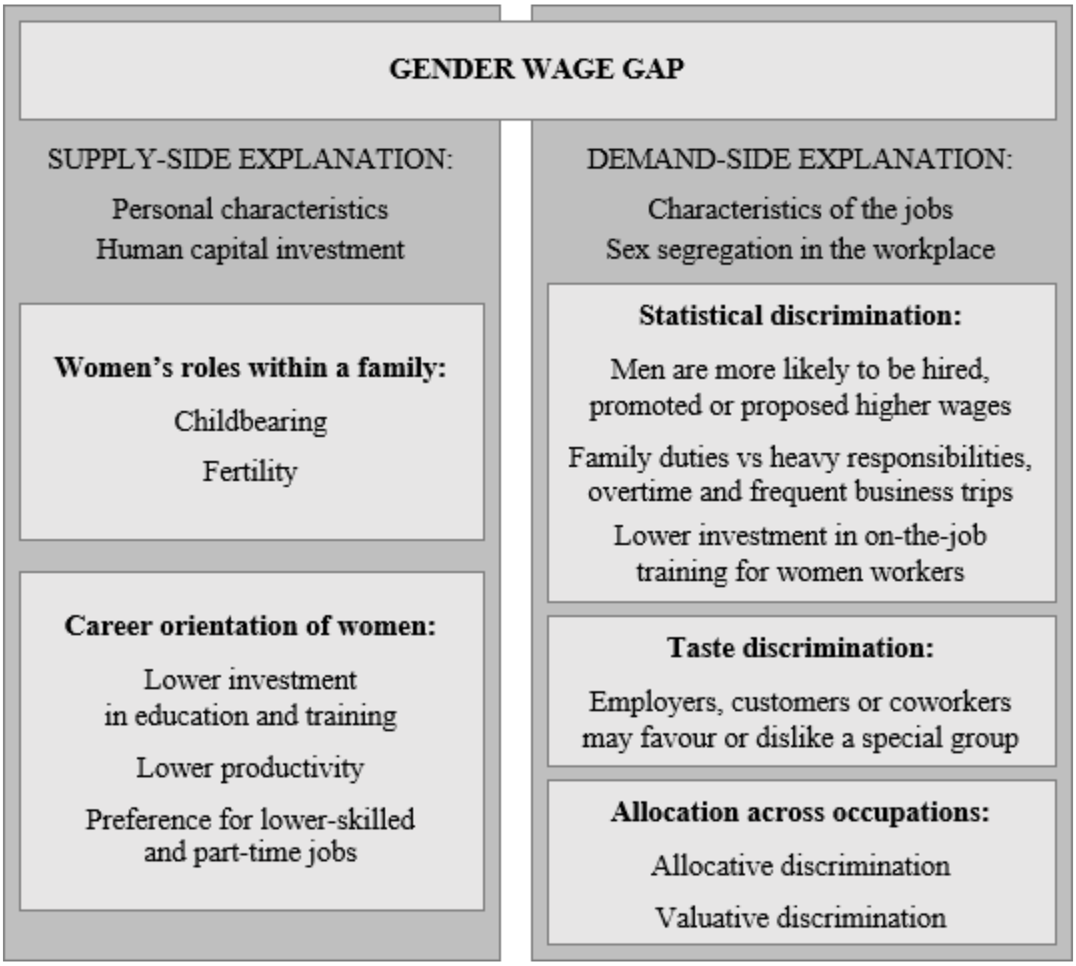

Figure 2. Explanations of gender wage gap (made by the author).

Basically, two schools of thought have developed (see Figure 2). The human capital explanation has a supply-side focus looking at the personal characteristics of working women and men. The sex-segregation-in-the-workplace or discrimination explanation has a demand-side focus looking at the characteristics of the jobs in which women and men typically work. The human capital model focuses on the voluntary choices made by women, while the discrimination model on the restrictions faced by women.

The initial proponents of supply-side explanations are human capital theorists Jakob Mincer and Solomon Polachek (1974). They propose that because of the sexual division of labour in marriage, women are more likely to disrupt their working lives while childbearing and hence are less likely to invest in education and training. Women consider it unprofitable to invest in market-oriented skills, because they expect to spend fewer years than men in the labour force. According to the human capital explanation, women's smaller human capital investment lowers their productivity, they have incentives to seek lower-skilled jobs, and hence their earnings are lower relative to men's. Polachek (1981) expands this argument further to suggest that in expecting a more interrupted working life women choose occupations that do not require frequent updating of skills (Figart, Varnecke 2013: 209). However, male and female workers still differ in their individual characteristics. In general, men have more labour market experience and seniority and less part-time employment. Men and women also tend to differ in their fields of study and in the selection of which college courses they participate in (Reskin, Bielby 2005: 75). Chevalier (2007) finds that women with a preference for childbearing earn less even before they have children due to their choice of college major and because they engage less intensively in job searching (as it was already shown by Goldin and Polachek 1987). (Grove *et al.* 2009: 3)

Arguably the variable most influencing women (and men's) lifetime work behavior is fertility. The greater the number of children in a family the more pronounced the division of labour. Two observable consequences appear from high fertility. Firstly, women are expected to drop out of the labour force more frequently, which suggests less market experience and less human capital investment (Mincer and Polachek 1974). Secondly, women are likely to exert less effort in market work (Becker 1985). Both eventually lead to a larger gender pay gap. (Polachek 2009: 18)

In addition, the earliest studies show, that male-female wage differences are relatively small (usually less than 10%) for single (especially never married) men and women, but considerably larger (roughly 40%) for married men and women (Blau and Kahn, 1992), and even greater for those men and women with children (Harkness and Waldfogel, 2003), especially children spaced widely apart (*Ibid* 2009: 2). It's obvious that single persons are more likely to spend their time on work and they may agree to different working conditions (shift work, business trips, higher responsibility, etc). Married men are used to working harder (and earning more) to guarantee an increase in the well-being of the family. At the same time, married women with children sacrifice their career ambitions to housekeeping.

The National Academy of Sciences (1981) found that less than one-half of the wage gap between the sexes could be explained by human capital variables alone (Levine 2003: 6). For a national sample of MBAs, 82 per cent of the gap is accounted for by incorporating non-cognitive skills (for example, confidence and assertiveness) and preferences regarding family, career, and jobs. Those two sources of gender heterogeneity account for a quarter of the "explained" pay gap, with half due to human capital variables and the other quarter due to hours worked and current job characteristics. (Grove *et al.* 2009: 1)

Studies conducted in developed market economies find that part of the gender pay differential is attributable to the variation in education and experience by gender (as was proposed by Blau 1998 and Gunderson 1989). Gender segregation was found to be particularly important in explaining male-female earnings differences in transition economies (Jurajda 2003, Ogloblin 1999). Nevertheless, these factors explain only a limited portion of the gender pay gap, and the remaining difference is typically regarded as a measure of gender discrimination. (Semykina, Linz 2007: 3)

Gender differences on the supply side are not the only explanation for gender inequality in the labour market. Women's disadvantages might also be due to discrimination in limiting the range of occupations in which women may work. In the literature, statistical discrimination and taste discrimination are common explanations. They called demand-side explanations.

Men and women's average investments in human capital or labour force participation are central to statistical discrimination theory. The principle is that employers do not treat female employees according to their individual characteristics, but judgments in hiring, promoting, or setting wages are usually based on the average productivity of women as a whole. Employers often prefer male workers because women are more likely to interrupt their working life, to take parental leave or to reduce their time in paid work. (Altonji, Blank 1999: 3180-3181) Employers are perhaps less prone to propose career opportunities and high wages to women when it seems that heavy responsibilities, much overtime or frequent business trips are difficult to combine with family duties. Furthermore, employers are not interested in replacing people in positions that require a high degree of on-the-job training because of great expenditures. This is the purpose for lower investments in on-the-job training for female workers. (Mincer and Jovanovic 1979). Given that women have a higher probability of being absent from work, employers are more prone to allocate women to positions with low turnover costs within a specific occupation (Bielby and Baron 1986). (Magnusson 2010: 6)

Another type of discrimination against women is taste discrimination, which means that employers, customers, or coworkers favour or dislike a special group. Becker (1957) suggests that male and female employers, workers, and customers may have a "taste for discrimination", which results from their subjective prejudice for the female sex and/or their ignorance of the economic efficiency of this sex (Figart, Varnecke 2013: 211). Employers are willing to pay higher wages to male workers and they artificially restrict supply to such jobs. The preferences might be due to customers objecting to interactions with this disadvantaged group or that employers prefer another group. Another reason might be that male employees, for example, refuse to work with women.

Becker argued the market mechanism would not support an employer with a taste for discrimination in the long run because the employer is paying a wage premium to keep male workers. The discriminating employer would have higher labour costs, making it ever more difficult for him or her to stay competitive against other producers (Pham 2011:15).

Besides gender differentials in human capital and discrimination, many previous researchers have focused on occupational characteristics to explain women's lower wages.

It is widely believed that women are differentially allocated to occupations and establishments that pay lower wages. This process is called "allocative discrimination", and it may involve discrimination partly through differential access to occupations and establishments and partly through subsequent promotions. On the other hand, occupations held primarily by women are paid lower wages than those held primarily by men, although skill requirements and other wage-relevant factors are the same. This process is addressed by comparable worth and is calls "valuative discrimination". (Petersen 1995: 330)

The sector of economics also plays an important role in causing wage gap. Public employment is another indicator of wage compression because public sectors are more inclined than private sectors to equalize wages for their employees (Polachek 2009: 20). This may be explained by the fact that data on earnings in the public sector should be available to the public. Private enterprises, in contrast, are not obliged to inform the public about the level of salaries and it is harder to detect if any employee is underpaid or not compared to others.

There are numerous studies with different sets of data performed during the last decades. All of them are observe why the wage gap between women and men is present in different countries and what are the reasons for its existance. Also studies try to understand how it influences the efficiency of resource allocation and economics of the countries.

When examined across time, the gender pay gap declines significantly in the United Kingdom, the United States, and France, starting out around 50% and ending up at about 25%. For France it declines from about 35% to 10% over 1970 - 2000. For other countries, such as Belgium, Luxembourg, Spain, Sweden, and Switzerland the gap has been relatively constant. (Polachek 2009: 2) Historically it could be said that wage gap is decreasing or staying the same, at least in developed countries, where the wage gap decreased 10 - 25% during the last decades.

Despite the increase in female labour force participation, numerous studies have documented that women's earnings remain significantly below men's earnings. In the United States, women employed full-time earn about 24% less than men with equal qualifications (Blau and Kahn 2002). Among individuals in the 25 European Union (EU) countries who are employed more than 15 hours per week, women are paid an average of 15% less than men (Eurostat 2006). In New Zealand, women working full-time earn about 18% less than men (Anonymous 2005), and in Japan, women employed full-time earn about 35% less than men (Nakata and Takehiro 2002). The trend is clear; despite significant increases in female labour force participation, women can expect to be paid less than their male counterparts. (Stickney 2007: 802)

Many OECD countries have made significant progress over the past few decades in narrowing the gender gap in education and employment. Results from PISA show that 15-year-old girls outperform boys in reading and have higher career aspirations (OECD, 2012a), and more women than men are now enrolled in tertiary education (OECD, 2012b). Despite these gains, inequities persist. Women are far less likely than men to pursue careers in science or technology and, with few exceptions, women earn less than men with similar levels of education (OECD, 2012a). (OECD Skills ... 2013: 108)

In different countries different demographic and institutional factors may affect the labour market, determining women's professional activity and readiness to make a career. This means that gender wage differences should be explored comparatively across countries (Polachek 2009: 2). To make research more competent it is necessary to have a lot of data that is comparable to each other. This is not the easiest task inside one country, not to mention the research among various countries.

The problem is that actual human capital investments are not directly observable. Most data contain years of school, some contain actual work experience (only up to the time the data were collected), but few are detailed enough to contain the particular subjects studied in school, types of on-the-job training, or subjective variables such as the quality of schooling (sometimes measured by courses studied or college major, if available) or motivation. Yet these latter, more subtle factors are important determinants of human capital investment but are rarely available when explaining the gender wage gap (Weinberger and Kuhn, 2005). (*Ibid.*: 3)

An alternative to using educational attainment indicators (schooling levels completed, schooling years) is to assess skills directly. Experiments on surveys seeking to measure the skills of workers directly (in terms of literacy, numeracy, and problem solving capacities) began in the 1990s (IALS surveys) for a pilot group of 12 countries. At present, survey data based on this approach (the Adult Literacy and Lifeskills – ALL – Surveys) are available only for a group of developed countries (see OECD, 1998; NCES, 2005). (Folloni 2010: 264)

The methods for estimating the gender pay gap are an important topic themselves. Among these methods, incorporating a dummy variable into the Mincer earnings equation and computing a discrimination coefficient based on the Blinder-Oaxaca decomposition appear to be the most common.

The Mincer earnings equation is probably the most widely adopted equation used to estimate the age-earnings profile, largely because of its estimation convenience and its explanatory power.

Mincer's work is the cornerstone of the literature on the relationship between earnings and human capital investments at the individual (or household) level. Its theoretical background is similar to Becker's (1964) and focuses on the relationship between completed schooling and average earnings over the lifecycle. It may be viewed as a specification of the more general approach using hedonic wage functions that connects wages, investment in education and ability (Rosen, 1974, 1977). (*Ibid*.: 260)

The classical Mincer approach links the logarithm of average earnings to completed years of schooling and years of experience (*Ibid*.: 260):

$$(1)\ \ln\left[w(s,x)\right] = \alpha_0 + \rho_s s + \beta_0 x + \beta_1 x^2 + \varepsilon$$

where $w(s,x)$ is the wage at schooling level *s* and work experience *x*,

ρ_s is the rate of return to schooling (assumed to be the same for all schooling levels),

ε is the mean zero residual.

Typically, raw wage gap is calculated in the studies. Then with the help of regression analysis the main influences of selected explanatory variables on salary are observed.

