The Impact of Skill Mismatch on Aggregate Productivity:

cross-country analysis in OECD economies

EIRINI ZIRA

KTH Industrial Engineering and Management

Master's Degree Project

Stockholm, Sweden June 2016

The Impact of Skill Mismatch on Aggregate Productivity:

cross-country analysis in OECD economies

Eirini Zira

Master of Science Thesis INDEK 2016:30
KTH Industrial Engineering and Management
SE-100 44 STOCKHOLM

KTH Industrial Engineering and Management

Master of Science Thesis INDEK 2016:30

The Impact of Skill Mismatch on Aggregate Productivity:

cross-country analysis in OECD economies

Eirini Zira

Approved	Examiner	Supervisor
2016-06-16	Hans Lööf	Kristina Nyström

Abstract

The present study explores the relationship between skill mismatch in two main categories, numeracy and literacy, and aggregate productivity as derived from a decomposition of productivity into *within-firm* productivity and allocative efficiency. Skill mismatch is considered a rather persistent phenomenon with long lasting effects in various aspects. In the analysis covered, OECD *Survey of Adult Skills* (PIAAC) database was employed for the aggregated indicators of skill mismatch while productivity was measured using ORBIS commercial database. The key findings reveal a strong and negative relationship between skill mismatch in numeracy and productivity, which stems from a negative relationship between the same category and the *within-firm* labor productivity. Under-skilling in numeracy exhibits a negative effect on productivity while over-skilling seems not to be related in the current specification. Based on the relationship between competition and productivity, market power is used to control for the competition in different sectors. The results suggest that higher market share translates to higher productivity and the relationship is statistically significant.

Key words: skill mismatch, aggregate productivity, PIAAC, ORBIS, allocative efficiency

Acknowledgements

Though only my name appears on the cover of this thesis, a great many people have contributed to its production.

My deepest gratitude is to my advisor, Kristina Nyström. I have been very lucky to have a supervisor who gave me the freedom to explore on my own, but at the same time useful guidance. I also owe my gratitude to Ingrid Viklund Ros. Without her precious guidance and help in the technical part of my work it would have been much harder to develop the present study. I would also like to thank all the researchers at Ratio Research Institute who with listened to the problems that arose during the process and gave me guidance.

To all my classmates who made this journey unforgettable, but most of all my co-worker, Arthur-Alexandre Mauriès, who has been always there to listen to me and give me advice. I would also like to thank all my friends, the ones I met here (Martha, Makis, Nikos) and my graduate experience amazing, in and out of the campus and the ones that I left behind (Christina, Yiota, Maria and Mariza, Giorgos) but they are still there to bear with me and give me support.

Most importantly, none of this would have been possible without the love and patience of my family (Marietta, Stamatis and Nikoletta), to whom this thesis is dedicated to. They have been a constant source of love, concern, support and strength all these years. Finally, to my partner Konstantinos who with great patience has been there for me all these years.

Contents

List of Tables

List of Figures

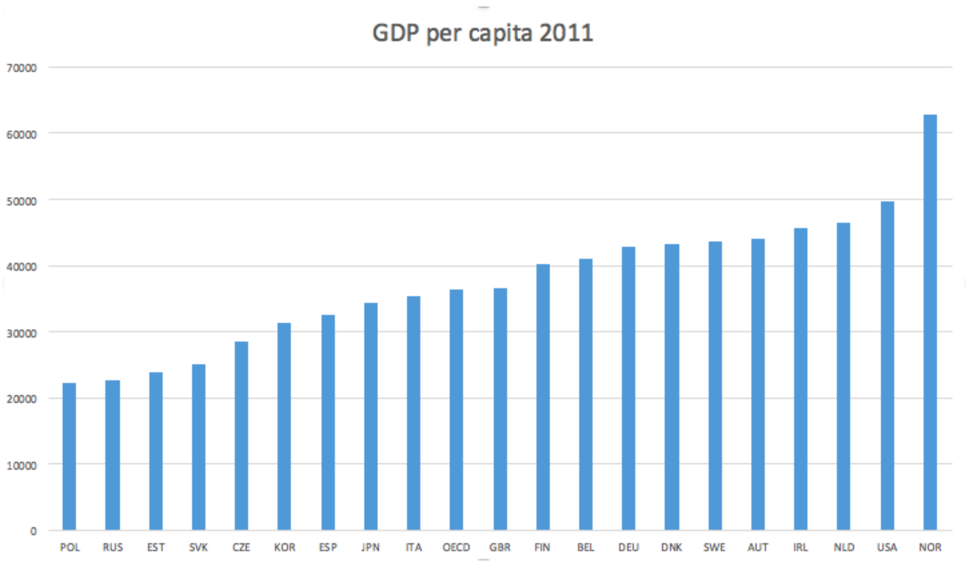
Chapter 1

Introduction

Skills are the new " global currency of the 21st-century economies " (OECD, 2012, p.5). But as every other currency, it depreciates when the labor market demands change and individuals lose them when they are not used. Skills are only of value when they are in use, be that in the labor market, academia, self-employment or other leisure activities; skills that are utilized improperly go to waste (OECD, 2012). Therefore, we define skill mismatch as the gap between the portfolio of skills possessed by workers and the package of skills the labor market demands. In order to expedite economic growth, skills should be allocated analogously throughout the economy (McGowan and Andrews, 2015).

When lack of skill-balance is observed, there is a high risk that the market does not operate efficiently as it does not exploit its dynamics. From a macroeconomic perspective, skill mismatch can eventually lead to depreciation of skills as well as rigidness in adapting to new technologies, which results in even more aggravate differences in GDP per capita among countries (OECD, 2012). It also affects the unemployment rates (Quintini, 2011a). As disruptive technologies have shifted the demand towards certain skills, skills that are not active become subject to atrophy in the course of years (OECD, 2013). Finally, skill mismatch has an impact on the individual and firm level, as it affects wages, job satisfaction and turnover (Allen and van der Velder, 2001; Mavromaras et al., 2015, 2009; Quintini, 2011b).

Figure 1.1: GDP per capita differences in OECD countries



Source: *Structural and Demographic Business Statistics (SDBS), OECD* (2009)

Differences in income per capita (GDP) across economies (see Figure 1.1), mirror the differences in labor productivity levels (Andrews and Cingano, 2014). This labor productivity, to a large extend, depends on the amount of human capital accumulated as well as the way this, is allocated throughout the economy. The accumulation of human capital has been the factor that accelerated economic performance and growth for the past century and its importance is believed to increase the need of skilled labor force in the upcoming decades. (Braconier et al., 2014) Therefore, in order to cope with the challenges of our technologically progressing and fast pace economies, the ability of countries to educate, inform and effectively allocate their human capital is of utmost importance and constitutes major priority for policy makers.

1.1 Baseline state of the art

Mismatch can be distinguished into two main types: qualification (educational attainment) and skill mismatch (numeracy and literacy skills). Research shows that the correlation between them is only weak (Allen and van der Velder, 2001; Quintini, 2011a) and therefore qualification match does not necessarily mean skill match. The present work does not take into account qualification mismatch and therefore it is important that these two terms are distinguished. Skill mismatch is considered a more relevant measure of one's skills as it takes into account skills that are gained or lost during their career cycle. On the contrary, qualification mismatch is restricted to the educational attainment of the individual, which, in some cases, is misleading.

Nevertheless, measuring skill mismatch is rather challenging, mostly because of the lack of relevant data. The present study, uses an alternative measure of skill mismatch with data derived from the newly released Survey of Adult Skills (PIAAC). The survey is constructed by the OECD in the context of the Programme for the International Assessment of Adult Competences (PIAAC). For simplicity both the programme and the survey will be referred to as PIAAC.

The impact on firm performance at the individual level through wages and other correlates has been strongly established (Battu et al., 1999; Büchel, 2002; Hartog, 2000) On the other hand, the literature, which estimates the effect on aggregate productivity is mostly country-specific (Kampelmann and Rycx, 2012; Mahy et al., 2013) and therefore misleading if one wants to draw generalized assumptions in a cross-country analysis. Finally, an emerging literature locates the problem in the effective allocation of human resources in a way that increases the aggregate level of productivity (McGowan and Andrews, 2015; Andrews and Cingano, 2014)

Finally, following the emerging literature in measuring aggregate productivity through allocative efficiency and *within-firm* productivity, across OECD economies, firm level-data are used, which are derived from ORBIS, a commercial databate. In the same context, a decomposition of skills is constructed in order to detect which types of skills are stronger associated with productivity. The categories are derived directly from PIAAC: literacy, numeracy and problem solving and the methodology will be analyzed in the respective section. However, since problem solving is a new category never been used and analyzed, is not available for all the counties in the sample and therefore will be excluded from the main analysis. Results with this category will be presented in the appendix instead (see Appendix D).

Perry et al. (2014); McGowan and Andrews (2015) and Gal (2013) are the baseline state of the art for the present study. The former one adds on the estimation of skill mismatch, with an alternative proposed methodology, while the last two contribute on the construction of the database to be used as well as the measurement of productivity.

1.2 Motivation & scientific questions

The main contribution to the existing literature is that it is, to the best of my knowledge, the first study that combines the particular measure of skill mismatch tested against aggregate productivity as a product of the *within-firm* productivity and allocative efficiency. It aims to prove that skill mismatch is a valid factor that influences labor productivity in the long run through the channel of not only *within-firm* productivity but also allocative efficiency, which means that is not only human capital accumulation that matters, but also the way this, is allocated throughout the economy. In addition to that, a decomposition of skill mismatch will be attempted in the same model in order to identify the types of skills that have a stronger effect on productivity.

Having all the above in mind, the thesis seeks to answer the following scientific questions:

Research question 1: *What is the link between skill mismatch, in numeracy and literacy, and aggregate labor productivity through the channel of within-firm productivity and allocative efficiency?*

Research question 2: *Which type of skills (numeracy or literacy) has a stronger effect on aggregate productivity?*

Based on the up-to-date literature in the field the main hypotheses are formed as following:

Hypothesis 1: *Skill mismatch in both categories is expected to be negatively correlated with aggregate productivity through within-firm productivity and allocative efficiency.*

Hypothesis 2: *Being under-skilled in either numeracy or literacy is assumed to be negatively related to aggregate productivity through both channels while over-skilling might exhibit a positive relationship with the within-firm labor productivity.*

Monitoring skill levels among young people has become increasingly acknowledged in the recent years. Literacy and numeracy skills go beyond the antiquated idea of being able to read and write and understand numbers. Literacy is about being able to comprehend complex texts and combine different sources in order to make assumptions using critical thinking (Department of Education and Skills, 2011). Numeracy involves the ability to use numerical understanding to solve problems, communicate in a quantitative way, being able to understand data, patterns, sequences, etc. (Department of Education and Skills, 2011).

These two kinds of skills are closely related to each other but still different in the sense that competence in one does not guarantee the other at the same level. When it comes to measure which one of them is more critical when not in match, it becomes rather difficult as one shall consider many different factors, such as the kind of position or industry under discussion, as it would be expected that in the ICT (Information and Communication Technology) industry, numeracy skills are vital for productivity and growth. Based on this and considering the trends in the economy the second assumption is the following.

Hypothesis 3: *Numeracy skill mismatch is expected to have a greater weight on productivity, with under-skilling to exhibit severe negative results.*

Accordingly, the paper proceeds as follows: In the first section the theoretical framework is presented along with the previous empirical findings, explaining the concepts in more detail. In the second section the empirical model and baseline results are presented and analyzed along with the extended version of the model which includes the two control variables (market power and managerial quality). In addition, the last section deploys a thorough discussion on the outcomes of the analysis, the limitations as well as the relative implications of those on different socio-economic sustainability aspects.

Chapter 2

Theoretical Framework

The accumulation of human capital is the engine of continuous economic growth (Romer, 1989). But what happens when skills demanded and skills possessed are not in equilibrium? Is human accumulation sufficient to drive progress and growth in the economy? Only skills in equilibrium can truly increase productivity and drive economic growth. For this to be achieved, many structural and systemic reforms should be tested and implemented. In the recent years, the issue of skill mismatch has been broadly acknowledged, drawing the attention of researchers and policy makers. It is considered as one of the core challenges of nowadays economies according to the European Union's report on New skills for New Jobs (European Commission, 2010).

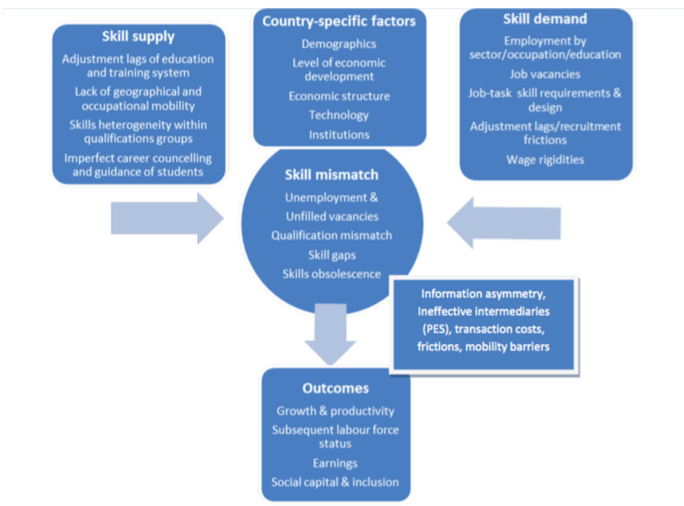
Differences in GDP per capita across countries mainly indicate differences in the level of productivity (Andrews and Cingano, 2014). Most of the literature to date attempts to explain these differences in GDP by estimating the differences in wages. Some others investigate the relationship between job satisfaction and skill mismatch while others tend to localize the problem in the misallocation of skill resources throughout the economy (McGowan and Andrews, 2015; Andrews and Cingano, 2014). Almost all the findings to date are aligned with the general notion that skill mismatch hampers economic growth in the long run.

2.1 Skill Mismatch

Skills are the pillar of the labor market. As in any other structure, pillars must be well-balanced to ensure a stable and solid construction. Skills can be cognitive, referring to numeracy and literacy skills, or non-cognitive, such as physical skills. Developing skills, increases workers' ability to understand and perform tasks. Numeracy and literacy skills are found to have a positive relationship with worker's satisfaction and economic growth (OECD, 2013). When skills are not in use we consider them as mismatched and hence we define skill mismatch as the gap between the skill portfolio possessed by individuals and the package of skills required in the labor market. More often, it is expressed as having excess or deficit of skills and therefore being over- or under- skilled (CEDEFOP, 2010).

Skill mismatch can be affected by both cyclical and structural determinants (see Figure 2.1) (Quintini, 2011a). On one hand, when economies face recessions, firms tend to assign under-skilled work force to more complex positions. On the other hand, when disruptive technologies are adopted, they shift the

Figure 2.1: Determinants and dynamics of skill mismatch



Source: European Commission (2012, p.5), *Employment and Social Developments in Europe 2012* demand towards certain types of skills and people are forced to adapt to these changes fast or compromise (Quintini, 2011a). Individuals who manage to adapt faster to such demand shifts are more likely to keep their jobs or be re-employed (Acemoglu and Autor, 2011). On the contrary, people who possess skills that are highly specialized to their occupation and hence not easily transferable, are prone to lose their jobs or compromise for positions that do not match their skill portfolios (Acemoglu and Autor, 2011).

Additionally, skill mismatch is linked to specific socio-economic factors. For instance, " barriers to equality of opportunity " raise behind the shadow of gender and racial discrimination (McGowan and Andrews, 2015). Women are more likely to be under-skilled than men at their occupation (Desjardins and Rubenson, 2011). Racial minorities and new labor market entrants are more prone to get a job with lower requirements than their skill level while the same applies to experienced workers who lack formal qualification (Quintini, 2011a). As graduates gain more experience by working, it becomes easier for them to signal their skills and be employed in more suitable jobs as they can refer to their past work experience (Desjardins and Rubenson, 2011; OECD, 2012).

On one hand, skill excess can be viewed as a " skill reserve " that is available for use once progress in technology permits (Perry et al., 2014, p.140). On the other hand, skills that are not in use, become subject to atrophy. Hence, skill surplus might lead to skill loss as skills are not fully utilized or exercised (OECD, 2013). As a result, labor and firm productivity will decrease and turnover costs will increase (Allen and van der Velder, 2001; OECD, 2012). On the other hand, skill deficit can hamper economic growth as individuals who master too few skills cannot easily cope with the challenges that disruptive technologies impose and therefore are phased out and forced to either adapt to the new technological reality or compromise. Only skills in equilibrium seem to be able to survive nowadays challenging working environments. And for this to be achieved, individuals and policy makers should be able to work together so as policy changes address perfectly prepared workers.

Skill mismatch has been increasingly linked to income inequality and lower productivity levels. It also affects health conditions, social participation and trust (OECD, 2013). According to the same report, people with low scores in numeracy and literacy are more likely to exhibit health problems, lack of trust in others as well as little participation in associative or volunteer activities (OECD, 2013). The survey also disclosed that the higher the literacy and numeracy inequality the higher the income inequality gets. Therefore, it is of increasing interest for policy makers to identify the causalities of skill mismatch in order to increase technological progress that will translate to economic growth.

Finally, skill mismatch seems to also affect outcomes in the individual level. One strand of research finds severe effects on worker's wages and job satisfaction. Skill mismatch has a strong impact on income inequality with over-skilled workers to generally face a wage penalty compared to their well-matched colleagues (Allen and van der Velder, 2001; Quintini, 2011a; Mavromaras et al., 2009). This happens because, typically, it is the pool of skills that are actually required the ones that are rewarded through wages (Tinbergen, 1956; Cingano, 2014). On the contrary, under-skilled employees earn a wage premium as it is considered that they use a bigger portion of their skill portfolio in order to cope with the challenges of their job (Perry et al., 2014).

Having presented and clarified the consequences caused by skill mismatch, it is easier to understand how important it is for governments and organizations to introduce structural reforms that aim to grasp this problem from the source. Evidence shows that the disequilibrium of skills is rather persistent and reveals the way how individuals respond to skill demand and the way firms build their recruitment and training processes (Mavromaras and McGuinness, 2012). Persistent differences in skill mismatch have shown that the allocation of resources or education-occupation system is problematic and hence, skill mismatch is reasonably related to productivity and growth (McGowan and Andrews, 2015). Finally, managerial practices have been proved rather significant, such as monitoring, in helping individuals adapt to new technologies or get a proper training in order increase the skills required to meet the needs of the job (McGowan and Andrews, 2015).

2.2 Skill mismatch and indirect productivity

The state of the art on the impact of skill mismatch on productivity draws on two basic theories. The first trend of literature relies on the Human Capital Theory (HCT) which states that in a perfectly competitive market, wages must reflect the marginal productivity of the workers and hence, it measures skill mismatch by estimating its effect on wages (Battu et al., 1999; Mavromaras et al., 2009; Mavromaras and McGuinness, 2012; Levels et al., 2014). The other approach measures individual productivity as a result of job satisfaction, absenteeism, turnover and other correlates (Allen and van der Velder, 2001; Büchel, 2002; Varhaest and Omey, 2006; Green and Zhu, 2010; Allen and van der Velder, 2001).

Results from previous studies suggest that over-skilled workers exhibit lower job satisfaction due to the fact that their skills are not fully in use (Allen and van der Velder, 2001). This, in turn, might lead to a routinized mechanical task performance which translates to less effort and hence lower productivity (Battu et al., 1999; Green and Zhu, 2010). This is also related to wage penalties, with people who are over-qualified and their skills underutilized, to suffer more (Green and Zhu, 2010). Indeed, it is plausible, if one thinks of over-skilled workers as workers in an assembly line of production for instance; rather extreme as a paradigm but it has a great explanatory power. After a certain period, depending on the individual's learning capabilities, people who repeat the same task every day tend to do it mechanically, and therefore suffer from dissatisfaction and hence are prone to commit mistakes.

On the same track, less job satisfaction might lead to higher turnover costs as over-skilled employees are more likely to search for other more suitable jobs than their well-matched colleagues (Quintini, 2011a; Chapple, 2009) But, higher turnover, translates to lower incentives for companies and employees to engage in training activities. This theory finds support in the study of Varhaest and Omey (2006) which presents evidence on the fact that matched workers are more likely to engage in on-the-job training than over-qualified individuals. The opposite is presented by Büchel (2002) as he argues that over educated workers in Germany are more productive, more likely to engage in on-the-job training and exhibit longer firm tenures, as on-the job training increases the likelihood of promotion.

As one might notice, the main drawback of the existing literature is that it addresses productivity in indirect ways, such as through wages, job satisfaction, etc. Existing studies that have measured productivity directly are very limited and in most cases country specific (Kampelmann and Rycx, 2012; Mahy et al., 2013; Grunau, 2014). It has been well established that a significant effect stems from the way human capital is allocated throughout the economy (Bartelsman et al., 2013; Olley and Pakes, 1996; McGowan and Andrews, 2015; Hsieh and Klenow, 2009). Hence, it is increasingly preferable by many scholars to measure productivity as a decomposition of these two components, *within-firm* productivity and allocative efficiency.

2.3 Skill mismatch and aggregate productivity

Emerging literature tends to locate the impact of skill mismatch on productivity through allocation effects. It mainly measures productivity as a factor of two components, namely i) the *within-firm* productivity and ii) the allocative efficiency (McGowan and Andrews, 2015; Andrews and Cingano, 2014). Indeed, for a single firm to hire an over-skilled worker might increase its productivity, assuming there are no adverse effects on job satisfaction or wages. On the other hand, this imposes another problem in the economy as a whole as highly skilled workers are utilized in positions with lower skill requirements and are not placed in positions where they can actually use their skills and knowledge in full extend. This results in skill shortages and firms that are relatively more productive cannot find suitable work force as the pool of knowledge available is narrow (McGowan and Andrews, 2015).