Blinder-Oaxaca decomposition is used to find the explained and unexplained part of the wage gap. More detailed information about this method is presented in Chapter 2.2. "Methodology of the Study".

1.3. Overview of Earlier Studies of Earnings

As was mentioned in the previous chapters, skills are composing human capital and salary is one of the personal economic benefits. Both skills (costs of learning) and earnings became a base for human capital measurement. There is a great amount of opinions all over the world about the returns to cognitive abilities, but there are few of them which study the effect of cognitive skills on gender wage gap.

Perhaps the research made by Hanushek *et al.* (2013) about returns to skills around the world is one of newest and most actual. It is based on the PIAAC survey (2013) of adult skills over the full lifecycle in 24 countries. Results of the study confirm that estimates based on early-career earnings underestimate the lifetime returns to skills. Across the countries studied, a one-standard-deviation increase in numeracy skills is associated with an average 18 per cent wage increase among prime-age workers (Hanushek *et al.* 2013: 2), but this masks considerable heterogeneity across countries. Also, estimates consistently indicate that better skills are significantly related to higher labour-market earnings.

Findings concerning the relation between cognitive skills and labour market outcomes are ambiguous. On the one hand, some studies consider there to be a substantial positive relationship between cognitive skills and earnings (see Appendix 1), among which are Cameron and Heckman (1993), Blackburn and Neumark (1993), and, more recently, Green and Riddell (2003), as well as Bronars and Oettinger (2006), who made a study of US and Great Britain labour markets. Richard J. Herrnstein and Charles Murray (1994) also support cognitive ability as the single most important determinant of labour market outcomes (Cawley *et al.* 2001: 433).

McIntosh and Vignoles (2000) used the U.K. National Child Development Study and International Adult Literacy Survey data sets and found that literacy and numeracy have a significant effect on earnings and are important determinants of economic outcomes. By using dummy variables for levels of numeracy, they were able to detect nonlinearity and found that its effect is strongest in the lowest part of its distribution. In spite of difficulties in obtaining consistent measures of individuals' literacy and numeracy skill in both data sets, they came to the conclusion that workers with higher level of numeracy and literacy are associated with 15% - 19% higher income.

Nordman *et al.* (2014) provide evidence for a poor country such as Bangladesh, where gender inequalities are found to be large and persistent. They conclude that reading and numeracy skills seem to confer benefits upon men and women differently, albeit positively, at different points of the distribution. When looking at decompositions, gender differences in both cognitive and non-cognitive skills matter. Including measures of cognitive skills and personality traits reduces the mean unexplained component by about 5 percentage points when firm effects are also accounted for. (Nordman 2014: 15)

Sowa (2014) evidences pay-offs in terms of wages from cognitive skills in the Swedish labour market, using data from OECD's PIAAC survey of adult skills. Results showed that both literacy and numeracy have a significant effect on wages in the Swedish labour market.

On the other hand, there are just as many studies suggesting that cognitive ability has barely any effect on earnings (Bound et al., 1986, or Murnane et al., 1995). Cawley et al. (2001), and Zax and Rees (2002) conclude that for the US and Great Britain that cognitive ability is a poor predictor of earnings compared to a direct measure of education, family background, and environment. Bowles *et al.* (2001) find that literacy skills have a very little impact on earnings.

Favaro and Magrini (2008) developed a non-parametric procedure (based on OLS coefficient estimates) to evaluate the probability distribution of the "unexplained" part of the wage gap for young females in north - eastern Italy. They conclude that the component of the wage gap due to differences in rewards based on human capital characteristics increased throughout the 1990s. Futhermore, the results have shown that highly educated women experience much higher increases in the wage gap, and it cannot be narrowed due to experience or tenure in the firm. (Addabbo 2011: 83)

Papapetrou (2008) concludes with his evidence on gender wage differentials in Greece that the wage differential between male and female employees is not attributed to employees' characteristics but rather to the unexplained part.

While the effect of an individual's skills on earnings have so far mainly been examined for the US and the UK, this study adds to the literature providing evidence for Estonia.

The gender wage gap in Estonia has been the topic of many articles and research papers. The gender wage gap is a real problem in Estonia. There has been an increase in the gender wage gap during recent years. According to the data collected by Eurostat men earned 24% more than women in 2000, whereas in 2013 the unadjusted gender wage gap rose to 30%.

For the European Union (EU-28), women's gross hourly earnings were 16.6% below those of men on average. Across Member States, the gender wage gap varied by 26.7 percentage points, ranging from 3.2 % in Slovenia to 29.9% in Estonia (see Figure 3).

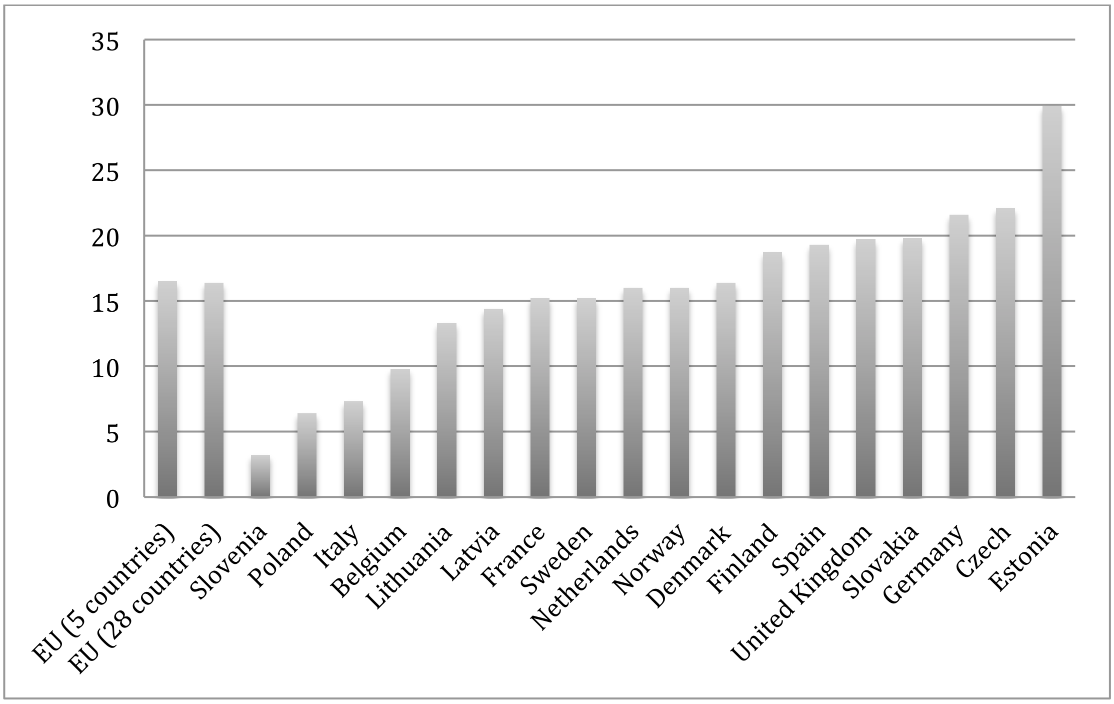

Figure 3. The unadjusted gender wage gap in European countries for data from 2013. (Made by the author based on Eurostat data).

During recent years the differences between the wages of men and women in Estonia have been thoroughly researched by Anspal *et al.* (2010). Previously, the differences and changes in the wages were also studied by Rõõm and Kallaste (2004), as well as by Kristjan-Olari Leping (2005), who dealt with the same topic and wrote the article “Human Capital and Wage Relations and Dynamics in Estonia”.

One of the newest papers on returns to cognitive skills was made by Mart Kaska (2014) in his master thesis “Returns to Numeracy Skills in Estonia Compared to Other OECD Countries Based on PIAAC Data”. The aim of his work was to investigate the returns to numeric skills among adults in Estonia and compare the results to other countries. In the empirical part the author investigates returns to numeracy skills in different regression models and compares Estonia’s results to other countries that participated in PIAAC in a supply and demand framework.

Meriküll and Mõtsmees (2014) studied the gender wage gap in desired wages, realised wages, and reservation wages in their research paper “Do You Get What You Ask? The Gender Gap in Desired and Realised Wages.”

The methodology of all the studies is based on the theory of human capital, which explains the gender wage gap due to the differences in efficiency between men and women. The aim of the studies was to show the influence of various factors on the gender wage gap and the way it has changed over time. What is more, Anspal *et al.* (2010) tested the segregation importance in wage gap formation.

All the authors use regression analysis (Mincer equation) in order to discover what part of the gender wage gap is explained by measurable factors of men and women, and how much of a gap remains unexplained by them. The influence of different explanatory variables is analysed by taking variables one by one from the regression equation and observing the change in the unexplained part.

The differences between the wages are identified with the addition of descriptive variables: the position of the employee (men who occupy highly paid positions usually work more than others), the industry where the company works (the increase in the gender segregation), the age (the unexplained difference in wages is bigger in case of younger employees and less in case of older ones) and the level of education (only when the regression does not contain the position of the employee and the descriptive statistics of the company).

The regression analyses of Leping (2005), Rõõm and Kallaste (2004), Anspal *et al.* (2010), and others are based on the personal data extracted from the studies of the Estonian labour market. The studies of the Estonian labour market focus on a selective questionnaire of households which has been conducted by the Estonian Department of Statistics since 1995. The collected data covers all the citizens of working age permanently living in Estonia aged from 15 to 74.

The Estonian labour force survey (LFS) is the source of official statistics for the labour market and is representative of all the demographic groups in the country. The Estonian labour force survey contains information about the main occupation of the primary employment, the position, the employment status, the type of working relations, the working hours, and existence of additional work. In addition to this information, the respondents are asked questions about their education, health, working conditions, travelling and general background information during the research. (Leping 2005: 22)

Meriküll and Mõtsmees (2014) use two data sources: the job-search database from CV Keskus and the Estonian labour force survey. The data from CV Keskus is used to provide information about the job seeker's expected wage. LFS is used to complement the analysis with realised wages and reservation wages.

Rõõm and Kallaste (2004) analysed the intensity of worksearch and its interconnection with the gender wage gap. It was discovered that men search for jobs more actively and this influences the wage as well. The reservation wage affects the probability of finding a job and its earning. According to Rõõm and Kallaste, the reservation wage of men is higher. The expectations of a higher wage serve as a signal to work effectively. Due to the high working efficiency, an employer agrees to pay a higher wage.

Anspal *et al.* (2010) discovered that the wage gap can be partially explained by different measurable characteristics of men and women. However, different research studies point out that the largest part of the wage gap is left unexplained. During the period of 2000 – 2008 the general gender wage gap comprised 29% on average, whereas the unexplained one was 24% on average. In addition, Rõõm and Kallaste found out that one-third of the wage gap can be explained on account of human capital and workplace differences in men and women. However, two-thirds are left unexplained.

During the analysis of the Mincer Earnings equations, Anspal *et al.* came to the conclusion that men who have a partner earn much more than those living alone, and the same effect was discovered among women, although smaller in size. Rõõm and Kallaste revealed that women with children earn less than women without children, while for men the difference is statistically insignificant. Obtaining higher education is more beneficial for women than for men. However, the size of man's wage depends on the obtained profession (Anspal 2010). In contrast to this, Rõõm and Kallaste received the opposite result: the future income of men is more influenced by education. Moreover, men who work in a private sector exceeding the average number of working hours earn more, while women are not affected by the same factors (Rõõm, Kallaste 2004).

Working in the public sector is negatively connected with women's wages; furthermore it affects men more strongly than women. Horizontal and vertical segregations are playing an important role on raw and unexplained wage gaps. (Anspal 2010)

Krillo and Masso found that the wage gap among women is mostly affected by such factors as position, age, and size of the company. As for men, the most important factors are connected with the employer, such as the size of the company and its ownership (domestic or foreign one). The results of the Oaxaca-Blinder decomposition show that horizontal segregation has the most influence on both men and women's characteristic differences in the wage gap.

Kaska M. concludes that simple Mincer equations with and without the inclusion of numeracy scores indicate fundamental differences between males and females in the Estonian labour market. Cognitive skills seem to explain most of the variance in education with respect to wages for males. For females, higher education is related to higher wages even after the variance of skills is accounted for. (Kaska 2014)

The results for Estonia are robust to different specifications of education (different number of levels) and skills (continuous or categorical with a different number of levels). They indicate that a 10-point increase in cognitive skills is associated on average with a 2.2% higher hourly income for males and 1.8% for females. The effect is similar only for full-time employees. (Kaska 2014) The author came to the conclusion that Estonia stands out from other countries in occupying the middle ground, due to its high level of the numeracy possessed by men and women.

The Meriküll and Mõtsmees study compared gender differences in desired wages, realised wages, and reservation wages to reveal gender differences in wage bargaining. It is found that the unexplained gender pay gaps in desired and realised wages are very similar and are 22–25% in Estonia. The unexplained gender gap in the reservation wage is much smaller, at 14%. Given their reservation wage, men ask for much higher wages than women do during their job search. Results also show that women have a much lower unemployment probability and that most of it can be explained by their segregation to more stable employment in terms of education, occupation, and industry. It can be concluded that women are more risk averse than men in their job search and that they have higher disutility from unemployment and a preference for more stable employment and shorter unemployment spells. (Meriküll 2014:24)

According to the decomposition in realised wages, women's lower expectations are revised upward rather than men's high expectations being revised downward on the job. Results also indicate that longer breaks between jobs can explain a small additional part of the gender wage gap, while occupational and sectoral mobility cannot add much to the explained part.

In this thesis the author will focus on the individuals' returns to skills. In previous research papers the education variable was the main point of interest, because of the lack of data concerning cognitive skills. However, it is often very hard to measure the quality of obtained education, so people of the same degree of education can have very different skills. The PIAAC data which will be used in this master thesis is unique in this sense. It will give an opportunity to control for the people cognitive skills, which were obtained during the PIAAC survey by testing individuals' numeracy, literacy, and problem solving abilities. With the help of this latest data, the author will answer the question: Is there still a wage gap between men and women if skills are taken into account? If so, then how much of the wage gap is explained by skill variables?