Grunau (2014) and Kampelmann and Rycx (2012) , examined the effect of educational mismatch on productivity using employer-employee panel data from Belgium, while Mahy et al. (2013) tested whether the direct relationship between mismatch and productivity varies across working environments using micro-level data of Belgian companies for the period 1999-2010. The results were in line with other studies in the subject revealing that mismatch has a strong negative effect on productivity. More specifically, the results suggest that extra years of education foster productivity and vice versa; while they did not find support for the hypothesis that over-education hampers individual productivity through the channel of less job satisfaction (Mahy et al., 2013).

This wouldn't be a problem in an economy of homogenous companies but this to be achieved is quite difficult in practice. Therefore, the problem of effective allocation of skills is of utmost importance. A number of other studies have tested how cross-country differences are related to the within-industry productivity and performance (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008). In their study, Hsieh and Klenow (2009), focus on resource allocation as a possible explanation of the TFP (Total Factor Productivity) levels in India and China versus the United States. The US serves as a benchmark in their study showing that if China and India adopted their strategy, they would experience an increase in TFP by 30-50 percent and 40-60 percent respectively.

On the same track, Bartelsman et al. (2013) investigated the effect of firm level policy-induced distortions to aggregate productivity. In their study of cross-country variation of human capital allocation, they proved that the within-industry productivity and size are closely related to each other and that there are countries which better manage to channel human capital to more productive firms relative to others. Indeed, according to OECD (2013), Korea, was found to successfully utilize the 32 percent of its individuals who scored top in numeracy and literacy. The opposite is observed in Norway, the Czech Republic, Italy and Poland (OECD, 2013). This strongly relates to the policies governing each country and calls for policy reforms that aim to identify the needs of the economy and allocate the work force analogously throughout the economy.

A similar pattern of the one in the US is observed in the northern countries of OECD while southern Europe exhibits a significantly lower allocative efficiency (Andrews and Cingano, 2014). The analysis on the correlation of productivity, allocative eficiency and policies revealed a negative-relationship between "policy-induced frictions" and productivity, bearing in mind that this is higly dependent on the policies under consideration (Andrews and Cingano, 2014; Restuccia and Rogerson, 2008). For instance, employment protection and Foreign Direct Investment (FDI) restrictions were found to worsen the allocative efficiency while reforms on entry policies (lower barriers) would have a reverse effect (Andrews and Cingano, 2014).

Finally, it has been increasingly acknowledged that the misallocation of resources between high- and low- growth firms hampers economic growth of innovative firms. Acemoglu et al. (2013) investigated the relationship between firm-level innovation productivity and reallocation. Subsidies in R&D or operating costs towards incumbent firms hampers economic growth while entry subsidies exhibits a positive but small effect. Furthermore, these policies would be beneficial to increase growth by approximately 1.6 percent if one would force "low-type" firms (low innovative activity) to exit the market in order to set resources free to be used by innovative "high-type" companies (new entrants and incumbents) which will be able to grasp their full potential and expand. (Acemoglu et al., 2013)

Positive effects from skill mismatch?

For the shake of argument, would it be possible that there are any positive effects stemming from skill mismatch? It is not realistic to assume that skill mismatch can be entirely eliminated and labor markets can operate without any even provisional imbalances. As technology progresses in tremendous speed, people need much longer time to adjust, learn and adopt. This increases the levels of skill mismatch in the short run (Desjardins and Rubenson, 2011). However, this is justified in a short-time frame as in the long run rising numbers of skill mismatch create a more persistent phenomenon, which implies actual economic and social losses.

Chapter 3

Data & Methodology

"Skills transform lives, generate propensity and promote social inclusion" (OECD, 2013, p.26). When not in equilibrium, progress does not lead to economic growth, people are isolated in the margins of the society and economies cannot cope with nowadays' challenges ending up lagging behind (OECD, 2013). According to the OECD Skills Outlook (2013), about 4.9 percent to 27.7 percent of adults scored high only in the lowest levels of literacy while 8.1 percent to 31.7 percent in numeracy. Finally, only 2.9-8.8 percent exhibit high score in the highest levels in problem solving in technology rich environments.

Bearing that in mind, this section is devoted to presenting, explaining and analyzing the data that were used in the present work as well as the methodology employed for the analysis, and it proceeds as follows: in the first part, the data for both skill mismatch and aggregate productivity are presented and analyzed continuing with an analysis of the methodology followed in order to obtain concrete results that aim to give an answer in the hypotheses formed in the beginning of this paper.

3.1 Data description

The measures of skill mismatch are constructed by using micro-level data retrieved from the *OECD Survey of Adult Skills*(PIAAC). In order to match these data with the productivity indicators used from ORBIS database, 1-digit industry classification is employed. The 1-digit industry level aggregates several similar industries into some main groups. This gives us the advantage of creating a much simpler database to analyze since only the main groups of industries are employed and better cell-sample representation is obtained.

3.1.1 Survey of Adult Skills (PIAAC) data

The present work explores a database developed for the Programme for the International Assessment of Adult Competences (PIAAC). PIAAC is an internationally harmonized test, which is based on a questionnaire that aims to assess the cognitive skills of individuals in literacy, numeracy and problem solving in technology-rich environments. These skills constitute "key competences" in many social and work related contexts. They are highly significant in order for individuals to fully integrate in the society and the labor market.

The survey took part in 24 OECD countries. The countries that participated are the following: Austria, Belgium, Canada, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russia[1], Slovakia, Sweden, United Kingdom and United States of America. Approximately 5000 individuals aged 16-65 participated from each country. The data were gathered in 2011-12 by the *Organization for Economic Co-operation and Development* (OECD) and the first results were published in 2013. PIAAC was renewed over 2014 and expanded the data-set including additional countries, in total 33. However, up to date, the results have not been publicly available and therefore in the present paper a smaller set of countries will be evaluated.

The target group of adults for the survey were the non-institutionalized individuals who lived in the country at the time of the data collection regardless of nationality, language spoken or citizenship. The sample sizes depended

[1] A note regarding the Russian Federation: The data from the Russian Federation are not permanent and may be subject to changes. Readers should be aware that the population of the Moscow municipal area is not included in the sample. The data published, hence, do not represent the entire population aged 16-65 in Russia.

on the number of languages administered as well as the number of cognitive domains evaluated. The survey was supervised by trained interviewers and it took approximately 90 minutes to complete (30-35 minutes for the questionnaire and around 50 minutes for the test). Depending on the computer skills of the respondent, the test was completed either in a computer or in a paper version using printed test booklets. Finally, to the best of my knowledge, the respondents participated in the test voluntarily without any financial compensation.

3.1.2 Assessed skills

The survey collects information on a wide range of skills. In addiction, it gathers information on the participants' generic skills and personal characteristics as well as their socio-economic background, occupation and the skills used at the workplace. These characteristics are gathered from a background questionnaire filled by participants prior to the main survey. It is designed in a way that it assesses various information about respondents on different numeracy or literacy related activities as well as the extend to which individuals use ICT technologies in their every day life. The language of the survey was the local language of each country or in some cases the widely spoken dialect. The survey was designed in a way to measure cognitive and workplace skills in more precision, compared to other surveys as it includes more dimensions for information-processing skills defined as:

- *Literacy*: is the ability to understand, assess and use texts in order for somebody to be able to communicate in social context, improve their knowledge and achieve their goals
- *Numeracy*: the ability to understand, analyze and interpret mathematical information in order to cope with different situations in every day as well as the professional life
- *Problem Solving in technology rich environments*: the ability to use information and communication technology as well as its tools in order

to process and assess information that will help them solve practical problems in real life

In PIAAC dataset, skills are estimated by using Item Response Theory (IRT) or latent trait theory, where each question depends on the persons' responses as well as the properties of the items (Embretson and Reise, 2010). Therefore, not all participants responded to the same set of items or their questions did not cover all possible skill domains (Embretson and Reise, 2010). The rest of the information was derived, by imputing the rest of the assessment scores. In order to correct for possible errors due to the imputations, 10 plausible values for each proficiency score, each participant and each domain are derived. Plausible values are very important in reducing biased estimates due to standard error, since this way competency scores resemble a distribution and not a static score (von Davier et al., 2009).

3.1.3 Productivity data

In the present work, the emerging literature is followed, which decomposes aggregate productivity into the following components, as developed by Olley and Pakes (1996): *i*) *within-firm* or unweighted average productivity and *ii*) allocative efficiency, which captures the extend to which, it is the more productive firms that possess a larger proportion of aggregate employment.

Although there are several sources of industry level productivity data such as EU KLEMS or OECD STAN, in the present paper, harmonized cross-country firm-level data from ORBIS database are employed, in order to be able to perform the above mentioned decomposition of aggregate productivity, which will be described in more detail in the following section. ORBIS is a commercial database provided to the OECD by Bureau Van Dijk.(Pinto Ribeiro et al., 2010) ORBIS combines firm-level data for a large number of countries, which enables firm-level analysis across countries. However, it has a number of drawbacks. Firstly, it does not cover all variables equally well for all the number of countries and industries included. Also, it under-represents small and young firms in certain industries and countries comparing to the rest.

In the analysis following, *labor productivity* is used as an index for productivity, using turnover-based operating revenue, as it is more widely available and hence does not require many imputations, and the total number of employees per country, industry, firm and sizeclass[2]. However, this measure neglects intermediate inputs usage and therefore might be a bit problematic especially in industries with high level of reselling activities, which would probably score top in this specific measure. But as reported by Andrews and Cingano (2014) the correlation between value-added and turnover labor productivity is reasonably high, which gives me confidence to proceed with the analysis.

Finally, the sample consists of 21 countries and 11 1-digit industry categories for which productivity data are available (see Table 3.1).This results in 220 country industry cells, which is considered a rather small sample and therefore results should be viewed with caution.

3.1.4 Database adjustments

In order to improve the representativeness in ORBIS database, a number of adjustments have taken place before the main model was constructed and estimated. To increase sample representativeness, the methodology of Gal (2013) is employed. Based on this paper, re-sampling weights are assigned using the total number of employees for each country, industry, and size-class from the OECD Structural and Demographic Business Statistics (SDBS). The SDBS database by OECD STAN is constructed by using administrative data from national sources on various economic and business demographic variables such as number of enterprises, number of employees, turnover, etc. on the country, industry and size-classes.

There are two variables used for counting the number of people in every firm, namely the *number of employees* and *the number of people engaged*[3]. The

[2]Size-classes are used as defines in SDBS database, and they are the following: 1-9, 10-19, 20-49, 50-249, 250+ employees

[3]The number of people engaged captures also managers, therefore the difference can

Table 3.1: Sample: countries and industries

Countries	Industries
1. Austria	
2. Belgium	
3. Czech Republic	
4. Denmark	
5. Estonia	
6. Finland	a. manufacturing
7. France	b. electricity, gas, steam and air-conditioning supply
8. Germany	c. water supply
9. Ireland	d. construction
10. Italy	e. wholesale and retail trade
11. Japan	f. transportation and storage
12. Korea	g. accommodation and food service activities
13. Netherlands	h. information and communication
14. Norway	i. real estate activities
15. Poland	j. professional, scientific and technical activities
16. Russia	k. administrative and support service activities
17. Slovakia	
18. Spain	
19. Sweden	
20. United Kingdom	
21. USA	

definition for the number of employees, though, is closer to the one used in ORBIS and therefore preferable for our analysis. However, in some country-industry cells, the number of employees is not reported while the number of people engaged is. The difference between the two variables is generally small, but in some cases, especially in small-size businesses, the difference can be quite substantial.

Therefore, in order to balance the SDBS dataset the *number of employees* is predicted for those country-industry-sizeclass cells where it is missing by using the *number of people engaged* interacting with country, and industry*sizeclass fixed effects. With the obtained SDBS database, the total number of employees is compared with the one in ORBIS for each country *

be quite substantial especially in small firms industry * sizeclass cell (denoted as c,i,s respectively).

$$w = \frac{L_{c,i,s}^{SDBS}}{L_{c,i,s}^{ORBIS}} \tag{3.1}$$

where L is the total number of employees, and the expected value of it is taken from the firms which belong to the same country, industry and sizeclass. The above weights aim to "scale up" ORBIS observations in each cell in a way that they match with the ones obtained in SDBS. The value of the weight is higher or equal to 1 in order to allow for randomly drawing firms without though losing the ones already in the dataset. With the resulted ORBIS-SDBS dataset *labor productivity* is measured, using the *turnover* and the *number of employees*. This is later plugged into the productivity equation, which allows the decomposition of the *aggregate productivity* (P_j) into two elements.

3.2 Methodology

The necessity to identify and measure skill mismatch has risen mostly in recent years. Therefore, datasets are in a more experimental stage while methodologies for skill mismatch are still debatable. However, there are a number of different approaches which will be discussed here. Furthermore, the methodology for labor productivity will also be presented an analyzed thoroughly.

3.2.1 Skill mismatch measure

The main idea behind measuring skill mismatch is to define the threshold points in proficiency scores for each occupation in each country. Then, if the value of the respondent's assessed skill is higher that this threshold point he will be classified as over-skilled and vice verca. Finally, if this value falls between the upper and down threshold point they will be classified as well matched. Another important decision one need to make is the selection of the category of skills to measure. Some researchers measure numeracy scores as it is argued that numeracy scores are more easily comparable between countries or they better explain income inequality (Perry et al., 2014; Allen et al., 2013). On the contrary, McGowan and Andrews (2015) and Desjardins and Rubenson (2011) measure literacy scores as they argue that they are increasingly important in nowadays ICT oriented economies.

As mentioned above, there are different approaches on measuring skill mismatch. One strand of literature involves self assessment of the workers regarding their portfolio of skills and the skills they use at the workplace. While this measure is appropriate for partial skill-evaluation, it does not capture the exceess or deficit of skills, especially the under-skilled, as reported by Allen and van der Velder (2001). Another approach is to combine the self-reported assessment of skill mismatch and skill use in order to define the threshold levels, as constructed by OECD (2013). One major drawback of this approach is that it neglects the heterogeneity within occupations. Also the base population is measured by self-assessment which can result in biased outcomes and finaly, that it employs only one of the plausible values , the first one. (Perry et al., 2014)

In the present paper an alternative measure of skill mismatch, proposed by Perry et al. (2014), is used. This measure corrects for the possible bias problem of the self-reported information about skill use by defining "bandwidths" for every occupation based on the average skill level. Contrary to other approaches mentioned above, 10 plausible values have been used and the procedure was repeated for each and every one of them. Furthermore, the threshold points distinguishing the matched from mismatched are derived based on the total population of workers, instead of the matched work force as in previous versions. This made it possible for 2-digit ISCO categorization to be used. Although, 2 digits (50 categories of occupations) allow for higher precision, due to the limited number of observations within each 1-digit category-cell, in the present paper, the 1-digit ISCO (10 categories of occupations) is employed.

The following four steps are computed according to the alternative measure:

- Average skill level and standard deviation (SD) are computed in each country over the 1-digit occupation categorization

- Cut-off points for match and mismatch are defined for each occupation measured as 1.5 SD from the mean
- Skill mismatch is defined based on cut-off points for each Plausible Value (PV) for each person (results in 10 skill mismatch variables per person)
- Average of estimates from 10 skill mismatch variables computed and included in the analysis

In the first step, the whole sample population is taken for all the countries included. From this sample, mean and standard deviation are computed over 1-digit occupation categories. In the second and third step 10 plausible values are measured taking the value of 1 or -1 if the observation is above or below the 1.5 SD cut-off point. Finally, the average of these 10 skill mismatch variables is used to define if the respondent is well-matched or mismatched (under- or over-skilled) The upper and lower intervals are then merged and constitute the category of mismatched workers while the in between interval describes the matched population. Finally, the share of mismatched workers is taken for each country and 1-digit industry category.

Because the 1.5 SD threshold points do not have strong theoretical support in this methodology, in order to check the robustness of the results, sensitivity tests are performed using 1.2 SD instead. Finally, due to the small sample size, two out of the ten occupations were not included in the sample, namely ISCO occupation-codes 0 (armed forces) and 6 (skilled agricultural and fishery workers), followed by McGowan and Andrews (2015). Also, ISCO occupation-codes 1(managers) and 2(professionals) are merged together. This results in 7 occupation categories in total.

3.2.2 Productivity Measure

The labor productivity index obtained, is plugged into Equation 3.2 in order to proceed with the decomposition of *aggregate productivity* into: *i within-*

firm productivity, which expresses the fraction of more productive relative to less productive firms and *ii* the Olley-Pakes co-variance term or allocative efficiency, which is expressed as a joint moment with the size distribution of the firm that mirrors the extend to which more productive firms are also larger in size. Note here, that labor productivity P_i is measured in logs as much of the recent literature (Bartelsman et al., 2013; Foster et al., 2001) The main advantage of measuring in logs is that the results can be expressed as the *percentage change* in productivity P_j due to the within-firm increase of productivity $\bar{P}_j$ or the allocation of human capital across firms in the same industry.

An indicator of productivity in industry j, expressed as the weighted mean of productivity of the firms within the industry ($P_j = \sum_{i \in j} \theta_i P_i$) can be written with the following formula:

$$\sum_{i \in j} \theta_i P_i = \bar{P}_j + \sum_{i \in j} (\theta_i - \bar{\theta}_j)(P_i - \bar{P}_j) \tag{3.2}$$

where $\bar{P}_j = \frac{1}{N_j} \sum_{i \in j} P_i$ is the *within-firm* or *unweighted* productivity mean, θ_i expresses the relative size of the firm, as this is measured by the share of firm employment and $\bar{\theta}_j$ is the average employment share at the industry.

Allocative efficiency can also be obtained if one subtracts the two terms. In the same context, a positive value for allocative efficiency would indicate an increase in industry productivity index resulted from the allocation of employment across firms within the respective industry. A value of zero would mean that employment is randomly allocated within industries, with more skilled labor force to be trapped in low productivity firms. This would imply that weighted productivity and *within-firm* productivity average have the same value.

One of the benefits of focusing on allocative efficiency and its relative contribution on the aggregate productivity as measured in (Equation 3.2) is that it only concentrates on the difference between the two terms and hence any factor affecting both measures is differenced out (Bartelsman et al., 2013). On the other hand, comparisons in the *weighted productivity* and *within-firm* productivity across industries and countries might be proved problematic due to measurement issues. In order to control for these issues, country and industry fixed effects are employed in all estimation models. Finally, the analysis of productivity as well as skill mismatch could be done in a number of levels of industry aggregation, but in order to achieve a better alignment with the mismatch data, 1-digit industry categorization is employed.

3.3 Empirical Model

In order to identify the relationship between mismatch and productivity, an industry level analysis is followed. The empirical model takes the following form:

$$prod_{c,i} = \alpha + \beta_1 Mismatch_{c,i} + \delta_c + \delta_i + \epsilon_{c,i} \tag{1}$$

where *prod* is a measure of labor productivity (weighted & within-firm productivity and allocative efficiency) in country c and industry i. $Mismatch$ refers to the measure of skill mismatch in the three different categories (numeracy, literacy). The model includes country and industry fixed effects, which aim to control for the omitted time-invariant country specific factors that might influence productivity, such as different policies, while industry fixed effects aim to control for industry related technological factors. Standard errors are clustered at the country level as regressors and errors are assumed to be correlated within each country but not across countries.

Based on the existing literature in the link between skill mismatch and labor productivity, two variables are added to the baseline model, namely *Managerial Quality* and *Market Power*. Although, alternative variables such as R&D intensity or capital intensity would better correlate with productivity, they were not available for all the industries of the current sample.

Taking into account the importance of competition for productivity, a *Market Power* index is calculated as $\sum_{t=1}^{N} s_i^2$, where s_i represents the market share of firm i in an industry with N number of firms (McGowan and Andrews, 2015). The above index is calculated using ORBIS database and aims to control for the market share each firm possesses, which is further associated with the competition it faces, such that a higher value of market power in a country industry cell reflects lower competitive pressures. This variable is expected to yield negative effects on productivity. This index, though, as a proxy for competition might be a bit problematic since the relative volume of gross output is not the best indicator for market power and competition. Product market regulation or mark-ups, which would be more appropriate in capturing this effect, are not available in the industry aggregation used in this paper.

The proxy for managerial quality represents the average scores of managers in literacy and is derived using PIAAC data. Literacy was a natural choice since it constitutes major qualities required of managers to fulfill. Observations were selected according to the question *'Are you managing employees in your current work?'* available in PIAAC dataset. Then mean proficiency scores in literacy were calculated in the 1-digit occupation categorization and for 1-digit industry classification, following McGowan and Andrews (2015).

Chapter 4

Empirical results

The baseline results are presented in Table 4.1, which shows the six basic models, which include the productivity measures as dependent variables estimated with skill mismatch in numeracy and literacy as independent x variables (odd columns). As an extension of the baseline specification, skill mismatch is decomposed into *over-skilled* and *under-skilled* for the same categories of skills (even columns).

The columns with the odd numbers should be interpreted as the estimated effect of an increase in the share of mismatched workers in one of the two skill categories at the expense of the respective omitted category, namely the share of well-matched. Same applies to the even-numbered columns, which contain the decomposition of mismatch into the two parts of over- and under-skilled. More specifically, coefficients in the extended baseline model should be interpreted as the effect on productivity of increasing the share of each of these categories (*e.g* over-skilled in numeracy) at the expense of the omitted one, which is the share of well-matched workers in numeracy, keeping all other variables constant (*i.e* under-skilled in numeracy and over- and under-skilled in literacy).