2. ANALYSIS OF THE EFFECTS OF SKILLS AND EDUCATION ON THE GENDER WAGE GAP IN ESTONIA

2.1. Introducing the PIAAC Survey

The Survey of Adult Skills is an international survey conducted in 33 countries as part of the Programme for the International Assessment of Adult Competencies (PIAAC). It has already been implemented in 24 countries, and Estonia is among them. The first results from the survey were released on 8 October 2013.

Estonia did not participate in earlier surveys like IALS and ALL, and thus, PIAAC has offered the first chance to get an internationally comparable picture of adults' information processing skills.

The PIAAC survey is unique not only for Estonia, but for other countries as well. Around 166000 adults aged 16 – 65 were surveyed in 24 countries and sub-national regions: 22 OECD member countries – Australia, Austria, Belgium (Flanders), Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, the Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), and the United States; and two partner countries – Cyprus and the Russian Federation. The target population for the survey were adults aged 16 – 65 residing in the country at the time of data collection, irrespective of nationality, citizenship, or language status. Data collection for the Survey of Adult Skills took place from 1 August 2011 to 31 March 2012 in most participating countries. (Skilled for life ... 2013: 5)

The survey provides a rich source of data on adults' proficiency in literacy, numeracy and problem solving in technology-rich environments – the key information-processing skills that are invaluable in 21st-century economies – and in various "generic" skills, such as co-operation, communication, and organising one's time.

Specifically, the following domains are defined in PIAAC (Technical ... 2013: 3):

- Literacy as: "understanding, evaluating, using, and engaging with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential" (OECD, 2012b).
- Numeracy as "the ability to access, use, interpret, and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life" (OECD, 2012b).
- Problem solving in technology-rich environments as "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks".

The Survey of Adult Skills focuses on how adults develop their skills, how they use those skills, and what benefits they gain from using them. To this end, the Survey of Adult Skills collects information on how skills are used at home, in the workplace, and in the community; how these skills are developed, maintained and lost over a lifetime; and how these skills are related to labour market participation, income, health, and social and political engagement. (OECD Skills ... 2013: 25)

Some general overviews and analysis concerning skills have already been performed by the OECD. Halapuu and Valk (2013) have also made an analysis using the PIAAC survey and presented adult skills for Estonia and other countries.

The main central message of the OECD skills analysis is that what people know and what they do with what they know has a major impact on their opportunities in life. The median hourly wage of workers who can make complex inferences and evaluate subtle truth claims or arguments in written texts is more than 60% higher than for workers who can, at best, read relatively short texts to locate a single piece of information. Those with low literacy skills are also more than twice as likely to be unemployed. However, the impact of skills goes far beyond earnings and employment. In all countries, individuals with lower proficiency in literacy are more likely than those with better literacy skills to report poor health, to believe that they have little impact on political processes, and not to participate in associative or volunteer activities. In most countries, they are also less likely to trust others. (*Ibid*: 3)

Halapuu and Valk's (2013) main conclusions are that skills are related to wage independently from education. In other words, it is not only an employee's degree that is important for wage rate, but the obtained skills level. It seems, however, that at least in Estonia a formal education degree is important and additional skills obtained after school are meaningful only with the official certificate. Additionally, the analysis shows that employment along with wage are influenced by education degree, and people who have left their educational path are in a worse position than those who are educated.

Some results of the PIACC have been gathered by the author (Appendix 3) to see where Estonia is positioned compared to other European countries, especially when looking at cognitive skills. The mean respondent age among represented countries (including Estonia) is 40 years. Years of education and years of experience do not differ much among countries, and Estonia's values (12.6 and 19.4 respectively) are very close to the mean scores of all countries. Estonia is a bit above the mean values of represented countries at numeracy and literacy skill scores. In general, there is no great difference in those test scores among countries.

Concerning problem solving scores, however, there is a remarkable inequality among EU countries. Estonia is among those countries who fall below the countries' mean score. The leaders in this test are Sweden and Finland with scores 292 points, while Estonia has 276 points, which is the lowest score along with Poland (277 points).

This was a general overview of the PIAAC survey and deeper analysis of Estonia's results will be presented next. Data from the survey of adult skills will be analysed in this research paper to determine whether skills proficiency plays an important role in the wage gap between men and women in Estonia.

2.2. Methodology of the Study

In order to perform a wage gap study, three sets of independent variables will be considered: theory-based, control- and focus variables.

There are a lot of opportunities to describe the links between the wages and human capital. The Mincer equation, which is commonly used in empirical works based on human capital theory, will serve as a basic model for this research. Variables that are described in human capital theory will be included and their influence on the wage gap will be analysed. The ordinary least squares method with robust standard errors is applied for assessing interlinks between the wage and explained variables. The general equation for research has following form:

$$(2)\quad \begin{aligned} &\log(wage) = \alpha_0 + \beta_0 \times male + \beta_1 \times \exp erince + \beta_2 \times \exp erience^2 + \\ &+\beta_3 \times education + \gamma_0 \times control \operatorname{var} iables \end{aligned}$$

The dependent variable used in the regression model (according to Mincer equation) is the logarithm of hourly wage.

All the age groups of respondents in the research will be included, because according to Hanushek (2013) there are insignificant interactions between returns to skills and different age groups in Estonia.

This is the first research in Estonia about the gender wage gap where cognitive skills are taken into account. The PIAAC data provides such a possibility, so scores of literacy, numeracy, and problem solving in technology-rich environments will be included as focus variables. Despite Hanushek's (2013) results - where it is concluded that the coefficient on literacy becomes statistically insignificant in Estonia - in this study it will be still taken into account.

The values of skills are derived by using plausible values. In PIAAC, skill scores were calculated using Item Response Theory (IRT), and 10 plausible values were derived for each respondent's skill, which are represented on a 500-point scale. The idea is that each individual only responds to a limited number of items in the test. To avoid the assignation of missing values in those items which have not been included in the test, the procedure predicts scores using answers from the test and background questionnaires of similar individuals. It generates a distribution of values for each individual and their associated probabilities, with ten plausible values randomly obtained for each individual. This method prevents bias coming from estimating the result based on a small number of test questions.

PIAAC also provides replicate weights (80 for most countries) to adjust variance estimates for the different complex survey designs of participating countries. The author also considers in this research the jackknife method (80 replicate weights) implemented in PIAAC to derive standard errors in wage regressions. More detailed information on the IRT and Jackknife method is presented in the Technical Report of PIAAC (Technical ... 2013).

The dummy variable for gender is introduced as an independent variable, which receives a value of one if the respondent is a male and a value of zero for female. The gender variable will give the possibility to measure wage gap between men and women.

Years of schooling and years of experience are classically used in the Mincer equation. These variables are included in the thesis as well, along with the respondent's age and level of education.

The author will follow the work of Addabbo, Favaro and Magrini (2011), who show how Italian female-to-male wage differentials in Italy strongly depend on workers' education attainment and that the trend of the gap across the female wage distribution is rather different between highly and low-educated women. They separate workers with a compulsory educational level (low-educated) from those with a higher-level diploma (highly educated) in their studies (Addabbo et al. 2011: 89). Level of education can give additional information about the role of the educational degree on a person's income.

The education level variable is derived from the PIAAC variable based on ISCED classification. They include 8 levels of education: primary education (Level 1), lower secondary education (Level 2), upper secondary education (Level 3), post-secondary non-tertiary education (Level 4), short-cycle tertiary education (Level 5), bachelor's or equivalent level (Level 6), master's or equivalent level (Level 7), doctoral or equivalent level (Level 8).

In order to avoid omitted variables bias some additional control variables will be also included. International evidence shows that sex segregation is extensive and accounts for a large fraction of the gender wage gap. The studies of Groshen (1991), Petersen, and Morgan (1995), Bayard et al. (2003), Gupta and Rothstein (2001), Meyersson Milgrom et al. (2001), Peterson et al. (1997) find evidence that accounting for sex segregation reduces the gender wage gap considerably, though the extent of within-job wage differentials between women and men varies across the labour markets. (Korkeamäki, Kyyrä 2005: 58). To control for that, the author will include variables of occupation, industries, and sectors of economics.

An occupation variable is obtained from the ISCO occupation variable in PIAAC, representing occupations in terms of 5 categories. It will be aggregated in two groups: white-collar and blue-collar workers. Blue-collar workers will be used as the reference category. The private/public sector variable is also introduced to check sector influence on wage gap.

The author will also include a dummy set to specify the industry where the individual is currently employed. The dummy set consists of 21 categories, and the agriculture industry will be taken as a reference category.

Two more dummy variables for whether the respondent has at least one child and wheather he lives with a spouse or not will be added, as it is also a well-known fact that family affects the income of men and women differently.

For example, Francine Blau and Lawrence Kahn illustrate that for single men and women the wage gap is negligible, but married women earn far less than married men (Polachek 2004:9). Also, women are expected to drop out of the labour force more frequently, which suggests less labour market experience and less human capital investment (Mincer and Polachek 1974). Chevalier (2007) finds that women with a preference for childbearing earn less even before they have children, due to their choice of college major and because they engage less intensively in seeking a job (also see Goldin and Polachek 1987). (Grove *et al.* 2009: 3). The author will control for those facts in the Estonian labour market.

After regression analysis, the Oaxaca-Blinder decomposition method is used in order to identify how Mincer equation variables and focus variables explain the wage gap and what part of it remains unexplained.

In the empirical analysis the estimation of the existence of wage premium among the male and female workers is based on the estimation of earnings equations for the men and for the women. In particular, the following two wage equations are estimated (Papapetrou 2008: 158):

$$(3)\ \text{male workers: } W_{male} = \beta_{male} X + \varepsilon_{male}$$

$$(4)\ \text{female workers: } W_{female} = \beta_{female} X + \varepsilon_{female}$$

where W_{male} and W_{female} are the logarithms of earnings for the male and female workers respectively, X is a vector of human capital, demographic and job characteristics variables, β_{male} and β_{female} are the returns to variables in X for the male and female, and the ε_{male} and ε_{female} are the error terms for both equations.

Following Oaxaca (1973) and Blinder (1973), the total difference in mean wages of men and women can be decomposed into two parts:

$$(5)\ \bar{W}^f - \bar{W}^m = (\bar{X}^f - \bar{X}^m)\hat{\beta}^f + \bar{X}^m(\hat{\beta}^f - \hat{\beta}^m)$$

where the left-hand side of the equation is the difference in the mean log hourly wages of males and females. $\bar{\mathrm{X}}^f$ and $\bar{\mathrm{X}}^m$ are average characteristics for males and females respectively and $\hat{\beta}^f$ and $\hat{\beta}^m$ are the coefficient estimates from gender-specific OLS regressions.

In particular, Oaxaca-Blinder decomposition (Blinder 1973; Oaxaca 1973) divides the wage differential between two groups. The first component is an "explained" part of the gap that can be attributed to the differences in mean human capital characteristics (education, work experience, i.e.) of the two groups. The second component is a residual part that cannot be accounted for by such differences in wage determinants and represents differences due to varying returns to the same characteristics. The second term is the unexplained component and is generally considered to be a reflection of discrimination. (Jann 2008: 1; Nordman 2014: 5)

This method allows for substantiating whether differences in employee earnings reflect differences in the productive characteristics of the employees (explained portion) or constitute the male advantage and the female disadvantage (unexplained portion).

It should be noted that various researchers have adopted a different terminology to label the second part of the wage gap. Some researchers call the second part “discrimination effect” and some others use the term “unexplained residual”. It must, however, be stressed that the unexplained part of the gender wage gap may be due to factors other than discrimination; for example, it may be caused by variables that are not included in the model. Thus, caution should be exercised when interpreting the unexplained part of the gender wage gap as labour market discrimination: it can in principle be related to anything that is not associated with the observable characteristics.

In this thesis the author will follow Fransen *et al.* (2012), who referred to the explained gap as the “quantity gap” (since it was explained by differences in the amount of the human capital) or “explained gap” and the “residual gap” (“unexplained gap”).

2.3. Descriptive Analysis

For descriptive statistics and for analysis below Stata 12.0 is used. First the descriptive statistics of males and females in Estonia is presented in Table 1.

The average salary for women is 31.7% less than men. The average age of male respondents is 40 years and for women 41 years. There are almost similar values for the variables that are meant to capture human capital attainment. Men have on average 12.1 years of education and 19.4 years of work experience, while women have 12.9 years and 19.2 years respectively.

The values for literacy, numeracy, and problem solving are the average of plausible values. Cognitive skills scores are practically the same for women and men, while women are a bit better in literacy and men in numeracy and problem solving.

Figure 4 shows the distribution of education levels among females and males. Men are more concetrated in upper secondary education (45%). Women are more successful in tertiary education, for instance master’s degree have 24% of females, whereas men have 18%; short-cycle tertiary have 21% of women, while men have 13%. This fact in Estonia is similar to other European countries studied by Castellano *et al.* (2014) in their paper.

Table 1. Descriptive statistics of females and males (mean, standard deviation, number of observations) in Estonia. Hourly wage is presented in euros, skills average are derived from average of plausible values.

Variable	Female	Male
Gross salary (hourly)	4,39 (3,63) 2021	6,43 (4,98) 1499
Age	41,38 (12,18) 2021	40,19 (12,39) 1499
Years of education	12,94 (2,52) 2021	12,13 (2,67) 1499
Years of experience	19,16 (12,39) 2018	19,37 (12,38) 1496
Literacy average	280,65 (38,82) 2021	278,61 (40,12) 1499
Numeracy average	274,43 (38,88) 2021	280,04 (41,66) 1499
Problem solving average	274,67 (38,98) 1559	278,84 (39,78) 1096

Source: author's estimates based on PIAAC data (2013).

One more observation is mentioned, in spite of fact, that average years of education for men and women are the same, women have a considerable higher education level. The reason for that could be incomplete education for men.

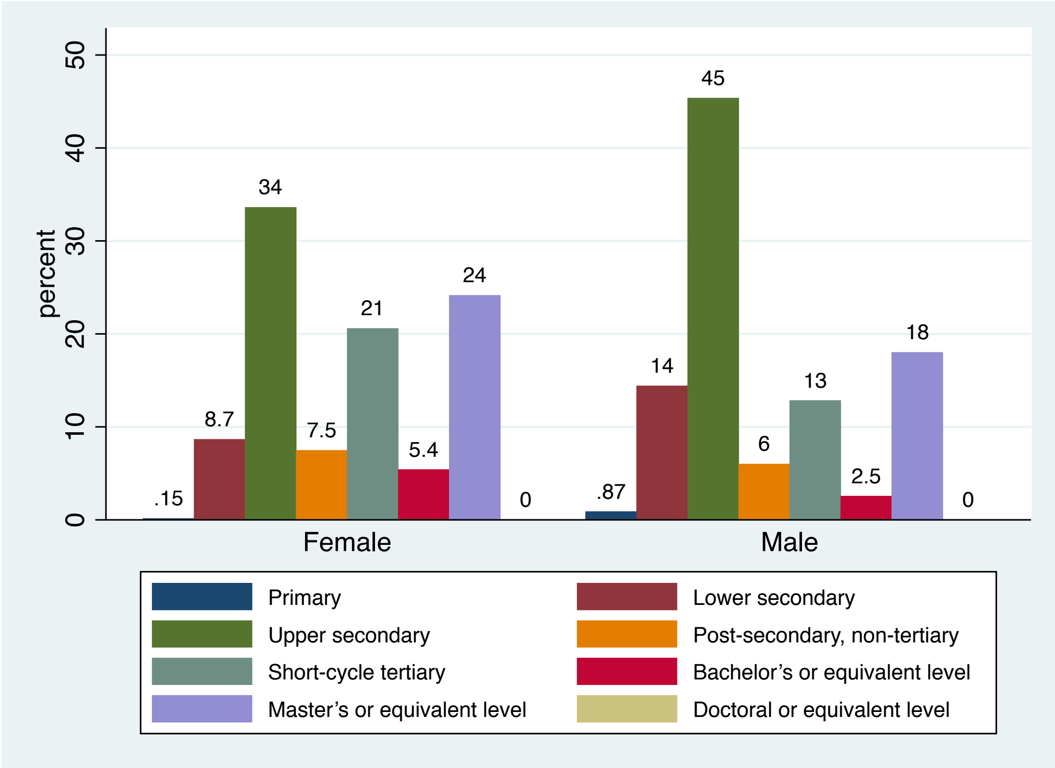

Figure 4. Education levels for females and males in percentage in Estonia (authors’s calculations based on PIAAC data 2013).

The next table (Table 2) describes the remaining variables which will be used in the model. Females are more likely to have a child than men, as 25 per cent of men do not have a child, while for women this value is 18%. There are 7% more males living with a spouse compared to females.

Table 2. Statistics for females and males in Estonia (in percentage).

Variable	Female	Male
Children	82	75
Living with a spouse	75	82
Working in private sector	66	84
Good health	70	69
White-collar occupations	57	42

Source: authors’s calculations based on PIAAC data 2013.

It is clear from Table 2 that gender disparity exists in the private sector of economy. Males work in the private sector to a much larger extent than females - 84% of the males compared to 66% of the females. According to statistics, white-collar occupations are female dominated, with 57% of females compared to 42% of males. Theres is no differences in health conditions between men and women, where about 70% of men and women have a good health and 30% bad or poor health.

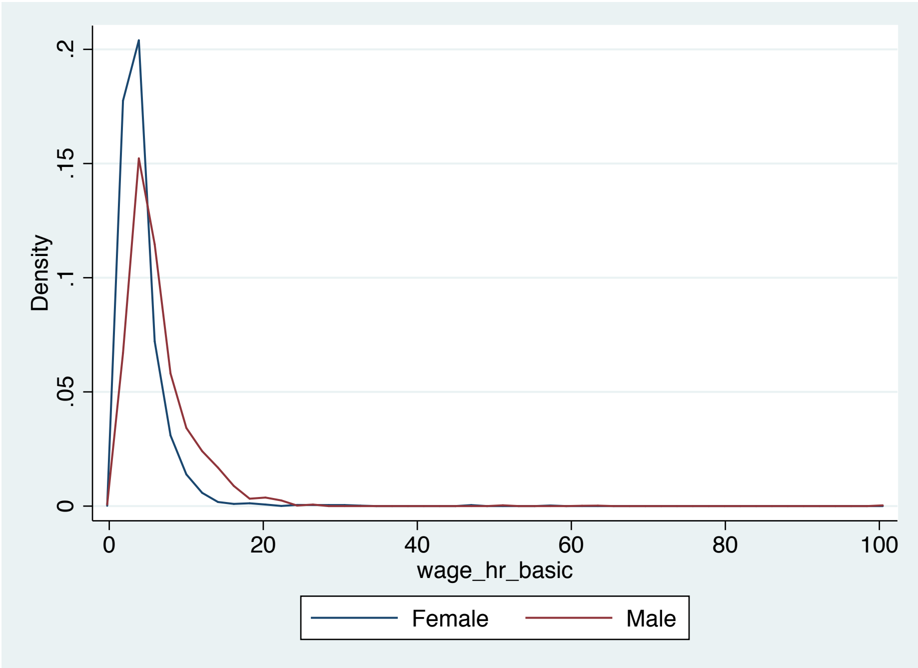

Figure 5. Kernel density estimates of hourly gross earnings in Estonia (author's calculations based on PIAAC data 2013).

Using non-parametric methods (kernel density estimators) employee gross wage distributions for men and women are estimated (Figure 5).

From Figure 5 two features can be detected: the female curve has one noticeable peak indicating that a lot of females have lower wage values; the male curve has better distribution and higher density of larger wage values.

Thus, Figure 5 clearly identifies that females are more frequently in the lower wage categories, comparing to males, as the women's density curve has considerably higher peak, corresponding to the hourly wage around 5 euro per hour.

While in the higher wage intervals (from c.a. 7 to c.a. 25 euro per hour) males' density exceeds the one of females, implying that males are more frequently occupying positions with the higer wage level.

This conclusion goes in line with the estimated gender difference in earnings presented in Table 1, as higher frequency in lower wage categories observed for females, while for males' wage distribution is more smooth and density corresponding to higher wage levels is bigger, apparently, explains lower average earnings of women.

2.4. Empirical Results

In this part the ordinary least square (OLS) regressions are done based on Mincer equation. Author starts with the simpliest model and extends it each time with adding step by step new control variables and focus variables (cognitive skills) into regression. Therefore author presents the Oaxaca-Blinder decomposition with some of derived models.

Empirical analysis is started with the regression where only demographics data and education are included (see Table 3, Model 1).

Table 3. Ordinary least square regressions.

VARIABLES	Model 1	Model 2	Model 3	Model 4
Male	0.428***	0.433***	0.427***	0.430***
	(0.0181)	(0.0182)	(0.0180)	(0.0181)
Age	0.0317***		0.0325***	0.0278***
	(0.00507)		(0.00503)	(0.00573)
$Age^2/100$[1]	-0.0462***		-0.0444***	-0.0396***
	(0.00606)		(0.00602)	(0.00660)
Education (1 level)	-0.106	-0.0966	-0.0769	-0.0822
	(0.133)	(0.134)	(0.132)	(0.132)
Education (3 level)	0.106***	0.102***	0.0917***	0.0941***
	(0.0302)	(0.0303)	(0.0300)	(0.0301)
Education (4 level)	0.139***	0.138***	0.119***	0.122***
	(0.0433)	(0.0434)	(0.0431)	(0.0431)

[1] The age squared coefficient in this and in the following models has been divided by 100 to reduce the number of noughts after the decimal point.

VARIABLES	Model 1	Model 2	Model 3	Model 4
Education (5 level)	0.266***	0.264***	0.236***	0.237***
	(0.0346)	(0.0347)	(0.0346)	(0.0346)
Education (6 level)	0.423***	0.439***	0.401***	0.410***
	(0.0510)	(0.0513)	(0.0507)	(0.0509)
Education (7 level)	0.611***	0.595***	0.569***	0.572***
	(0.0335)	(0.0334)	(0.0337)	(0.0337)
Years of experience		0.0132***		
		(0.00265)		
Years of experience^2/100[2]		-0.0438***		
		(0.00597)		
Good health			0.160***	0.159***
			(0.0208)	(0.0208)
Children				0.0485*
				(0.0278)
Constant	0.580***	1.011***	0.423***	0.491***
	(0.0995)	(0.0340)	(0.101)	(0.108)
Observations	3,520	3,514	3,520	3,520
Adjusted R-squared	0.245	0.239	0.257	0.258

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: author's estimates based on PIAAC data. The dependent variable is the natural logarithm of the hourly gross wage.

The first and the simpliest model contains age and education level variables. Analysis shows that male's wages are on average 42.8% greater, than female's, which is quite large difference. It was decided to include in the analysis education levels instead of years of education in order to control for how education levels are affecting wages: with the growth of education level wages increase. Begining from upper-secondary education the influence of education level become greater with the next level. The earnings differentials relative to lower secondary education are 42.3% for barchelor's degree and 61.1% for master's degree. Such trend was concluded by other researchers also including Blackburn and Neumark (1993).

With every year person gets older his salary on average increases aproximately 3 per cent. However, as indicated by negative value of age square variable, from some point

[2] The years of experience squared coefficient has been divided by 100 to reduce the number of noughts after the decimal point.

the impact of age becomes negative, as becoming older person retires and earnings decrease.

From the simple model it is already clear that when age and education are taken into account, the wage difference between men and women is 42.8%. Number of control variables is very small yet, so it is logical on this stage that the wage difference between men and women coming from all other factors is high, as a lot of variables are omitted. After including new variables step by step, the coefficient of the gender should decrease, as higher share of wage difference is expected to be explained by additional factors.

It is assumed that age itself should not be important determinant of wages, but a proxy for experience, thus experience variable is added into the Model 2. Because of very strong correlation between age and experience variables, age variable is dropped out of the model. Instead of it experience variable is used, as it should be more important factor and more strongly influence salary than age of person.

With adding experience to the model (Model 2) the average wage difference between men and women increases by 0.5 percentage points, which means that the assumption is wrong. As with the age every experience year gives additional units to salary, and experience square variable influences negatively. Every year of experience gives only 1.3% of salary increase and other coefficients of the variables are practically the same. As the Model 1 is better according to adjusted R squared value, age variable will be used in next regression models.

Before taking cognitive skills into the analysis, health variable is added (Model 3), as it is one of the parts of human capital theory. It is seen from Model 3 results, that wage difference between men and women is still the same 42.7%, also age coefficient is practically the same. Good health is an important factor in getting better earnings, which gives about 16% of wage increase. At the same time coefficients of all education levels decreased in average by 1-4%.

It is expected that having children should effect salaries because it’s common that younger females are taking maternity leave and loose their qualification, thus are simply exposed to human capital "drain" and after re-entering labour market have lower competitivness. The wage difference incresed to 43% in Model 4, children control variable increases wage by 4.9% at 0,1 significance level.

Table 4. Ordinary least square regressions.

VARIABLES	Model 5	Model 6	Model 7
Male	0.419***	0.409***	0.440***
	(0.0182)	(0.0184)	(0.0179)
Age	0.0283***	0.0263***	0.0243***
	(0.00572)	(0.00573)	(0.00554)
$Age^2/100$	-0.0398***	-0.0376***	-0.0345***
	(0.00659)	(0.00660)	(0.00638)
Education (1 level)	-0.0882	-0.101	-0.102
	(0.132)	(0.132)	(0.127)
Education (3 level)	0.0976***	0.0945***	0.0306
	(0.0300)	(0.0300)	(0.0292)
Education (4 level)	0.128***	0.122***	0.0418
	(0.0430)	(0.0429)	(0.0418)
Education (5 level)	0.251***	0.245***	0.0935***
	(0.0347)	(0.0346)	(0.0348)
Education (6 level)	0.436***	0.421***	0.210***
	(0.0512)	(0.0513)	(0.0513)
Education (7 level)	0.596***	0.588***	0.347***
	(0.0342)	(0.0342)	(0.0364)
Good health	0.160***	0.158***	0.128***
	(0.0208)	(0.0207)	(0.0201)
Children	0.0501*	0.0201	0.0297
	(0.0278)	(0.0287)	(0.0278)
Private/public sector	0.0788***	0.0793***	0.124***
	(0.0202)	(0.0202)	(0.0197)
Living with a spouse		0.0901***	0.0661***
		(0.0228)	(0.0221)
White-collar occupations			0.330***
			(0.0209)
Constant	0.410***	0.413***	0.382***
	(0.110)	(0.110)	(0.106)
Observations	3,520	3,520	3,520
Adjusted R-squared	0.261	0.264	0.312

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: authors' estimates based on PIAAC data. The dependent variable is the natural logarithm of the hourly gross wage.

From the descriptive statistics above (see Table 2) it is conducted that males are working more in private sector and their salaries are typically higher. Model 5 controls for effect of working in private or public sector of an economy (see Table 4).

Working in private sector gives on average 7.9% higher salary relative to public sector of an economy. When controlling newer model the coefficient of gender implies 41.9% higher wage for males, which is for about 1% smaller value in comparison with the previous model. Thus working in private sector favours reduction of wage difference between males and females.

It is seen from Model 6 that influence of "living with a spouse" on wage is approximately 9%, which can be explained by the fact that people with families are motivated to earn more for their well-being. The same conclusion was done by Anspal *et al.* (2010), where they found that person living with a partner earns much more than living alone. In contrary having children becomes insignificant variable. Wage difference in this model decreased by 1%.

In addition to the models above in Model 7 (see Table 4) the category of occupation is added and model's explanatory power became better (adjusted R-square is 0.312). Females having the same experience, education and occupation, working in the same sector earn 44% less than men. It is also clear, that wage is very dependent on occupation, namely for white-collar occupations, comparing to blue-collar, wage is on average 33% higher.