The results show that there is a strong and significant relationship between the aggregate measure of skill mismatch in numeracy and aggregate productivity, which gives support to Hypothesis 3. The effect is statistically significant at the 5% level and has a negative sign as expected. Both liter-

Table 4.1: Baseline models

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		Within-firm Productivity	
Mismatch in Numeracy	-0.0216**		-0.0014		-0.0230*	
	(0.0121)		(0.0067)		(0.0121)	
Mismatch in Literacy	0.0060		-0.0009		0.0068	
	(0.0057)		(0.0053)		(0.0081)	
Over-skilled (Numeracy)		-0.0124		0.0040		-0.0129
		(0.0109)		(0.0103)		(0.0168)
Over-skilled (Literacy)		-0.0078		-0.0079		-0.0154
		(0.0068)		(0.0075)		(0.0151)
Under-skilled (Numeracy)		-0.0342*		0.0063		-0.0406*
		(0.0164)		(0.0128)		(0.0213)
Under-skilled (Literacy)		0.0196*		-0.0124		0.0275*
		(0.0099)		(0.0161)		(0.0135)
R2	0.920	0.921	0.462	0.432	0.779	0.782
Observations	220	220	220	220	220	220

Note: The dependent variables are as measured in (3.2) for the year of 2011. All the models include industry and country fixed effects and standard errors are clustered in the country level. Estimates are weighted by available observations in the country-industry cell. Standard errors are reported in parenthesis and the stars denote significance level (*** at 1%, level ** at 5% level and * at 10% level)

acy and numeracy skill mismatch is negatively related to allocative efficiency, though the result is not statistically significant. Therefore, the negative effect of mismatch in numeracy on productivity results from a strong and negative relationship between skill mismatch in numeracy and the *within-firm* labor productivity. The result is statistically supported at the 10% level.

The aggregated variable of skill mismatch in numeracy in the first model is sourced from a significant and negative relationship between under-skilling in numeracy and aggregate productivity at the 10% level, which supports the Hypotheses 2 & 3. This is located in the strong and negative effect of under-skilled people in numeracy, associated with the *within-firm* labor productivity. The result is statistically significant at the 10% level. Model 6 shows that the negative relationship between under-skilling and the weighted productivity is entirely captured through the channel of the *within-firm* productivity, since skill mismatch measures are not related with allocative efficiency. In terms of economic importance, it translates to an approximately

4% decrease in labor productivity if the share of under-skilled workers in numeracy increased by 1%.[4]

Skill mismatch in literacy is statistically insignificant in most specifications. However, being under-skilled in literacy exhibits a positive and significant relationship with labor productivity which is entirely captured through the channel of the *within-firm* labor productivity, which contradicts Hypothesis 2 which states that being underskilled in any of the two categories will have a negative impact on productivity. In terms of economic interpretation, this means that a one standard deviation increase in the percentage of under-skilled workers in literacy is associated with an increase in labor productivity by approximately 10% [5]. This result is quite surprising as one would expect under-skilling to have a negative effect on productivity. In their study McGowan and Andrews (2015) did not find any significant relationship between under-skilling in literacy and productivity even when controlling for market power and managerial quality, while the result had a negative sign in most cases. However, this could be explained in terms of work effort as one would expect under-skilled workers to give a greater effort to minimize the gap between the skills they possess and the skills required, through personal learning, training activities, etc. This could possibly translate to higher productivity.

4.1 Robustness checks

A number of robustness checks are performed so as to make sure that the results hold in different possible cases. At first, two control variables are added to the baseline models, namely market power and managerial quality. Additionally, countries with a high value of skill mismatch in numeracy or literacy are removed one at a time. Same is applied for certain industries, which exhibit extreme values in skill mismatch. Furthermore, in order to

[4]This is calculated as β * 100, since productivity is measured in logs, which is -0.0406 * 100

[5]This is calculated as β * standard deviation of under-skilled workers in literacy * 100, which is 0.0275 * 5.3 * 100

verify that the measure of skill mismatch holds, the baseline models were also estimated using 1.2 times the standard deviation (SD) as this number does not have any clear theoretical support (see Appendix C). Finally, the baseline models are also estimated using different base category, namely the well-matched people in each mismatch category. Results show that in all cases almost all coefficients remain intact in volume and sign and the level of significance also holds.

4.1.1 Controlling for Market Power

Table 4.2 shows the baseline models extended using *market power* as control variable, following McGowan and Andrews (2015), in order to test the robustness of the results as well as to identify the extend to which market competition impacts both skill mismatch and labor productivity. The existing literature on the impact of competition on productivity is rather ambiguous. One strand of literature direct its focus on the Schumpeterian theory, which states that past and current profits are important for the investment necessary to increase productivity. According to this theory, increasing competition and the possible decrease in profits may result in lower productivity as it reduces the investment funds and incentives (Rogers, 2004).

The other strand of literature, which refers to the agency problem according to which some firms have a principal agent problem and therefore distinguishes the managerial from non-managerial firms suggesting that increased competition will reduce the information asymmetry and will increase the effort of managers. However, the results with this approach are rather ambiguous with some researchers to have found a positive effect while others negative or no relationship (Rogers, 2004). Furthermore, market share can be viewed as an indicator of the past success of the firm rather than the current competition the firm faces. Hence, market share might reveal some unobserved characteristics of the firm rather than the competitive forces challenging the firm (Rogers, 2004).

Results here show that, after controlling for market power, which indicates the extent to which firms face less competition, the main results remain

Table 4.2: Extended model: controlling for market competition

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		Within-firm Productivity	
Mismatch in Numeracy	-0.0178*		0.0019		-0.0195*	
	(0.0088)		(0.0067)		(0.014)	
Mismatch in Literacy	0.0043		-0.0011		0.0049	
	(0.0052)		(0.0056)		(0.0086)	
Over-skilled (Numeracy)		-0.0130		0.0004		-0.0134
		(0.0107)		(0.0106)		(0.0162)
Over-skilled (Literacy)		-0.0077		0.0075		-0.0153
		(0.0051)		(0.0156)		(0.0155)
Under-skilled (Numeracy)		-0.0269*		0.0072		-0.0341*
		(0.0132)		(0.0124)		(0.0174)
Under-skilled (Literacy)		0.0153		-0.0084		0.0237*
		(0.0092)		(0.0074)		(0.0128)
Market Power Index	2.7416***	2.7145***	0.2741	0.2852	2.4716*	2.4293*
	(0.4832)	(0.4881)	(1.0532)	(1.0699)	(1.3488)	(1.3597)
R2	0.932	0.932	0.465	0.467	0.787	0.789
Observations	220	220	220	220	220	220

Note: The dependent variables are as measured in (3.2) for the year of 2011. All the models include industry and country fixed effects and standard errors are clustered at the country level. Estimates are weighted by available observations in the country-industry cell. Robust standard errors are reported in parenthesis and the stars denote significance level (*** at 1%, level ** at 5% level and * at 10% level).

almost intact. Mismatch in numeracy remains significantly negative in model 1 and 5 which is located in the negative relationship that stems from under-skilling in numeracy in both models 2 and 6. Finally, the volume and signs of the coefficients is essentially the same for all models. Important to be mentioned here is that, market power, in the current specification, exhibits a significantly positive relationship with aggregate productivity through the channel of *within-firm* productivity.

This is explained if one thinks of scale economies. Higher market share means that the capacity of the respective company must increase in order to cover the needs of the economy. This results in greater gross output and maybe labor productivity. Furthermore, less competition translates to higher profits and therefore higher investments and higher productivity growth, according to the Schumpeterian view. As mentioned above, this measure as a proxy for competition is a bit problematic, as market share might illustrate a past success of the firm rather than the competitive pressures it faces. Alternative measures such as mark-ups or product market regulation would be more appropriate for this analysis, but unfortunately not available for the current industry aggregation.

4.1.2 Controlling for Managerial Quality

In this section the link between skill mismatch and productivity is explored, when controlling for managerial quality(Table 4.3). According to recent literature, better managerial practices increase the *within-firm* labor productivity as well as the aggregate productivity (Bloom et al., 2013a). Indeed, it has been increasingly acknowledged that better management of human resources results in higher productivity levels.

However, the effect of higher managerial quality and skill mismatch has not been extensively estimated. In their study, McGowan and Andrews (2015) found a significant correlation between labor productivity and managerial

Table 4.3: Extended model-controlling for managerial quality

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		Within-firm Productivity	
Mismatch in Numeracy	-0.0178*		0.0019		-0.0197*	
	(0.0089)		(0.0072)		(0.0106)	
Mismatch in Literacy	0.0043		-0.0019		0.0062	
	(0.0052)		(0.0050)		(0.0076)	
Over-skilled (Numeracy)		-0.0132		-0.0006		-0.0125
		(0.0110)		(0.0107)		(0.0162)
Over-skilled (Literacy)		-0.0079		0.0063		-0.0142
		(0.0053)		(0.0141)		(0.0143)
Under-skilled (Numeracy)		-0.0268*		0.0076		-0.0345*
		(0.0130)		(0.0129)		(0.0178)
Under-skilled (Literacy)		0.0152		-0.0091		0.0243*
		(0.0091)		(0.0080)		(0.0128)
Market Power Index	2.7409***	2.7122***	0.2548	0.2719	2.4861*	2.4403*
	(0.4867)	(0.4881)	(1.0747)	(1.0833)	(1.3768)	(1.3791)
Managerial Quality	0.0001	0.0006	0.0038	0.0034	-0.0036	-0.0028
	(0.0032)	(0.0031)	(0.0061)	(0.0055)	(0.0057)	(0.0050)
R2	0.932	0.933	0.466	0.468	0.787	0.789
Observations	220	220	220	220	220	220

Note: The dependent variables are as measured in (3.2) for the year of 2011. All the models include industry and country fixed effects and standard errors are clustered at the country level. Estimates are weighted by available observations in the country-industry cell. Standard errors are reported in parenthesis and the stars denote significance level (*** at 1%, level ** at 5% level and * at 10% level).

quality in the extend to which, under-qualification became statistically insignificant when controlling for managerial quality. In further analysis, managerial quality was found to be positively correlated with aggregate productivity through the channel of *within-firm* productivity while the findings also suggest a negative and significant relationship with skill mismatch (in literacy).

Table 4.4: The relationship between managerial quality and productivity

	Weighted Productivity	Allocative Efficiency	Within-firm Productivity
Managerial Quality	0.0011	-0.0067	0.0079
	(0.0026)	(0.0049)	(0.0064)
Constant	4.8851***	0.0247	4.8603***
	(0.0752)	(0.0256)	(0.1050)
Observations	220	220	220
R2	0.858	0.421	0.700

Table 4.5: Instrumental variables estimation of the link between mismatch, managerial quality and productivity

Panel A: First Sttage Regressions - dependent variable: mismatch indicators						
	(1)	(2)	(3)	(4)	(5)	(6)
	Mismatch in Literacy	Mismatch in Numeracy	Over-skilled (Numeracy)	Under-skilled (Numeracy)	Over-skilled (Literacy)	Under-skilled (Literacy)
Managerial Quality	0.07487*	0.0244	0.0405*	-0.0160	0.0689**	-0.0060
	(0.0425)	(0.0310)	(0.0210)	(0.0293)	(0.0285)	(0.0371)
Constant	7.9718***	7.3000***	3.3463***	3.9544***	3.5265***	4.4452***
	(1.4232)	(1.0378)	(0.7029)	(0.9828)	(0.9539)	(1.2425)
AdjR2	0.157	0.249	0.2163	0.373	0.169	0.295
Observations	220	220	220	220	220	220

Panel B: Second Stage Regressions - dependent variable: labor productivity indicators						
	(1)	(2)	(3)	(4)	(5)	(6)
	Mismatch in Literacy	Mismatch in Numeracy	Over-skilled (Numeracy)	Under-skilled (Numeracy)	Over-skilled (Literacy)	Under-skilled (Literacy)
Weighted Productivity	0.0105	0.0321	0.0194	-0.0492	-0.0434	0.1309
	(0.0533)	(0.1807)	(0.0974)	(0.2421)	(0.0872)	(0.4990)
Allocative Efficiency	0.0505	0.1544	0.0934	-0.2362	0.0549	0.6282
	(0.0989)	(0.4414)	(0.1836)	(0.5914)	(0.0860)	(0.6945)
Within-firm Productivity	-0.0399	0.1222	0.0739	0.1869	0.0114	-0.4973
	(0.0938)	(0.3758)	(0.1766)	(0.5602)	(0.0568)	(0.3645)
Observations	220	220	220	220	220	220

Note: The dependent variables in Panel B are as measured in (3.2) for the year of 2011. In each model, skill mismatch indicators are included separately. All the models include industry and country fixed effects and standard errors are clustered at the country level. Standard errors are reported in parenthesis and the stars denote significance level.

In the present analysis though, no statistically significant relationship was detected between managerial quality and labor productivity. Table 4.4 shows that the mean scores of managers in literacy (*i.e* managerial quality) is not significantly related with productivity while in the analysis following which explores the relationship when managerial quality is used as instrumental variable, suggests that the relationship between them is only weak.

Contrary to the study of McGowan and Andrews (2015), managerial quality seems to have the opposite impact on skill mismatch (see Table 4.5). More specifically, managerial quality seems to have a negative impact on over-skilling, increasing thus the shares of over-skilled workers, while it has a negative relationship with under-skilling but it is not statistically significant. The sign and volume of the results are in line with McGowan and Andrews (2015) while the significance levels are not.

The result, though, is not surprising since, the mean scores of managers in literacy, does not capture in full extend the impact management has on reducing skill mismatch. Over-skilled workers are many times preferable from managers, and this constitutes an expedient strategy on behalf of the firms, as they not only exploit the full dynamics of their employees but also benefit from the potential spillovers the particular employees can contribute at the workplace (Battu et al., 2003). This, results in higher levels of mismatched workers.

The opposite is observed with under-skilling, where skill mismatch has a positive effect but the result is not statistically significant. In such analysis though, one should possibly control for other characteristics as for instance the state of the economy at the moment. Especially in times of recessions, individuals are quite often assigned more complex tasks than their level of competence (under-skilled) as firms face skill shortages pressure. To conclude, the results should be viewed with caution since there are various factors affecting productivity and skill mismatch and management impacts productivity in various other ways other than through the channel of skill mismatch.

Chapter 5

Limitations of the study & sustainability aspects

Sustainability aspects

The present study aims to explore the link between skill mismatch and labor productivity through the channels of *within-firm* productivity and allocative efficiency. In addition to that, it attempts to shed light on the question of what types of skills are more strongly associated with productivity, if there are any, as well as to find a link with policy related factors that would give a hint on what policies and structural factors affect skill mismatch. If the results were interpreted causally, it would suggest that mismatch is a factor that might contribute to explaining cross-country differences in labor productivity. However, the question of what actually causes mismatch remains unanswered.

Skill mismatch has significant implications in sustainability aspects. Sustainability aspects are often distinguished into social, economic and environmental. In this particular case, one could relate skill mismatch with several socio-economic implications rather than environmental. More specifically, for the individuals, over-skilling translates to lower returns on investment in education, wage penalties and job dissatisfaction. At the firm level, it can actually decrease the level of productivity while it might increase the turnover cost as employees are likely to search for other more suitable positions. In a macro-economic glance, skill mismatch slows down GDP growth as it affects productivity through the under-utilization of human capital, while it also affects unemployment rates. For the society as a whole, skill mismatch necessitates a waste and misallocation of public funds especially the ones directed for the initial education and training. Finally, the society loses the potential output could have been generated from a well functioning economy.

The road to a sustainable and socially inclusive growth highly depends on the available work force as well as the way this is allocated throughout the economy. Globalization and the fast technological change require a high level of skills, which are distributed analogously in order to expedite economic growth and surpass the long-term economic challenges. This requires that the education-occupation system builds upon the needs of nowadays economies and brings a balance between the supply and demand of skills in the market.

However, this becomes even more difficult to achieve with Europe struggling to surpass the worst crisis in its recent history. In such conditions, where unemployment rates reach unimaginable numbers and GDP growth loses ground, skill mismatch gets beyond control. According to the European Commission (2012), in the 4^{th} quarter of 2011, more that six people accounted for a single vacant position. This results in individuals retaining their student status for longer period, companies facing pressures from skill shortages, average age of the employees increasing and under-utilization of skills growing higher. This leads to skill obsolescence as workers compromise for less challenging jobs and individuals with lower skills are phased out

In order to tackle this phenomenon, it is necessary that the education-occupation system is build in a way that promotes specialization according to the market demands and also promotes the active participation of students in the market through effective programs. It is also important that firms build their recruitment system in a way that ensures that candidates will be placed in the right positions so as to increase productivity and job satisfaction.

Limitations of the study

One of the main limitations of the current study is that is employs a 1-digit industry aggregation in order to achieve a better alignment with the aggregation provided in PIAAC data and so as to increase the number of observations per country-industry cell. This level of aggregation, though, imposes other problems as it neglects the separate affects of the industries within the main aggregated industries. For instance, manufacturing in the highest aggregation level, consists of more that 10 manufacturing codes. When employed as one main code is as assuming all the industries included are homogenous when they are not.

Additionally, the methodology for the indicators of skill mismatch as well as the PIAAC data employed are questionable in the sense that they are quite recent and their coverage is limited. This makes them very sensitive to the methodology one employs to obtain the specific indicators, as the way one defines the boundaries between mismatched and matched might change the picture in each country-industry cell (see Table B.1 and Table B.2).

Furthermore, labor productivity as a proxy for productivity might impose certain problems as it neglects the intermediate inputs usage. This actually means that firms which have a high reselling activity would score very high in the specific measure. However, it would be really difficult to use value added using ORBIS database as the specific measure was unavailable for many of the firms in the countries and industries used. This would require a great amount of imputations which is a rather sensitive strategy of handling data. Therefore, one suggestion for future work would be to use TFP or value added as a proxy for productivity, once the coverage of firm-level data permits.

As described in earlier sections, there are a lot of factors contributing to productivity. Two of those were employed in the present analysis, namely market power and managerial quality. However, market share as a proxy for market power and less competition is a bit problematic since it might exhibit adverse effects. One one hand, higher gross output might indicate greater market share but this does not necessarily translate to less competition. Therefore, alternative options such as mark-ups or product market regulation would be more appropriate for the kind of assumption attempted, if available for the specific aggregation, which was not the case in the present study.

Finally, managerial quality as measured by the mean scores of managers in literacy might also be a bit problematic as it expresses only some qualities managers shall fulfill. As not all managerial practices have the same effect on productivity and it highly depends on the country of origin as well as the type of industry examined, it would probably be fruitful if one controlled for managerial quality with different weights representing certain managerial practices that aim to reduce skill mismatch and/or increase productivity, taking into consideration the heterogeneity of countries and industries, as well as the impact the size of the firm has on the kind of practices performed.

Chapter 6

Conclusion & suggestions for future work

The present study explores the relationship between skill mismatch in two different categories (numeracy and literacy) and labor productivity. Employing skill mismatch indicators aggregated from micro-level data derived from the PIAAC, the key findings suggest that there is a strong relationship between mismatch in numeracy and productivity through the channel of *within-firm* labor productivity. The negative effect of the aggregated indicator of mismatch in numeracy hides a strong and negative relationship between mismatch and under-skilling in the same category while under-skilling in literacy seemed to be positively correlated with the *within-firm* productivity. This could probably be explained by the fact that under-skilled workers have been found to give a greater effort to engage in on the job training in order to balance their skills with the ones required at their workplace. This in turn might translate to higher productivity.

Although the paper itself does not estimate the causal relationship between skill mismatch and productivity, the key findings suggest that skill mismatch is a valid factor that might explain cross-country differences in labor productivity. The results indicate that skill mismatch is worth monitoring in a cross-country scope, which makes it highly important to policy makers as it reveals that there is not only one channel through which, skill mismatch might affect labor productivity. Instead, there are at least two, as described earlier, which might indeed have contradicting effects.This makes it even more complicated and sensitive to changes. Hence, in order for policy makers to be able to test and implement effective structural reforms, it is of utmost importance that this factor is monitored at a cross-country level.

In general, the paper adds weight to the idea that is not only human accumulation the engine of growth but also the way this is distributed throughout the economy. But what causes skill mismatch remains unanswered. One suggestion for future work would be that, one shall analyze the effect of skill mismatch in a cross-country analysis at the industry level using a lower level of aggregation so as to take into consideration the heterogeneity of the industries within the main groups. Furthermore, as industry fixed effects are not sufficient to explain cross country technological variation in full extend, it would be of interest to policy makers if one explored the link between mismatch and productivity based on the technological characteristics of each industry in order to test for signs of stronger effect in sectors with higher R&D or ICT intensity. This would be possible to achieve using data from countries which run in the frontiers of progress and development such as the United States. Finally, once the coverage of PIAAC database permits, a panel data approach would be interesting to explore so as to examine for trends in a time line instead of a single point in time.

Bibliography

Acemoglu, D., Akcigit, U., Bloom, N. and R. Kerr, William (2013), 'Innovation, Reallocation and Growth', *NBER Working Papers* (18993).

Acemoglu, D. and Autor, D. (2011), Skills, tasks and technologies: Implications for employment and earnings, *in* 'Handbook of Labour Economics', Vol. 4b, Elsevier B.V., pp. 1043–1171.

Allen, J., Levels, M. and van der Velden, R. (2013), 'Skill Mismatch and Skill Use in Developed Countries: Evidence from the PIAAC Study', *Research Centre for Education and the Labour Market Working Papers* (17).

Allen, J. and van der Velder, R. (2001), 'Educational mismatches versus skill mismatches-effects on wages, job satisfaction and on-the-job search', *Oxford Economic Papers* **53**(3), 434–452.

Andrews, D. and Cingano, F. (2014), 'Public Policy and Resource Allocation: Evidence from Firms in OECD Countries', *Economic Policy* **29**(78), 253–296.