Model 8 becomes better, when the set of industries' control variables are included (see Appendix 4). The adjusted R-squared still increasing - 0.351 and the wage difference is 35.7% what is 7.1 percentage points smaller comparing to the initial model.

According to the study's goals cognitive skills will be added into the model (see Table 5), complete results are presented in Appendix 5. Jackknife replication method is used in regression models (Models 9-12) below, because of plausable values. It was decided to make analysis for all cognitive skills separately because it is assumed and confirmed by the test that cognitive skills are in strong correlation, but author also tries later to include all of them in one model (Model 12).

Table 5. Ordinary least square regressions.

VARIABLES	Model 9	Model 10	Model 11	Model 12
Male	0.352***	0.336***	0.367***	0.352***
	(0.0194)	(0.0198)	(0.0233)	(0.0239)
Age	0.0239***	0.0238***	0.0314***	0.0300***
	(0.00510)	(0.00505)	(0.00594)	(0.00598)
Age square/100	-0.0331***	-0.0329***	-0.0375***	-0.0371***
	(0.00567)	(0.00562)	(0.00678)	(0.00679)
Education (1 level)	-0.0494	-0.0372	0.0255	0.0674
	(0.155)	(0.150)	(0.177)	(0.181)
Education (3 level)	0.0192	0.00240	0.0105	-0.00596
	(0.0300)	(0.0300)	(0.0373)	(0.0374)
Education (4 level)	0.0244	0.00562	0.0188	0.00503
	(0.0376)	(0.0383)	(0.0460)	(0.0467)
Education (5 level)	0.0553	0.0331	0.0135	-0.00257
	(0.0340)	(0.0345)	(0.0402)	(0.0413)
Education (6 level)	0.160***	0.138***	0.159***	0.127**
	(0.0497)	(0.0504)	(0.0576)	(0.0595)
Education (7 level)	0.283***	0.246***	0.236***	0.204***
	(0.0358)	(0.0375)	(0.0426)	(0.0455)
Good health	0.126***	0.124***	0.127***	0.135***
	(0.0196)	(0.0195)	(0.0232)	(0.0234)
Children	0.0313	0.0293	0.0167	0.0170
	(0.0281)	(0.0278)	(0.0310)	(0.0306)
Private/public sector	0.139***	0.134***	0.130***	0.132***
	(0.0267)	(0.0269)	(0.0363)	(0.0362)
Living with a spouse	0.0629***	0.0600***	0.0543**	0.0532**
	(0.0191)	(0.0192)	(0.0237)	(0.0237)
White-collar occupations	0.302***	0.288***	0.268***	0.267***
	(0.0187)	(0.0183)	(0.0206)	(0.0203)
Literacy average	0.00117***			0.000386
	(0.000279)			(0.000573)
Numeracy average		0.00172***		0.00159***
		(0.000264)		(0.000559)
Problem solving average			0.00143***	-0.000228
			(0.000328)	(0.000556)
Constant	0.0293	-0.0684	-0.0933	-0.131
	(0.144)	(0.134)	(0.167)	(0.171)
Controls for industries	Yes	Yes	Yes	Yes
Observations	3,520	3,520	2,655	2,655
R-squared	0.361	0.366	0.348	0.352

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: authors' estimates based on PIAAC data. The dependent variable is the natural logarithm of the hourly gross wage. Controls are 21 industries.

Literacy is significant in the model, wage difference become for 0.5 percentage points smaller, from 35.7% to 35.2%. So with the same experience, occupation, industry and literacy level females wage is on average 35.2% less than males. One point increase in literacy will on average give only 0.1% supplement to salary, but it should be considered that 1 point (out of maximum 500) in literacy score is very small number. It is better to estimate for how much the wage will change when the result is 10 points better, and this already gives 1.2% to the wage increase. The effect is small, which is in accordance with findings by Bowles *et. al* (2001) and Papapetrou (2008), where literacy also has very little impact. Also other studies about USA and Great Britain markets state the same.

Next numeracy is estimated and the same test (Model 10) perfomed (see Table 5). Numeracy is significant, but as literacy does not have considerable effect on salary, 10 points increase in numeracy gives 1.7% of wage growth. Including average numeracy skill into the model wage difference continues decreasing. Females with the same experience, occupation and numeracy skill earn 33.6% less than males.

In the next model (Model 11) problem solving is taken into account. With problem solving skill the results are very similar to the Model 9 for literacy skill. Wage difference becomes bigger (36.7%). Every increase on 10 points of problem solving skills increases wage on average 1.4%. Obtained results are similar to Kaska (2014) results regarding cognitive skills where he got an average increase of wage 1.8-2.2%.

When including all cognitive variables into the model (Model 12), only numeracy is significant, but wage difference declined to 35.2%. This means that in the latest model only numeracy have some effect on wage gap in Estonian market. Model 10, where only numeracy is taken among focus skill variables, adjusted R-squared is the best and wage difference is the smallest comparing to all models in the study.

VIF test is also done to control whether there is multicollinearity issue in the model (Appendix 6). The VIF values are high for the age and age squared variables, but that is expected. It can be concluded that multicolliniarity doesn't affect the model significantly.

Appendix 7[3] gives results of Oaxaca - Blinder decomposition for the regression models 1, 7, 10 and 12. The estimated difference in the wage between male and female employees is 37.2%. for Models 1-3 and 40.5% for Model 4. In Model 1 (for OLS model 1) the explained difference is -15% and in the last model it is 12.7%. So with adding control variables and the variables of skills, an explained part of wage gap is getting higher. The author can conclude that industry and skills matter significantly in widening the explained part of gap.

In Model 1 when the author considers only age and education, females were supposed to earn more (positive explained difference here means that females have better characteristics than males with reference to considered set of controls).

In Model 3 (for OLS model 10) the explained difference is negative, it means that smaller wages for females come from objective reasons: females have worse characteristics, comparing to males. In this particular model negative explained gap is quite natural, as the author controls for industry (and females are frequently working in less profitable sectors) and numerical skills (which are also higher among males regarding descriptive statistics). In this case some part of total gap is quite objective.

The majority of individual covariates of independent variables are statistically significant in Model 3. With respect to education, the explained part of the wage gap is enhanced by 0.02 points, favoring females, which can be explained with the higher rate of tertiary education of females.

Living with a spouse has negative influence on explained part of wage gap. It is obvious, because when getting married, females are more likely to be responsible for households jobs and males are the main prosperity makers. Also the percentage of males living with a spouse is higher than the same indicator for females.

White-collar occupation coefficient is 0.055, favoring females. It can be also explained by the fact, that females dominate in white-collar occupations in Estonia.

[3] The author presents the output of Oaxaca-Blinder separate equations for men and women in the Appendix 8.

Private/public sector coefficient is negative, it means that females are simply more frequently working in public sector where wages are lower, comparing to private, so their loss of earning comparing to males here is natural. This result is similar to Anspal *et. al* (2010) research where was found that working in public sector is negatively connected to women's wages.

Industry has also negative effect, it is likely to happen because of the segregation of females in less paid industries. Average of numeracy skills along with the industry has negative effect on explained part, which is also logical, because males are on average have better numeracy skills.

The independent variables' effect on the wage premium of males in Model 4 are very similar to Model 3. Literacy and problem solving are not significant in explained part of difference. However the explained part is bigger (12.7%) in Model 4 comparing to Model 3.

The unexplained part of wage gap dominates in the Oaxaca-Blinder decomposition. But comparing Model 1, Model 3 and Model 4, it is clear, that industry and skills (in a greater degree numeracy skills) make the unexplained part smaller, so they have positive effect on explaining gender wage gap.

Comparing to Estonia researches author got the results with 37.2% wage gap what is higher than Rõõm, Kallaste (2004) result (27.3%), Anspal *et. al* (2010) result (29%) and also unadjusted wage gap (30%) published by Eurostat (2013). This fact proves that high wage gap is still a huge problem in Estonia.

CONCLUSIONS

The main result of this study is an evaluation of the impact cognitive skills have on the wage gap between males and females in Estonia based on the PIAAC survey. To make the evaluation possible, human capital theory is described as the key point in explanation of the gender wage gap. The wage gap itself is also discussed in the thesis as a popular topic of various studies in different countries. There are a lot of studies done with cognitive skills as the main topic in other countries, but there has been no such a research done in Estonia. The author presents earlier studies in this thesis to make possible a comparison with the obtained results.

Nowadays human capital theory plays an important role in economy. Material and technological values are shifted to the background and human skills, competencies, and health take the stage as the main factors of personal, social, and economic well-being. Those with good skills become more successful in their careers and this spreads out into economy as a whole.

One of the most popular problems studied today is the wage gap between men and women. The author elaborates statistics and trends regarding the wage gap in different countries and some explanations that have been proposed by different researchers.

In general, the gender wage gap has trend to decrease in some developed countries. The best results here are in the United Kingdom, USA and France. For some European countries like Belgium, Luxembourg, Spain, Sweden and Switzerland the wage gap remains constant. Human capital theory is used mostly to explain wage gap. Researchers typically explain about half of the wage gap.

The human capital theory gives a so-called supply-side explanation to the gender wage gap. It concerns a woman's aspiration to bear children and interrupt the working period as the main reason for lower investment in education and training and preference for part-time or lower-skilled jobs. Another explanation of the wage gap has a demand-side focus, i.e. it underlines employers' readiness to hire, promote, train and award men (so-called discrimination).

Previous studies described in this paper show that the wage gap depends on the economic situation and whether the country is developed or not. Estonia in this researches is the leader, with the largest percentage of wage gap (around 30%). In addition, according to earlier studies there was an increase in the wage gap during recent years: when calculated in 2000 it was 24%, but in 2013 it was already 30%. In the European Union the average gap between men and women is 16.6%, with the lowest rate in Slovenia (3.2%).

Additionally, the earlier studies point out that the largest part of the wage gap remains unexplained in Estonia, and it fall into interval between 20 and 25 per cent. The main variable used in these studies was education, because of the lack of data concerning cognitive skills.

With the appearance of the PIAAC survey implemented in 24 countries it has become possible to conduct research based on cognitive skills. The author introduces analysis based on the PIAAC survey to discover, how congnitive skills affect the gender wage gap in Estonia. According to the PIAAC data, Estonia has quite good results in cognitive skills: it is a bit above the mean value of literacy and numeracy results, but a bit below in problem solving ability.

Two main tests were performed by the author: OLS regression analysis and Oaxaca-Blinder decomposition. Numeracy has a good impact on decreasing wage difference between men and women. It decreases wage gap by 2.1%, and this the best rate among cognitive skills (where problem solving increased the difference by 1% and literacy decreased it by 0.5%). Results show that the wage gap between males and females is very large – 37.2% (when numeracy is taken into the model), and 40,5% (when all focus skills are presented in the model).

Using Oaxaca-Blinder decomposition, the wage gap between men and women is divided into explained and unexplained parts. According to the results, 9.8% of the gap is explained, when numeracy is taken into account, and 12.7% when all skills are included into the model. The author obtained a result similar to studies previously performed: the unexplained part of the wage gap dominates in Oaxaca-Blinder decomposition. In response to the aim of this thesis, the unexplained wage gap still remains after skills are taken into account, but the author can say that with the addition of skills to the model the unexplained part is decreased.

This thesis makes the problem of the wage gap in Estonia clearer for further studies. At the same time, it once again raises the question of the high level of wage gap between men and women.

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APPENDICES

Appendix 1. Overview of earlier studies of relationship between cognitive skills and earnings.

Study	Data	Goals	Main results
"Omitted-ability bias and the increase in the return to schooling." (1993) Blackburn L.M., Neumark D.	National Longitudinal Survey Youth Cohort (1979-1987)	Identifies the effect of ability overtime by assuming that log wages are a linear function of cognitive ability and education.	The increase in the return to education has occured largely for workers with higher levels of "academic" ability.
"Measuring and Assessing the Impact of Basic Skills on Labour Market Outcomes." (2000) McIntosh S., Vignoles A.	The UK National Child Development Study and the International Adult Literacy Survey	Identifies the effect of basic literacy and numeracy skills on labour market outcomes.	Found evidence of a large positive effect on earnings and employment rates from having better numeracy skills. Not taking into account other factors that influence earnings, individuals with higher numeracy and literacy skills earn around 15-19% more than those with skills below this level.
"Literacy and earnings: an investigation of the interaction of cognitive and unobserved skills in earnings generation." (2003) Green D. A., Riddell W.	International Adult Literacy Survey (IALS), Canada	Examine the influence of cognitive and unobserved skills on earnings.	Find that cognitive skills contribute significantly to earnings and that their inclusion in a regression leads to a reduction in the measured impact of schooling on earnings. This finding points partly to the importance of cognitive skills in earnings generation, but is also consistent with non-cognitive skills being even more important.
"Estimates of the return to schooling and ability:	National Longitudinal Survey of Youth	To obtain OLS, family fixed effects, and fixed effects instrumental	Controlling for aptitude test scores has a substantial impact on estimated returns to schooling even within

evidence from sibling data." (2006) Bronars S. G., Oettinger G. S.		variable estimates of the return to schooling for a large sample of non-twin siblings.	families, and there is a large return to test scores that is comparable in size within and between families. Find significantly higher returns to schooling for females than for males.
"Returns to Skills around the World: Evidence from PIAAC." (2013) Hanushek E.A. *et al.*	Programme for the International Assessment of Adult Competences (PIAAC)	Examine returns to cognitive skills.	Results confirm that estimates based on early-career earnings underestimate the lifetime returns to skills, in our analyses by an average of about one quarter. Across the 22 countries, a one-standard-deviation increase in numeracy skills is associated with an average 18 per cent wage increase among prime-age workers.
"Cognitive, Non-Cognitive Skills and Gender Wage Gaps: Evidence from Linked Employer-Employee Data in Bangladesh." (2014) Nordman C.J. *et al.*	The Bangladesh Enterprise-based Skills Survey (ESS) for 2012	Explain gender wage gaps by the inclusion of measures of cognitive and non-cognitive skills.	Reading and numeracy skills seem to confer benefits to men and women differently, albeit positive, at different points of the distribution. Reading score seems to have a higher correlation at the lower percentiles than higher ones but the reverse is true for numeracy scores. Gender differences in both cognitive and non-cognitive skills matter. Including measures of cognitive skills and personality traits reduces the mean unexplained component by about 5 percentage points when firm effects are also accounted for.
"Men and Women's Return to Cognitive Skills. Evidence from PIAAC." (2014) Sowa V.	PIAAC	Answer the question, do men and women receive different pay-offs, in terms of wages from cognitive skills, in the Swedish labor market?	Cognitive ability of a person does in fact affect the wages in the Swedish labor market. For wage differences due to cognitive skills, literacy seems to be a stronger predictor in the Swedish labor market. The difference in pay-offs for cognitive skills, with the industry control applied, is 2.34 per cent for one extra standard deviation in the numeracy score, to the men's advantage, and 2.25 per cent for one extra standard deviation in the literacy score.