Bartelsman, E., Haltiwanger, J. and Scarpetta, S. (2013), 'Cross-country differences in productivity: The role of allocation and selection', *American Economic Review* **103**(1), 305–334.

Battu, H., Belfield, C. R. and Sloane, P. J. (1999), 'Overeducation Among Graduates: a cohort view', *Education Economics* **7**(1), 21–38.

Battu, H., Belfield, C. R. and Sloane, P. J. (2003), 'Human Capital Spillovers within the Workplace: Evidence for Great Britain', *Oxford Bulletin of Economics and Statistics* (65), 575–594.

Bloom, N., Mahajan, A., McKenzie, D. and Roberts, J. (2013a), 'Does Management Matter? Evidence from India', *Quarterly Journal of Economics* **128**(1), 1–51.

Braconier, H., Nicoletti, G. and Ben, W. (2014), 'Policy Challenges for the Next 50 Years', *OECD Economics Department Policy Papers* (9).

Büchel, F. (2002), 'The effects of overeducation on productivity in Germany - The firms' viewpoint', *Economics of Education Review* **21**(3), 263–275.

CEDEFOP (2010), *The Skill Matching Challenge: Analysing Skill Mismatch and Policy Implications*, Publications Office of the European Union.

Chapple, S. (2009), 'Oecd Social , Employment and Migration', *OECD Social, Employment and Migration Working Papers* **88**, 1–47.

Cingano, F. (2014), 'Trends in Income Inequality and its Impact on Economic Growth', *OECD Social, Employment, and Migration Working Papers* (163), 0_1,5–59.

Department of Education and Skills (2011), 'Literacy and numeracy for learning and life: The national strategy to improve literacy and numeracy among children and young people 2011-2020'. Accessed: 2016-04-22.

Desjardins, R. and Rubenson, K. (2011), 'An Analysis of Skill Mismatch Using Direct Measures of Skills', *OECD Education Working Papers* **63**.

Embretson, S. E. and Reise, S. (2010), *Item response theory for psychologists*, L. Erlbaum Associates.

European Commission (2010), 'New skills for new jobs: Action now: Report by the expert group on new skills for new jobs prepared for the european commission.'.

European Commission (2012), The skill mismatch challenge in europe, *in* 'Employment and social developments in Europe 2012', Luxembourg: Office for Official Publications of the European Communities., chapter 6.

Foster, L., Haltiwanger, J. C. and Krizan, C. (2001), Aggregate Productivity Growth. Lessons from Microeconomic Evidence, *in* 'New Developments in Productivity Analysis', Vol. 63, University of Chicago Press, pp. 303–372.

Gal, P. N. (2013), 'Measuring Total Factor Productivity at the Firm Level using OECD-ORBIS', *OECD Economics Department Working Papers* (1048).

Green, F. and Zhu, Y. (2010), 'Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education', *Oxford Economic Papers* **62**(4), 740–763.

Grunau, P. (2014), The impact of overeducated and undereducated workers on firm-level productivity - First evidence for Germany. mimeo.

Hartog, J. (2000), 'Over-education and earnings: Where are we, where should we go?', *Economics of Education Review* **19**(2), 131–147.

Hsieh, C. and Klenow, P. (2009), 'Misallocation and Manufacturing in TFP in China and India', *Quarterly Journal of Economics* **124**(4), 1403–1448.

Kampelmann, S. and Rycx, F. (2012), 'The impact of educational mismatch on firm productivity: Evidence from linked panel data', *Economics of Education Review* **31**(6), 918–931.

Levels, M., Van Der Velden, R. and Allen, J. (2014), 'Educational mismatches and skills: New empirical tests of old hypotheses', *Oxford Economic Papers* **66**(4), 959–982.

Mahy, B., Rycx, F. and Vermeylen, G. (2013), Educational Mismatch and Firm Productivity: Do Skills, Technology and Uncertainty Matter? mimeo.

Mavromaras, K. and McGuinness, S. (2012), 'Overskilling dynamics and education pathways', *Economics of Education Review* **31**(5), 619–628.

Mavromaras, K., McGuinness, S. and Fok, Y. (2009), ' Assessing the Incidence and Wage Effects of Overskilling in the Australian Labour Market', *The Economic Record* **85**(268), 60–72.

Mavromaras, K., McGuinness, S. and Pouliakas, K. (2015), 'Decomposing wage penalties of overeducated workers: Evidence from the Cedefop European Skills and Jobs survey'.

McGowan, M. and Andrews, D. (2015), 'Labour Market Mismatch and Labour Productivity', *OECD Economics Department Working Papers* (1209).

OECD (2012), *Better Skills, better jobs, better lives: A strategic approach to skills policies*, OECD.

OECD (2013), *Skills Outlook 2013*, OECD.

Olley, S. and Pakes, A. (1996), 'The Dynamics of Productivity in the Telecommunications Equipment Industry', *Econometrica* **64**(6), 1263–1297.

Perry, A., Wiederhold, S. and Ackermann-Piek, D. (2014), 'How Can Skill Mismatch be Measured ? New Approaches with PIAAC', *Methods, Data, Analyses* **8**(2), 137–174.

Pinto Ribeiro, S., Menghinello, S. and De Backer, K. (2010), 'The OECD ORBIS Database: Responding to the Need for Firm-Level Micro-Data in the OECD ', *OECD Statistics Working Papers* (1).

Quintini, G. (2011a), ' Right for the Job: Over-qualified or Under-skilled?', *OECD Social, Employment and Migration Working Papers* (120).

Quintini, G. (2011b), 'Over-qualified or under-skilled: A review of existing literature', *OECD Social, Employment and Migration Working Papers* (121), 1–47.

Restuccia, D. and Rogerson, R. (2008), 'Policy distortions and aggregate productivity with heterogeneous establishments', *Review of Economic Dynamics* **11**(4), 707–720.

Rogers, M. (2004), 'Competition, agency and productivity', *International Journal of the Economics of Business* **11**(3), 349–367.
URL: *http://dx.doi.org/10.1080/1357151042000286447*

Romer, P. (1989), 'Human Capital and Growth: Theory and Evidence', *NBER Working Papers* (3173).

Structural and Demographic Business Statistics (SDBS), OECD (2009), `http://www.oecd.org/std/business-stats/structuralanddemographicbusinessstatisticssdbsoecd.htm`. Accessed: 2016-04-30.

Tinbergen, J. (1956), 'On the theory of income distribution', *Weltwirtchaftliches Archiv* **77**, 156–175.

Varhaest, D. and Omey, E. (2006), ' The Impact of Overeducation and its Measurement ', *Social Indicators Research* **77**, 419–448.

von Davier, M., Gonzalez, E. and Mislevy, R. J. (2009), 'What are plausible values and why are they useful?', *IERI monograph series: Issues and methodologies in large-scale assessments* (2), 9–36.

Appendix A

Comparison of skill mismatch measures

McGowan and Andrews (2015)

- Sample selected according to people who report themselves as well-matched in their current occupation
- Proficiency scores of self-reported people are measured, and 5th and 95th percentile thresholds are defined for each of the 1-digit occupations in each country
- Bandwidths are constructed using the defined thresholds and an average of the 10 plausible values for each respondent is calculated
- Finally, if the average value falls lower than the lower band the respondent is under-skilled, above the upper band is over-skilled while in between is well-matched

Perry et al. (2014)

- Mean and standard deviation (SD) are calculated for the entire population of the sample

- Bandwidths are constructed as the plus or minus 1.5 the SD
- Ten plausible values are calculated for each respondent and take the value of 1 if they fall above the threshold, -1 under and 0 in between
- Finally, the average of these values is calculated and follows the same procedure in order define the over- and under-skilled.

Appendix B

Discriptive statistics

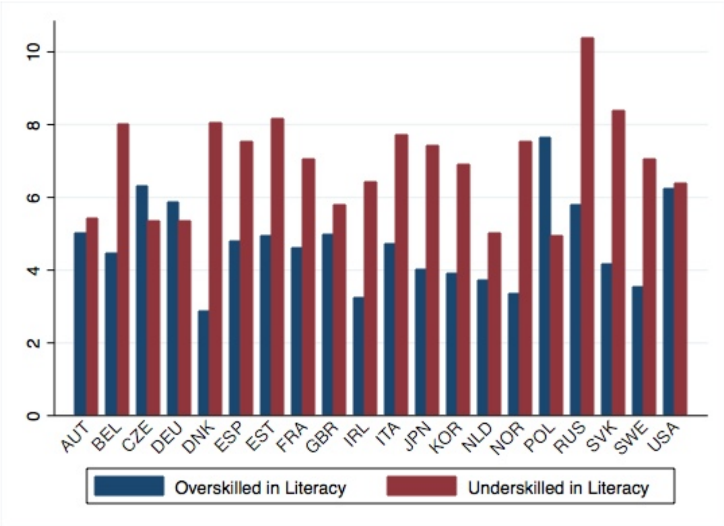
Table B.1: Descriptive statistics for skill mismatch (1.5 SD)

	Mean	Standard Deviation	Minimum	Maximum
Over-skilled Numeracy	3.61	2.75	0.00	14.28
Under-skilled Numeracy	5.45	4.06	0.00	25
Mismatch in Numeracy	9.06	4.22	0.00	33.33
Over-skilled Literacy	4.70	3.44	0.00	20.83
Under-skilled Literacy	6.99	5.35	0.00	50
Mismatch in Literacy	11.68	5.46	0.00	50
Over-skilled Problem Solving	22.48	11.99	0.00	75
Under-skilled Problem Solving	4.97	3.28	0.00	25
Mismatch in Problem Solving	27.46	12.27	0.00	75

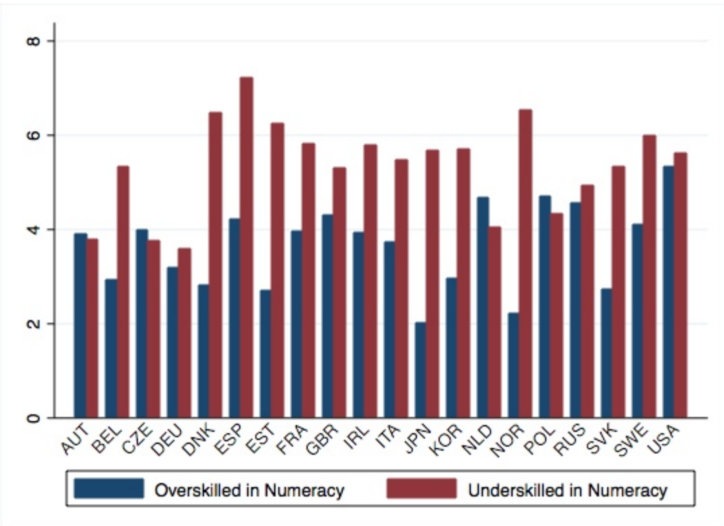
Table B.2: Descriptive statistics for skill mismatch (1.2 SD)

	Mean	Standard Deviation	Minimum	Maximum
Over-skilled Numeracy	9.59	4.75	0.00	23.07
Under-skilled Numeracy	10.72	6.80	0.00	50
Mismatch in Numeracy	20.31	6.27	0.00	50
Over-skilled Literacy	9.43	5.04	0.00	30.43
Under-skilled Literacy	10.62	6.31	0.00	50
Mismatch in Literacy	20.05	6.65	0.00	50
Over-skilled Problem Solving	26.20	11.69	0.00	75
Under-skilled Problem Solving	8.81	4.54	0.00	25
Mismatch in Problem Solving	35.02	12.10	0.00	75

Figure B.1: Over- versus Under-skilled in Numeracy and Literacy



(a) Over- versus Under-skilled in Literacy



(b) Over- versus Under-skilled in Numeracy

Table B.3: Pairwise correlation between aggregated indicators of skill mismatch

	Mismatch in Numeracy	Mismatch in ,Literacy	Mismatch in, Problem Solving
Mismatch in Numeracy	1.0000		
Mismatch in Literacy	0.3486	1.0000	
Mismatch in Problem Solving	0.1137	0.3057	1.0000

Note: Pairwise correlation between the over- and under- skilled in *Numeracy*, *Literacy* and *Problem Solving*.The categories are defined with 1.5 SD threshold points and are the ones used in the main analysis.