Source: made by author.

Appendix 2. Overview of wage studies in Estonia.

Study	Data	Method	Dependent variable	Main results
"Females-Males in Estonian labour market: evaluation of wage differences" Rõõm, Kallaste (2004)	The Estonian labour force survey (LFS) 1998 - 2000	Regression analysis (Mincer equation); Oaxaca-Blinder decomposition	Logarithmic values of net monthly wages	The general gender wage gap was 27,3%, unexplained wage gap accounted for 20,5 – 21,4% One third of differences in wages can be explained by the dissimilarity between human capital and workplaces of men and women. Two thirds of the gender gap cannot be explained by these factors. Women in Estonia ask for a lower wage and look for a new job less actively than men.
"Human Capital and Wage Relations and Dynamics in Estonia" Leping K.-O.(2005)	LFS 2002 - 2003	Regression analysis (Mincer equation)	Logarithmic values of net monthly wages	The results of the analysis emphasize that the level of education of employee is positively connected with their wage. In general specific work experience increases an employee wage while with the growth of work experience this influence decreases. Also one of the factors connected with human capital is the knowledge of the English language, which has a positive influence on the wage size. Along with the factors connected with human capital there are also other wage influencing factors connected with employees themselves (gender, nationality, marital status) as well as with the working place itself like the scope of the company, the position, the number of employees in the company and its location.
"Gender Wage Gap in Estonia". Empirical analysis. Anspal jt. (2010)	LFS 2000 - 2008	Regression analysis (Mincer equation); Oaxaca-Blinder decomposition; quantile	Logarithmic values of net monthly wages	The general gender wage gap was 29%, the unexplained one composed 24%. The wage gap is mostly influenced by adding the descriptive variables of the position of an employee and the scope of the company. The wage gap is explained by different characteristics

		regression		of men and women among employees possessing higher education or leading positions as well as officers working in the public sector.
"The Part-Time/Full-Time Wage Gap In Central And Eastern Europe: The Case Of Estonia." Krillo K., Masso J.(2010)	Estonian Labour Force Survey (1997 - 2007)	Heckman selection model; Oaxaca-Blinder decomposition	Logarithmic values of net monthly wages	According to the results of the wage decomposition, both female and male part-time employees are 'worse' endowed compared to full-timers. The human capital variables are of minor importance in explaining the wage penalty of part-time employees.
"Returns to Numeracy Skills in Estonia compared to Other OECD Countries Based on PIAAC Data " Kaska (2014)	PIAAC 2013	Regression analysis (Mincer equation)	Logarithmic values of net monthly wages	Simple Mincer equations with and without the inclusion of numeracy scores indicate fundamental differences between males and females. Cognitive skills seem to explain most of the variance of education with respect to wages for males. For females, higher education is related to higher wages even after the variance of skills is accounted for. The results for Estonia are robust to different specifications of education (different number of levels) and skills (continuous or categorical with different number of levels). They indicate that a 10-point increase in cognitive skills is associated, on average, with a 2,2% higher hourly income for males and 1,8% for females. The effect is similar for only full-time employees.
"Do You Get What You Ask? The Gender Gap in Desired and Realised Wages" Meriküll, Mõtsmees (2014)	LFS 2009 CV Keskus (CV Centre in english) 2009	Regression analysis (Mincer equation); Oaxaca-Ransom decomposition	Logarithmic values of gross monthly wages	The unexplained gender pay gaps in desired and realised wages are very similar and are 22–25% in Estonia. The unexplained gender gap in the reservation wage is much smaller at 14%.

Source: made by author.

Appendix 3. Cognitive skills' results among countries.

Country	Age	Years of education	Years of experience	Literacy average	Numeracy average	Problem solving average
Belgium	40,55	.	19,19	288,14	282,21	283,46
	(11,32)	.	11,57	44,71	41,87	38,91
	2896	0	2891	2896	2896	2565
Czech	38,88	13,68	17,20	281,69	279,72	285,79
	(12,55)	2,65	12,42	39,40	36,91	41,14
	2947	2947	2942	2947	2947	2384
Denmark	43,82	13,24	**23,57**	284,30	273,95	282,21
	(13,13)	2,71	13,23	47,22	43,64	38,36
	4558	4558	4557	4558	4558	4006
England	39,05	13,34	18,97	274,66	283,26	285,37
	(11,93)	2,31	11,64	44,22	39,90	36,38
	4033	4033	4031	4033	4033	3694
Estonia	40,95	12,62	19,37	277,98	279,65	276,15
	(12,19)	2,59	12,27	39,96	39,35	39,78
	4618	4618	4609	4618	4618	3463
Finland	42,47	13,13	19,85	**293,16**	**297,56**	**291,67**
	(12,12)	2,93	12,27	43,15	41,46	37,77
	3077	3077	3076	3077	3077	2698
France	41,66	12,07	19,77	264,48	268,19	.
	(11,39)	3,42	11,92	51,52	44,61	.
	3750	3750	3738	3748	3748	0
Ireland	39,78	**15,64**	18,36	268,28	277,31	280,59
	(11,26)	2,84	11,16	44,83	40,48	36,31
	2925	2925	2924	2925	2925	2202
Italy	41,84	12,41	18,03	259,54	258,53	.
	(10,58)	3,77	11,14	45,34	41,09	.
	2334	2334	2328	2334	2334	0
Netherlands	40,81	13,43	19,86	288,05	290,11	289,38
	(13,15)	2,57	12,20	42,26	40,65	35,67
	3282	3282	3280	3282	3282	3051
Norway	40,10	14,54	18,78	287,99	285,72	290,34
	(12,97)	2,44	12,17	47,09	41,41	35,50
	2829	2829	2828	2829	2829	2577
Poland	31,72	13,16	10,17	268,19	275,02	277,66
	(11,97)	2,67	11,26	43,56	41,67	44,15
	4706	4706	4653	4706	4706	3111
Slovakia	40,47	13,64	18,59	284,72	279,21	280,26

	(11,53)	2,57	11,75	37,77	32,75	33,17
	3103	3103	3099	3103	3103	2147
Spain	40,66	11,96	17,57	253,79	257,37	.
	(11,06)	3,55	11,44	46,09	44,42	.
	6050	6050	6040	6050	6050	0
Sweden	43,04	12,84	21,13	289,96	288,74	**291,77**
	(12,41)	2,44	12,73	49,34	44,94	39,62
	2662	2662	2659	2662	2662	2424
Total	**40,21**	13,15	18,55	276,16	277,23	284,31
	(12,35)	3,01	12,33	46,23	42,72	38,62
	53770	50874	53655	53768	53768	34322

Source: authors' estimates based on PIAAC data. Standard deviations for continuous variables are shown in brackets.

Appendix 4. Ordinary least square regression for Model 8.

VARIABLES	Model 8
Male	0.357***
	(0.0190)
Age	0.0234***
	(0.00543)
Age square/100	-0.0333***
	(0.00625)
Education (1 level)	-0.0864
	(0.124)
Education (3 level)	0.0335
	(0.0286)
Education (4 level)	0.0298
	(0.0409)
Education (5 level)	0.0798**
	(0.0342)
Education (6 level)	0.210***
	(0.0502)
Education (7 level)	0.341***
	(0.0358)
Good health	0.122***
	(0.0196)
Children	0.0308
	(0.0271)
Private/public sector	0.149***
	(0.0330)
Living with a spouse	0.0566***
	(0.0215)
White-collar occupations	0.315***
	(0.0213)
Mining	0.424***
	(0.0936)
Manufacturing	0.0553
	(0.0462)
Electricity, gas	0.238**
	(0.0967)
Water supply	0.189*
	(0.115)
Construction	0.351***
	(0.0520)
Sales	-0.0256
	(0.0486)
Transportation	0.187***
	(0.0549)
Accommodation and food services	-0.109*
	(0.0612)
Information and communication	0.234***

	(0.0678)
Finance and insurance	0.309***
	(0.0733)
Real estate	-0.00359
	(0.0879)
Professional, scientific activities	0.145**
	(0.0661)
Administration and support	0.0719
	(0.0616)
Public administration and defense	0.255***
	(0.0615)
Education	-0.00683
	(0.0588)
Healthcare	0.122**
	(0.0593)
Arts, entertainment	-0.0801
	(0.0756)
Other services	0.102
	(0.0866)
Constant	0.341***
	(0.117)
Observations	3,520
Adjusted R-squared	0.351

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: authors' estimates based on PIAAC data.

Appendix 5. Ordinary least square regressions for Models 9-12.

VARIABLES	Model 9	Model 10	Model 11	Model 12
Male	0.352***	0.336***	0.367***	0.352***
	(0.0194)	(0.0198)	(0.0233)	(0.0239)
Age	0.0239***	0.0238***	0.0314***	0.0300***
	(0.00510)	(0.00505)	(0.00594)	(0.00598)
Age square/100	-0.0331***	-0.0329***	-0.0375***	-0.0371***
	(0.00567)	(0.00562)	(0.00678)	(0.00679)
Education (1 level)	-0.0494	-0.0372	0.0255	0.0674
	(0.155)	(0.150)	(0.177)	(0.181)
Education (3 level)	0.0192	0.00240	0.0105	-0.00596
	(0.0300)	(0.0300)	(0.0373)	(0.0374)
Education (4 level)	0.0244	0.00562	0.0188	0.00503
	(0.0376)	(0.0383)	(0.0460)	(0.0467)
Education (5 level)	0.0553	0.0331	0.0135	-0.00257
	(0.0340)	(0.0345)	(0.0402)	(0.0413)
Education (6 level)	0.160***	0.138***	0.159***	0.127**
	(0.0497)	(0.0504)	(0.0576)	(0.0595)
Education (7 level)	0.283***	0.246***	0.236***	0.204***
	(0.0358)	(0.0375)	(0.0426)	(0.0455)
Good health	0.126***	0.124***	0.127***	0.135***
	(0.0196)	(0.0195)	(0.0232)	(0.0234)
Children	0.0313	0.0293	0.0167	0.0170
	(0.0281)	(0.0278)	(0.0310)	(0.0306)
Private/public sector	0.139***	0.134***	0.130***	0.132***
	(0.0267)	(0.0269)	(0.0363)	(0.0362)
Living with a spouse	0.0629***	0.0600***	0.0543**	0.0532**
	(0.0191)	(0.0192)	(0.0237)	(0.0237)
White-collar occupations	0.302***	0.288***	0.268***	0.267***
	(0.0187)	(0.0183)	(0.0206)	(0.0203)
Mining	0.475***	0.467***	0.383***	0.408***
	(0.0945)	(0.0927)	(0.111)	(0.112)
Manufacturing	0.0574	0.0515	-0.0338	-0.0253
	(0.0538)	(0.0525)	(0.0613)	(0.0623)
Electricity, gas	0.219***	0.207***	0.112	0.120
	(0.0669)	(0.0673)	(0.0939)	(0.0956)
Water supply	0.195**	0.184*	0.144	0.156
	(0.0963)	(0.0967)	(0.111)	(0.112)
Construction	0.345***	0.335***	0.287***	0.289***
	(0.0664)	(0.0656)	(0.0755)	(0.0763)
Sales	-0.0375	-0.0490	-0.114*	-0.108*
	(0.0588)	(0.0579)	(0.0602)	(0.0608)
Transportation	0.183***	0.177***	0.0977	0.107*
	(0.0553)	(0.0544)	(0.0629)	(0.0638)
Accommodation and food	-0.126**	-0.136**	-0.179**	-0.169**
services	(0.0631)	(0.0617)	(0.0695)	(0.0699)
Information and communication	0.208**	0.190**	0.115	0.119

	(0.0805)	(0.0796)	(0.0843)	(0.0849)
Finance and insurance	0.305***	0.290***	0.234***	0.243***
	(0.0743)	(0.0736)	(0.0809)	(0.0814)
Real estate	-0.0123	-0.0220	-0.0569	-0.0584
	(0.0813)	(0.0815)	(0.107)	(0.106)
Professional, scientific activities	0.118	0.106	0.0412	0.0447
	(0.0772)	(0.0766)	(0.0852)	(0.0850)
Administration and support	0.0357	0.0304	-0.0325	-0.0217
	(0.0860)	(0.0857)	(0.0910)	(0.0922)
Public administration and defense	0.240***	0.230***	0.153**	0.165**
	(0.0525)	(0.0520)	(0.0679)	(0.0680)
Education	-0.0158	-0.0172	-0.114	-0.106
	(0.0559)	(0.0556)	(0.0694)	(0.0692)
Healthcare	0.110*	0.0980	0.0168	0.0154
	(0.0595)	(0.0589)	(0.0729)	(0.0733)
Arts, entertainment	-0.0689	-0.0670	-0.179	-0.165
	(0.0946)	(0.0935)	(0.121)	(0.122)
Other services	0.108	0.0961	0.00857	0.0237
	(0.0993)	(0.101)	(0.119)	(0.123)
Literacy average	0.00117***			0.000386
	(0.000279)			(0.000573)
Numeracy average		0.00172***		0.00159***
		(0.000264)		(0.000559)
Problem solving average			0.00143***	-0.000228
			(0.000328)	(0.000556)
Constant	0.0293	-0.0684	-0.0933	-0.131
	(0.144)	(0.134)	(0.167)	(0.171)
Observations	3,520	3,520	2,655	2,655
R-squared	0.361	0.366	0.348	0.352

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: authors' estimates based on PIAAC data.