Table B.4: Pairwise correlation of over- and under-skilled

	Over-skilled Numeracy	Over-skilled Literacy	Over-skilled Problem Solving	Under-skilled Numeracy	Under-skilled Literacy	Under-skilled Problem Solving
Over-skilled in Numeracy	1.0000					
Over-skilled in Literacy	0.4022	1.0000				
Over-skilled in Problem Solving	-0.1515	-0.1378	1.0000			
Under-skilled in Numeracy	-0.3253	-0.2872	0.1817	1.0000		
Under-skilled in Literacy	-0.3628	-0.3216	0.3594	0.6180	1.0000	
Under-skilled in Problem Solving	-0.2593	-0.2458	-0.0149	0.3849	0.3160	1.0000

Note:Pairwise correlation between the over- and under- skilled in *Numeracy*, *Literacy* and *Problem Solving*. The categories are defined with 1.5 SD threshold points and are the ones used in the main analysis.

Table B.5: Initial results - Examining the effect of the correlation among the variables

	Weighted Productivity			Allocative Efficiency			Within-firm Productivity		
Mismatch in Numeracy	-0.0193 (0.0127)			0.0027 (0.0086)			-0.0220* (0.0112)		
Mismatch in Literacy		0.0003 (0.0069)			0.0013 (0.0058)			-0.0010 (0.0053)	
Mismatch in Problem Solving			-0.0058 (0.0075)			0.0033 (0.0046)			0.0092 (0.0073)
R2	0.869	0.864	0.852	0.445	0.445	0.3318	0.730	0.725	0.664
Observations	220	220	187	220	220	187	220	220	184

Appendix C

Accounting for country outliers

Table C.1: Baseline models excluding Finland with the highest share of mismatched workers in numeracy

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		Within-firm Productivity	
Mismatch in Numeracy	-0.0236**		-0.0012		-0.0249*	
	(0.0106)		(0.0073)		(0.0129)	
Mismatch in Literacy	0.0064		-0.0001		0.0065	
	(0.0055)		(0.0054)		(0.0082)	
Over-skilled(Numeracy)		-0.0129		0.0016		-0.0145
		(0.106)		(0.0112)		(0.0173)
Over-skilled(Literacy)		-0.0070		0.0086		-0.0157
		(0.068)		(0.0164)		(0.0163)
Under-skilled(Numeracy)		-0.0377**		0.0056		-0.0233*
		(0.169)		(0.0139)		(0.0127)
Under-skilled(Numeracy)		-0.0201*		-0.0069		0.0270*
		(0.099)		(0.0076)		(0.0138)
R2	0.920	0.921	0.454	0.456	0.781	0.779
Observations	210	210	210	210	210	210

Note:The dependent variables are as measured in (3.2) for the year of 2011. All the models include industry and country fixed effects and standard errors are clustered at the country level. Estimates are weighted by available observations in the country-industry cell-size of the industry. Standard errors are reported in parenthesis and the stars denote significance level (*** at 1%, level ** at 5% level and * at 10% level)

Table C.2: Basic models excluding Finland and Russia with the highest share of mismatched workers in literacy

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		Within-firm Productivity	
Mismatch in Numeracy	-0.0242*		-0.0030		-0.0273*	
	(0.0117)		(0.0081)		(0.0147)	
Mismatch in Literacy	0.0076		-0.0010		0.0086	
	(0.0061)		(0.0057)		(0.0088)	
Over-skilled(Numeracy)		-0.0098		0.0041		-0.0139
		(0.103)		(0.0116)		(0.0173)
Over-skilled(Literacy)		-0.0096		0.0084		-0.0180
		(0.0073)		(0.0166)		(0.0163)
Under-skilled(Numeracy)		-0.0461**		0.0086		-0.0385**
		(0.182)		(0.0167)		(0.0127)
Under-skilled(Numeracy)		-0.0284**		-0.0092		0.0376**
		(0.099)		(0.0097)		(0.0138)
R2	0.907	0.910	0.454	0.456	0.733	0.738
Observations	200	200	200	200	200	210

Note:The dependent variables are as measured in (3.2) for the year of 2011. All the models include industry and country fixed effects and standard errors are clustered at the country level. Estimates are weighted by available observations in the country-industry cell-size of the industry. Standard errors are reported in parenthesis and the stars denote significance level (*** at 1%, level ** at 5% level and * at 10% level)

Table C.3: Baseline models using 1.2 SD

	Weighted Productivity		Allocative Efficiency		Within-firm Productivity	
Mismatch in Numeracy	-0.0109		0.0401		-0.0311	
	(0.0157)		(0.0263)		(0.0400)	
Mismatch in Literacy	0.0191		-0.0387*		0.0378*	
	(0.0130)		(0.0203)		(0.0107)	
Over-skilled in Numeracy		-0.0106		0.0347		-0.0454
		(0.0170)		(0.0210)		(0.0342)
Over-skilled in Literacy		0.0053		-0.0111		0.0164
		(0.0185)		(0.0102)		(0.0206)
Under-skilled Numeracy		-0.0201		0.0614		-0.0816
		(0.0193)		(0.0488)		(0.0246)
Under-skilled in Literacy		0.0342		-0.0713		0.0105
		(0.0170)		(0.0543)		(0.0066)
R2	0.908	0.0911	0.530	0.0546	0.792	0.805
Observations	220	220	220	220	220	220

Note:The dependent variables are as measured in (3.2) for the year of 2011. All the models include industry and country fixed effects and standard errors are clustered at the country level. Estimates are weighted by available observations in the country-industry cell-size of the industry. Standard errors are reported in parenthesis and the stars denote significance level (*** at 1%, level ** at 5% level and * at 10% level)

Table C.4: Baseline models using the share of well-matched

	Weighted Productivity		Allocative Efficiency		Within-firm Productivity	
Well-matched	0.0377**	0.0129	-0.0056	-0.0016	0.0433*	0.0145
Numeracy	(0.0169)	(0.0106)	(0.0139)	(0.0112)	(0.0400)	(0.0173)
Well-matched	-0.0201*	0.0070	0.0069	-0.0086	-0.0271*	0.0157
Literacy	(0.0099)	(0.0068)	(0.0076)	(0.0164)	(0.0138)	(0.0163)
Over-skilled in	0.0248		-0.0040		0.0288	
Numeracy	(0.0213)		(0.0169)		(0.0266)	
Over-skilled in	-0.0272*		0.0156		-0.0428	
Literacy	(0.0137)		(0.0218)		(0.0250)	
Under-skilled		-0.0248		0.0040		-0.0288
Numeracy		(0.0213)		(0.0169)		(0.0266)
Under-skilled in		0.0272*		-0.0156		0.0428
Literacy		(0.0137)		(0.0218)		(0.0250)
R2	0.921	0.0921	0.457	0.0457	0.781	0.781
Observations	220	220	220	220	220	220

Note:The dependent variables are as measured in (3.2) for the year of 2011. All the models include industry and country fixed effects and standard errors are clustered at the country level. Estimates are weighted by available observations in the country-industry cell-size of the industry. Standard errors are reported in parenthesis and the stars denote significance level (*** at 1%, level ** at 5% level and * at 10% level)

Appendix D

Baseline model: including mismatch in problem solving

Table D.1 is an extension of the basic models and explores the link between skill mismatch and labor productivity including mismatch in problem solving. The volume and signs of almost all basic coefficients remain intact while skill mismatch in numeracy becomes slightly insignificant for the *within-firm* productivity. The correlation between under-skilling in literacy and productivity also becomes insignificant, which might be interpreted as that skill mismatch in problem solving

The significance level remains the same for the weighted average labor productivity with mismatch in numeracy to exhibit a negative and significant influence. This is mainly attributed to the under-skilling in numeracy which sustains its significant and negative relationship with productivity. The economic magnitude of this relationship can be interpreted as a standard deviation increase increase in mismatch in numeracy would result in a decrease in weighted average productivity by approximately 14% [6].

[6] Calculated as β * percentage standard deviation of mismatch in numeracy * 100, which is -0.0252 * 4.2 * 100

Table D.1: Baseline model-including problem solving

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		Within-firm Productivity	
Mismatch in Numeracy	-0.0252*		-0.0062		-0.0190	
	(0.0120)		(0.0087)		(0.0164)	
Mismatch in Literacy	0.0045		-0.0005		0.0040	
	(0.0070)		(0.0084)		(0.0123)	
Mismatch in Problem-solving	-0.0015		0.0082		-0.0098	
	(0.0066)		(0.0104)		(0.0124)	
Over-skilled (Numeracy)		-0.0113		-0.0088		-0.0044
		(0.0206)		(0.0202)		(0.0311)
Over-skilled (Literacy)		-0.0130		0.0213		-0.0339
		(0.0122)		(0.0296)		(0.0293)
Over-skilled (Problem-solving)		-0.0040		0.0127		-0.0171
		(0.0069)		(0.0146)		(0.0166)
Under-skilled (Numeracy)		-0.0345*		0.0002		-0.0337
		(0.0170)		(0.0119)		(0.0202)
Under-skilled (Literacy)		0.0225		-0.0121		0.0345
		(0.0142)		(0.0160)		(0.0246)
Under-skilled (Problem-solving)		-0.0196		0.0084		-0.0274
		(0.0183)		(0.0279)		(0.0381)
R2	0.917	0.920	0.421	0.429	0.768	0.772
Observations	187	187	187	187	187	187

Note: The dependent variables are as measured in (3.2) for the year of 2011. All the models include industry and country fixed effects and standard errors are clustered at the country level. Estimates are weighted by available observations in the country-industry cell-size of the industry. Standard errors are reported in parenthesis and the stars denote significance level (*** at 1%, level ** at 5% level and * at 10% level). In this model 18 countries are included in the sample since mismatch in problem solving is not available for France, Italy and Spain.