Appendix 6. VIF-test for regression.

Variable	VIF	1/VIF
Age	66.65	0.015004
Age square/100	59.70	0.016750
Literacy average	6.75	0.148188
Industry 16	6.74	0.148418
Industry 3	6.54	0.152873
Numeracy average	6.48	0.154314
Industry 15	5.73	0.174445
Industry 7	5.57	0.179667
Problem solving average	5.17	0.193399
Education (level 7)	4.41	0.226983
Industry 17	3.73	0.267772
Private/public sector	3.58	0.279307
Education (level 3)	3.47	0.288483
Industry6	3.43	0.291957
Education (level 5)	3.02	0.330972
Industry 8	2.86	0.349445
Industry 9	2.44	0.409195
Industry 13	2.43	0.412192
Industry 10	2.28	0.439231
Industry 14	2.19	0.456953
Industry 11	2.04	0.490889
Industry 18	2.00	0.499906
Children	1.96	0.511472
Education (level 4)	1.77	0.563948
Education (level 6)	1.76	0.567722
White-collar	1.69	0.589973
Industry 19	1.43	0.697421
Industry 4	1.40	0.716190
Industry 12	1.39	0.717077
Male	1.39	0.721800
Industry 2	1.38	0.724320
Industry 5	1.25	0.799381
Living with a spouse	1.23	0.812347
Good health	1.16	0.862023
Education (level 1)	1.06	0.947291
Mean VIF	6.46	

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

Source: authors' estimates based on PIAAC data. A value above 10 indicates that there is a problem with multicollinearity.

Appendix 7. The Oaxaca-Blinder decomposition.

EQUATION	VARIABLES	Model 1	Model 2	Model 3	Model 4
Overall	Female	1.303***	1.303***	1.303***	1.372***
		(0.0123)	(0.0123)	(0.0123)	(0.0139)
	Male	1.675***	1.675***	1.675***	1.778***
		(0.0154)	(0.0154)	(0.0154)	(0.0171)
	Difference	-0.372***	-0.372***	-0.372***	-0.405***
		(0.0197)	(0.0197)	(0.0197)	(0.0221)
	Explained	0.0558***	0.0678***	-0.0363**	-0.0516***
		(0.00870)	(0.0110)	(0.0149)	(0.0167)
	Unexplained	-0.428***	-0.440***	-0.336***	-0.354***
		(0.0183)	(0.0179)	(0.0193)	(0.0226)
Explained	Age	0.0379***	0.0291**	0.0294**	0.0608***
		(0.0146)	(0.0122)	(0.0122)	(0.0191)
	Age square/100	-0.0426**	-0.0318**	-0.0312**	-0.0600***
		(0.0170)	(0.0134)	(0.0131)	(0.0185)
	Education	0.0605***	0.0323***	0.0233***	0.0169***
		(0.00796)	(0.00579)	(0.00529)	(0.00579)
	Good health		0.00109	0.000999	-0.000628
			(0.00201)	(0.00185)	(0.00208)
	Children		0.00222	0.00263	0.00203
			(0.00217)	(0.00209)	(0.00267)
	Private/public sector		-0.0231***	-0.0260***	-0.0252***
			(0.00389)	(0.00649)	(0.00725)
	Living with a spouse		-0.00465***	-0.00368**	-0.00246
			(0.00180)	(0.00166)	(0.00153)
	White-collar occupations		0.0627***	0.0553***	0.0473***
			(0.00676)	(0.00629)	(0.00666)
	Industry			-0.0775***	-0.0758***
				(0.0118)	(0.0131)
	Literacy average				-0.000745
					(0.00121)
	Numeracy average			-0.00959***	-0.0145**
				(0.00272)	(0.00624)
	Problem solving average				0.000873
					(0.00221)
Unexplained	Age	-1.621***	-0.673	-0.847*	-0.977*
		(0.422)	(0.461)	(0.451)	(0.507)
	Age square/100	0.957***	0.490**	0.547**	0.560**
		(0.226)	(0.237)	(0.232)	(0.249)
	Education	0.114**	0.0512	0.0681	0.00705

	(0.0477)	(0.0493)	(0.0506)	(0.0668)
Good health		-0.0223	-0.0315	-0.0449
		(0.0293)	(0.0284)	(0.0387)
Children		-0.0624	-0.0368	-0.0252
		(0.0443)	(0.0428)	(0.0456)
Private/public sector		-0.0837***	-0.0497	-0.0944*
		(0.0285)	(0.0487)	(0.0558)
Living with a spouse		-0.148***	-0.108***	-0.0936**
		(0.0400)	(0.0385)	(0.0437)
White-collar occupations		0.0421**	0.0147	0.0303
		(0.0200)	(0.0207)	(0.0270)
Industry			-0.0282	0.0422
			(0.0888)	(0.116)
Literacy average				0.493
				(0.351)
Numeracy average			-0.285**	-0.538
			(0.137)	(0.335)
Problem solving average				-0.0329
				(0.291)
Constant	0.122	-0.0328	0.420	0.319
	(0.201)	(0.219)	(0.273)	(0.324)
Observations	3,520	3,520	3,520	2,655

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: authors' estimates based on PIAAC data.

Appendix 8. The output of Oaxaca-Blinder separate equations for men and women.

	Coef.	Std. Err.	z	P>z	95% Conf. Interval	
b1						
age	.0190764	.0084224	2.26	0.024	.0025688	.035584
age_sqr_100	-.021897	.0098524	-2.22	0.026	-.0412074	-.0025865
edu_level1	.0030408	.1952899	0.02	0.988	-.3797204	.3858019
edu_level3	-.0428161	.0491468	-0.87	0.384	-.1391421	.0535099
edu_level4	-.046133	.0587732	-0.78	0.432	-.1613264	.0690604
edu_level5	-.000282	.0531774	-0.01	0.996	-.1045077	.1039437
edu_level6	.1351347	.0684314	1.97	0.048	.0010116	.2692579
edu_level7	.2422987	.0594287	4.08	0.000	.1258205	.3587769
health	.0946869	.031033	3.05	0.002	.0338634	.1555104
child_ex	.0097074	.0401385	0.24	0.809	-.0689626	.0883774
private_public	.0976715	.0454652	2.15	0.032	.0085613	.1867816
living_with	.0099695	.0296225	0.34	0.736	-.0480895	.0680286
white_collar	.2926193	.029746	9.84	0.000	.2343181	.3509205
industry2	.1874248	.24866	0.75	0.451	-.29994	.6747895
industry3	-.0119886	.0907591	-0.13	0.895	-.1898732	.165896
industry4	.1018154	.1712148	0.59	0.552	-.2337594	.4373903
industry5	.3429238	.1738054	1.97	0.048	.0022714	.6835762
industry6	.1199029	.1386145	0.87	0.387	-.1517765	.3915823
industry7	-.0646876	.0906096	-0.71	0.475	-.2422793	.112904
industry8	.0044748	.1187204	0.04	0.970	-.2282129	.2371626
industry9	-.1113687	.1022107	-1.09	0.276	-.3116981	.0889607
industry10	.2021962	.1255207	1.61	0.107	-.0438198	.4482122
industry11	.2599946	.1164651	2.23	0.026	.0317272	.488262
industry12	.0077341	.169002	0.05	0.963	-.3235039	.338972
industry13	.1216568	.1157419	1.05	0.293	-.1051931	.3485067
industry14	.1005677	.1174536	0.86	0.392	-.1296372	.3307725
industry15	.2462123	.1054621	2.33	0.020	.0395103	.4529142
industry16	-.0874134	.1025961	-0.85	0.394	-.288498	.1136712
industry17	.0578422	.1012571	0.57	0.568	-.1406181	.2563024
industry18	-.1798541	.1278992	-1.41	0.160	-.430532	.0708237
industry19	.0607013	.1810478	0.34	0.737	-.2941458	.4155484
pvlitav	.0013028	.0008207	1.59	0.112	-.0003059	.0029114
pvnumav	.000428	.0007093	0.60	0.546	-.0009622	.0018181
pvpslav	-.0000712	.0006528	-0.11	0.913	-.0013507	.0012082
_cons	.1095781	.2120396	0.52	0.605	-.3060118	.525168
b2						
age	.0446698	.0102828	4.34	0.000	.024516	.0648236
age_sqr_100	-.05703	.0121755	-4.68	0.000	-.0808936	-.0331664
edu_level1	.0322464	.2335067	0.14	0.890	-.4254184	.4899111
edu_level3	.0020757	.0550178	0.04	0.970	-.1057573	.1099086
edu_level4	.0526115	.0838507	0.63	0.530	-.1117328	.2169558
edu_level5	-.0386931	.065204	-0.59	0.553	-.1664906	.0891044
edu_level6	.1041079	.0901487	1.15	0.248	-.0725802	.2807961
edu_level7	.1544494	.0701951	2.20	0.028	.0168695	.2920294

health	.152979	.0394673	3.88	0.000	.0756244	.2303335
child_ex	.0441399	.0470508	0.94	0.348	-.0480779	.1363577
private_public	.2282424	.0630839	3.62	0.000	.1046002	.3518846
living_with	.1289894	.0469264	2.75	0.006	.0370153	.2209635
white_collar	.2376455	.0390332	6.09	0.000	.1611418	.3141493
industry2	.4397408	.1175604	3.74	0.000	.2093267	.6701549
industry3	-.0145465	.0810717	-0.18	0.858	-.1734441	.1443511
industry4	.1674659	.1090778	1.54	0.125	-.0463228	.3812545
industry5	.0454487	.1328841	0.34	0.732	-.2149993	.3058968
industry6	.2825522	.0887751	3.18	0.001	.1085562	.4565482
industry7	-.0946854	.0889867	-1.06	0.287	-.2690962	.0797253
industry8	.1592821	.0912978	1.74	0.081	-.0196583	.3382225
industry9	-.1709901	.1199264	-1.43	0.154	-.4060416	.0640613
industry10	.0666268	.1044814	0.64	0.524	-.1381529	.2714065
industry11	.2687337	.1297343	2.07	0.038	.0144592	.5230082
industry12	-.122281	.2346078	-0.52	0.602	-.5821039	.3375419
industry13	-.0068605	.1181433	-0.06	0.954	-.2384172	.2246961
industry14	-.0802989	.1406194	-0.57	0.568	-.3559079	.1953102
industry15	.0854502	.1043306	0.82	0.413	-.119034	.2899345
industry16	-.1490276	.1085072	-1.37	0.170	-.3616977	.0636426
industry17	.0324185	.1462048	0.22	0.825	-.2541376	.3189746
industry18	-.1633702	.2949449	-0.55	0.580	-.7414516	.4147112
industry19	-.0406516	.2078668	-0.20	0.845	-.4480631	.3667599
pvlitav	-.0004458	.0009389	-0.47	0.635	-.002286	.0013943
pvnumav	.0023259	.0009387	2.48	0.013	.000486	.0041657
pvpslav	.0000445	.0008251	0.05	0.957	-.0015726	.0016616
_cons	-.2099006	.2451653	-0.86	0.392	-.6904158	.2706146
b_ref						
age	.0304512	.0065086	4.68	0.000	.0176946	.0432078
age_sqr_100	-.0372746	.0076171	-4.89	0.000	-.0522038	-.0223454
edu_level1	.0462069	.1903266	0.24	0.808	-.3268264	.4192401
edu_level3	-.0178079	.0375019	-0.47	0.635	-.0913103	.0556946
edu_level4	-.0163512	.0493302	-0.33	0.740	-.1130365	.0803342
edu_level5	-.01264	.0419312	-0.30	0.763	-.0948236	.0695437
edu_level6	.128378	.0546117	2.35	0.019	.021341	.235415
edu_level7	.2059719	.0460661	4.47	0.000	.1156841	.2962597
health	.125343	.0246217	5.09	0.000	.0770854	.1736007
child_ex	.0234808	.0305132	0.77	0.442	-.0363239	.0832856
private_public	.141749	.0382328	3.71	0.000	.0668142	.2166838
living_with	.0452769	.0246688	1.84	0.066	-.0030731	.0936269
white_collar	.2686627	.0237291	11.32	0.000	.2221545	.315171
industry2	.4158297	.1024195	4.06	0.000	.2150911	.6165683
industry3	-.012619	.0608973	-0.21	0.836	-.1319755	.1067376
industry4	.1495078	.0875638	1.71	0.088	-.022114	.3211297
industry5	.1620433	.1081942	1.50	0.134	-.0500135	.3741001
industry6	.3025534	.0721109	4.20	0.000	.1612186	.4438882
industry7	-.0965084	.0624776	-1.54	0.122	-.2189622	.0259454
industry8	.127125	.0724076	1.76	0.079	-.0147913	.2690414
industry9	-.1497832	.0751389	-1.99	0.046	-.2970527	-.0025136
industry10	.1332977	.0823017	1.62	0.105	-.0280106	.2946061

industry11	.2339949	.0859618	2.72	0.006	.0655129	.402477
industry12	-.030773	.1301648	-0.24	0.813	-.2858915	.2243454
industry13	.0570579	.0817096	0.70	0.485	-.1030899	.2172057
industry14	.015236	.0895589	0.17	0.865	-.1602963	.1907683
industry15	.1753982	.0738768	2.37	0.018	.0306023	.320194
industry16	-.0952367	.0726209	-1.31	0.190	-.237571	.0470976
industry17	.0345066	.0743795	0.46	0.643	-.1112744	.1802877
industry18	-.1741538	.1146249	-1.52	0.129	-.3988145	.0505069
industry19	.020063	.1371992	0.15	0.884	-.2488426	.2889685
pvlitav	.0005454	.0006332	0.86	0.389	-.0006957	.0017865
pvnumav	.0014364	.0005781	2.48	0.013	.0003033	.0025695
pvpslav	-.0002093	.000525	-0.40	0.690	-.0012383	.0008198
_cons	-.1549449	.1630428	-0.95	0.342	-.4745028	.1646131
x1						
age	39.28993	.3015577	130.29	0.000	38.69889	39.88097
age_sqr_100	16.85378	.2459796	68.52	0.000	16.37167	17.3359
edu_level1	.0019243	.0011103	1.73	0.083	-.0002518	.0041004
edu_level3	.2950609	.0115544	25.54	0.000	.2724147	.3177072
edu_level4	.0724824	.0065689	11.03	0.000	.0596075	.0853572
edu_level5	.2148813	.010406	20.65	0.000	.194486	.2352767
edu_level6	.0628608	.0061491	10.22	0.000	.0508089	.0749127
edu_level7	.2809493	.011387	24.67	0.000	.2586312	.3032675
health	.7677999	.0106972	71.78	0.000	.7468337	.7887661
child_ex	.7844772	.0104172	75.31	0.000	.7640598	.8048947
private_public	.6048749	.0123856	48.84	0.000	.5805996	.6291502
living_with	.7485568	.0109913	68.10	0.000	.7270142	.7700993
white_collar	.6504169	.0120806	53.84	0.000	.6267395	.6740944
industry2	.0019243	.0011103	1.73	0.083	-.0002518	.0041004
industry3	.1488133	.0090167	16.50	0.000	.1311409	.1664858
industry4	.0025657	.0012816	2.00	0.045	.0000538	.0050777
industry5	.0038486	.0015687	2.45	0.014	.0007741	.0069232
industry6	.0141116	.0029883	4.72	0.000	.0082547	.0199685
industry7	.1661321	.0094296	17.62	0.000	.1476505	.1846137
industry8	.0262989	.0040541	6.49	0.000	.018353	.0342449
industry9	.0525978	.0056555	9.30	0.000	.0415133	.0636823
industry10	.0262989	.0040541	6.49	0.000	.018353	.0342449
industry11	.0327133	.0045067	7.26	0.000	.0238804	.0415462
industry12	.0121873	.0027798	4.38	0.000	.0067391	.0176355
industry13	.0378448	.0048344	7.83	0.000	.0283695	.04732
industry14	.0333547	.0045491	7.33	0.000	.0244386	.0422708
industry15	.1051956	.0077728	13.53	0.000	.0899612	.1204301
industry16	.1763951	.0096565	18.27	0.000	.1574688	.1953215
industry17	.096857	.0074931	12.93	0.000	.0821708	.1115431
industry18	.0288647	.0042417	6.80	0.000	.0205511	.0371782
industry19	.0134702	.0029205	4.61	0.000	.0077461	.0191943
pvlitav	280.9582	.9940466	282.64	0.000	279.0099	282.9065
pvnumav	278.5996	.9785575	284.70	0.000	276.6816	280.5175
pvpslav	274.6741	.9872915	278.21	0.000	272.7391	276.6092
_cons	1	.	.	.	.	.

x2						
age	37.29288	.3492639	106.78	0.000	36.60834	37.97743
age_sqr_100	15.24333	.2796138	54.52	0.000	14.6953	15.79136
edu_level1	.0072993	.0025724	2.84	0.005	.0022574	.0123411
edu_level3	.4279197	.0149521	28.62	0.000	.3986141	.4572253
edu_level4	.0565693	.0069813	8.10	0.000	.0428862	.0702525
edu_level5	.1332117	.0102688	12.97	0.000	.1130852	.1533382
edu_level6	.0328467	.0053863	6.10	0.000	.0222899	.0434036
edu_level7	.2217153	.0125534	17.66	0.000	.1971112	.2463195
health	.7728102	.0126626	61.03	0.000	.7479919	.7976285
child_ex	.6979927	.0138748	50.31	0.000	.6707986	.7251868
private_public	.7828467	.0124599	62.83	0.000	.7584258	.8072677
living_with	.8029197	.0120213	66.79	0.000	.7793584	.826481
white_collar	.4744526	.0150902	31.44	0.000	.4448763	.5040288
industry2	.0191606	.0041428	4.63	0.000	.0110408	.0272804
industry3	.2390511	.0128889	18.55	0.000	.2137893	.2643129
industry4	.0191606	.0041428	4.63	0.000	.0110408	.0272804
industry5	.0100365	.0030123	3.33	0.001	.0041326	.0159404
industry6	.149635	.0107798	13.88	0.000	.1285069	.1707631
industry7	.1076642	.0093668	11.49	0.000	.0893056	.1260229
industry8	.0894161	.008623	10.37	0.000	.0725152	.1063169
industry9	.020073	.0042383	4.74	0.000	.011766	.02838
industry10	.0419708	.0060598	6.93	0.000	.0300939	.0538477
industry11	.0164234	.0038409	4.28	0.000	.0088954	.0239513
industry12	.0082117	.0027272	3.01	0.003	.0028664	.0135569
industry13	.0328467	.0053863	6.10	0.000	.0222899	.0434036
industry14	.0319343	.0053134	6.01	0.000	.0215202	.0423484
industry15	.0875912	.0085431	10.25	0.000	.070847	.1043355
industry16	.0556569	.0069282	8.03	0.000	.042078	.0692359
industry17	.0164234	.0038409	4.28	0.000	.0088954	.0239513
industry18	.0109489	.0031448	3.48	0.000	.0047853	.0171125
industry19	.0082117	.0027272	3.01	0.003	.0028664	.0135569
pvlitav	282.3246	1.180874	239.08	0.000	280.0101	284.639
pvnumav	288.7221	1.158911	249.13	0.000	286.4507	290.9935
pvpslav	278.846	1.201596	232.06	0.000	276.4909	281.2011
_cons	1	.	.	.	.	.

RESÜMEE

OSKUSTE MÕJU SOOLISELE PALGALÕHELE EESTIS: *PIAAC* UURINGU ANDMETEL PÕHINEV ANALÜÜS

Oksana Boiko

Viimastel aastakümnetel on meie elu märgatavalt muutunud. Tänapäeval on meil kasutusel ja toeks tehnoloogiad ja seadmed, mida ei saadud aastal 1980 isegi ette kujutada. Elamise ja töötamise viisid on sügavalt teisenenud, seega on muutunud ka nende oskuste kogum, mida vajame üha enam aktiivseks osalemiseks teadmistepõhises majanduses. Siit tulenevalt on ootuspärane, et kasvab ka huvi ja ootused täiskasvanute oskuseid käsitlevate uuringute vastu.

Teadmistepõhises ühiskonnas on tõeliseks väljakutseks suurenev nõudlus kvalifitseeritud tööjõule, mis pani suhteliselt hiljuti OECD läbi viima kahte võrdlevat uuringut: aastatel 1994-1998 riiki hõlmav Rahvusvaheline täiskasvanute kirjaoskuse uuring (*International Adult Literacy Survey* ehk *IALS*) ning aastal 2003 kuut riiki hõlmav Rahvusvaheline täiskasvanute kirjaoskuste ja elutarbeliste pädevuste uuring (*International Adult Literacy Survey* ehk *ALL*).

Antud uurimistöö põhineb viimasele OECD uuringule – Rahvusvahelisele täiskasvanute oskuste uuringule (*Programme for the International Assessment of Adult Competences* ehk *PIAAC*), mis käivitati 33 riigis ning 24 riigis (k.a Eestis) viidi juba läbi. Tegemist on seni ainsa rahvusvahelise uuringuga, milles osales ka Eesti ning mille esmased tulemused avaldati 8. oktoobril 2013. a. *PIAAC* uuring võimaldab mõõta täiskasvanute infotöötlusoskusi ehk lugemisoskust, matemaatilist oskust ja probleemilahendusoskust. Uuring keskendub sellele, kuidas täiskasvanud arendavad ja kasutavad oma oskuseid ning mis kasu saavad oskuste rakendamisest. *PIAAC* uuring on kinnitanud, et Eesti täiskasvanute kognitiivsed oskused on kõrgelt arenenud: üle keskmise tulemuse jääb

lugemisoskuse ja matemaatilise oskuse tase ning probleemilahendusoskuse tase jääb keskmisest tulemusest veidi allapoole.

Varasemalt on erinevates riikides läbi viidud mitmeid uuringuid käsitlemaks soolist palgalõhet, kuid vähe osa neist võtab arvesse kongitiivsete oskustega seotud infot. Eesti kohta varasemalt läbi viidud uurimused on käsitlenud haridustaseme mõju sissetulekutele, kuid puudulike andmete tõttu ei algatatud uuringuid, mis hõlmaksid töötajate oskused. Käesoleva magistritöö raames analüüsitakse meeste ja naiste palgalõhet Eestis võttes arvesse lisaks muudele isikupõhistele tunnustele ka infot *PIAAC* uuringu raames mõõdetud inimeste oskuste (lugemisoskuse, matemaatilise oskuse ja probleemilahendusoskuse) kohta. Eesti jaoks on soolise palgalõhe põhjalik analüüs oluline, kuna võrreldes teiste Euroopa riikidega on sooline palgalõhe Eestis üks kõrgemaid.

Käesoleva magistritöö eesmärk on kindlaks määrata, kas Eestis jääb selgitamata palgalõhe meeste ja naiste vahel püsima oskuste ja kompetentside arvessevõtmisel tuginedes *PIAAC* uuringu raames saadud andmetele.

Vastavalt uurimistöö eesmärgile seati järgmised uurimisülesanded:

- välja selgitada inimkapitali teooria peamised aspektid;
- anda ülevaade inimkapitali mõõtmisest;
- esitada selgitused soolise palgalõhe kohta;
- esitada ülevaade soolise palgalõhe uuringutest Eestis ja teistes riikides;
- anda ülevaade *PIAAC* uuringust ja selle raames kogutavast infost inimeste oskuste kohta;
- selgitada käesoleva uuringu metodoloogiat;
- selgitada, kui suur on sooline palgalõhe Eestis kasutades *PIAAC* andmeid ning võttes seeläbi arvesse ka info oskuste kohta.

Magistritöö teoreetiline osa põhineb varasematel artiklitel, uuringutel ja uurimistöödel. Magistritöö empiirilises osas spetsifitseerib töö autor ökonomeetrilised mudelid hindamaks kognitiivsete oskuste võimalikku mõju soolisele palgalõhele Eestis.

Paljude varasemate uurimistööde ja arutelude objektiks on olnud soolise palgalõhe selgituste otsimine, mille tulemusel on välja kujunenud kaks põhilist lähenemist - pakkumisepoolne ja nõudlusepoolne. Inimkapitali teooria annab n-ö pakkumisepoolse selgituse soolisele palgalõhele. See sätestab, et naised püüdlevad lastekasvatuse ja tööelu katkestamise poole, seega investeerivad vähem hariduse omandamisse või täiendõppe läbimisse ning eelistavad osalise või paindliku tööajaga vähem kvalifitseeritud töökohti. Nõudlusepoolne selgitus toob esile diskrimineerimise mõiste ehk väidab, et värbamisel, edutamisel, väljaõpetamisel ja premeerimisel eelistavad tööandjad meessoost töötajaid.

Inimkapitali teooria on üks mõjuvaid ja enamkasutatud teooriaid, mis võimaldab selgitada inimeste vahelisi palagaerinevusi tööturul. Aluseks on arusaam haridusest kui investeeringust tulevikus teenitava tulu nimel. Õpingute käigus omandatud teadmised ja oskused tõstavad inimkapitali väärtust suurendades samaaegselt tööhõivet, sissetuleku potentsiaali ja tootlikkust. Inimkapitali hindamisel lähtutakse OECD 2001 aasta definitsioonist, mille kohaselt inimkapital on indiviidi iseloomustavate teadmiste, oskuste, kompetentside ja omaduste kogum, mis aitab kaasa personaalse, sotsiaalse ja majandusliku heaolu tõstmisele. Inimkapitali mõõtmisel on enim kasutatavad kulupõhine lähenemine, tulupõhine lähenemine ja haridusel põhinev ehk indikaatorite lähenemine. Igal meetodil on oma eelised ja puudutused, mistõttu on otstarbekas võtta need kasutusele kombineeritult.

Käesoleva magistritöö raames pandi paika ökonomeetriline mudel kirjeldamaks meeste ja naiste sissetulekuid Eestis tuginedes *PIAAC* andmetele ning teoreetilises osas käsitletud soolise palgalõhe selgitustele. Ökonomeetrilise mudeli aluseks on Minceri võrrand (1974) ehk inimkapitali teoorial põhinevates empiirilistes töödes kõige sagedamini kasutatav instrument. Mudeli baasil viidi läbi klassikaline vähimruutude regressioonanalüüs (*OLS*) ja Oaxaca-Blinder dekompositsioon.

PIAAC andmetele tugineva analüüsi tulemused kinnitavad varasemate uuringute tulemusi, et sooline palgalõhe on Eestis suur, ca 37.2%. Matemaatilise oskuse arvesse võtmine vähendab palgalõhet 2,1% ja tegemist on parima määraga võrreldes teiste kognitiivsete oskustega: probleemilahendusoskuse sissetoomine mudelisse on suurendanud erinevust 1% võrra ja lugemisoskuse lisandumisega vähenes erinevus ligikaudu 0,5% võrra. Vastavalt Oaxaca-Blinderi dekompositsiooni tulemustele autor tuli sarnasele eelmistel uuringutel saadud tulemusele, et selgitamata osa palgalõhest jääb domineerivaks.

Vastavalt magistritöö eesmärgile saab järeldada, et selgitamata osa soolisest palgalõhest Eestis jääb püsima ka siis, kui oskused ja kompetentsid on arvesse võetud. Kuigi peab rõhutama, et oskuste lisamine mudelisse aitas palgalõhe selgitamata osa vähendada antud analüüsi raames.

Kokkuvõtteks, käesolev magistritöö selgitab probleemi seoses soolise palgalõhega Eestis ning tekitab eeldusi järgnevateks uuringuteks. Samal ajal empiiriline uuring jällegi rõhutab meeste ja naiste vahelise palgalõhe püsimist kõrgel tasemel.

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