The impact of public policies on skill mismatch:

cross-country analysis in OECD economies

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Abstract

Governments aim at reducing skill mismatch because of the adverse effects that it can trigger at the individual and firm level as well as at the country level. Skill mismatch has been defined as a persistent phenomenon with long lasting cross-country differences (Mavromaras et al., 2013). This phenomenon could thus be explained by equivalent cross-country differences in national public policies. The purpose of this thesis is to test the impact of public policies on the probability of being skill mismatched across OECD countries. This thesis explores the recent OECD Survey of Adult Skills from the Programme for the International Assessment of Adult Competencies using an alternative measure of skill mismatch. Data for public policies come from a wide variety of sources. The results show that both policies targeted on firms ('demand side of skills') and policies dealing with the available workforce ('supply side of skills') can result in a reduction of skill mismatch levels. Regarding the demand side of skills, countries with smooth regulations on the firing of permanent employees, with efficient policies increasing the allocative efficiency and with a strong focus on entrepreneurship seem to experience lower levels of skill mismatch. For the case of the supply side of skills, housing policies efficient at increasing labour mobility together with a higher participation in lifelong learning and higher investments in active labour market programmes and education are expected to be associated with a reduction of skill mismatch.

Key words: skill mismatch, public policies, OECD countries, Programme for the International Assessment of Adult Competencies, allocative efficiency

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1. Introduction

Human skills are often considered to be at the core of our modern knowledge based economies (OECD, 2013). But however high they might be, they must be put at effective use in order to contribute to personal success in the workplace and overall economic growth.

Skill mismatch refers to the gap between skills possessed by workers and skills required at their job. Presence of skill mismatch is often considered to have several adverse effects at different levels. It can negatively impact a worker's earnings, job satisfaction and human capital accumulation (Allen and Van der Velden, 2001, Mavromaras et. al, 2013, Quintini, 2011). At a more aggregate level, skill mismatch is associated with lower labour productivity through a less efficient allocation of resources (Adalet McGowan and Andrews, 2015a).

Reducing skill mismatch thus seems to be of utmost importance for countries aiming at reaching economic growth by efficiently exploiting the dynamics of their labour markets needs and demands. Recent research has highlighted that levels of skill mismatch have increased over time (European Commission, 2013) and OECD calculations have concluded that a substantial share of workers can be defined as skill mismatched across OECD countries (Fig.1.1).

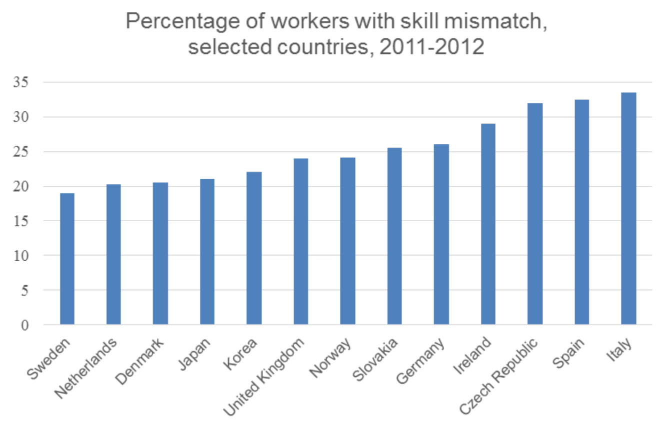

Fig. 1.1: Cross-country differences in skill mismatch
Source: OECD calculations based on the Survey of Adult Skills, 2011-2012

Besides, skill mismatch has been defined a persistent phenomenon with long lasting cross-country differences (Mavromaras et al., 2013), giving support to the idea that the structure of the national policy environment could partly explain why some countries experience lower levels of skill mismatch than others. Using the recent OECD Survey of Adult Skills from the Programme for the International Assessment of Adult Competencies (PIAAC) and policy variables from different sources, this thesis explores the relationship between skill mismatch and the impact of public policies which could eventually reduce it.

Though the main focus of this thesis is on the impact of public policies, individual and firm characteristics (such as age, gender, migrant status or firm size) have also been defined as factors influencing the probability of being skill mismatched. The preliminary part of the analysis will thus deal with this body of characteristics influencing skill mismatch before introducing any policy variable.

Last but not least, defining skill mismatch is one thing, but measuring it is another. Measuring skill mismatch is an artificial process. Indeed, no skill mismatch measure has been broadly accepted in the scientific community. On the contrary, different skill mismatch measures seem to sometimes result in large differences of results even when using the same dataset (Perry et al., 2014). Due to the availability of data, a cross-country analysis of this kind has for a long time been impossible. On this matter, the recently published Programme for the International Assessment of Adult Competencies (PIAAC) dataset gives a new opportunity to obtain a direct measure of skill mismatch around the world.

1.1 Motivation

Though the literature on the characteristics of mismatched workers and the adverse effects that skill mismatch can trigger is large, the literature on the policies aiming at reducing it is much scarcer. To the best of my knowledge, only one paper (Adalet McGowan and Andrews, 2015b), has attempted to directly test the impact of public policies on skill mismatch.

This thesis thus aims at filling this gap by testing the consistency of their results with an alternative measure of skill mismatch and by testing the impact of additional policies. The additional policies include efficient active market labour programmes to help mobilize more fully the labour resources of a country, high investments in education to adapt to labour market needs and entrepreneurship as a way to flee from an unsuited and unsatisfying job. Throughout the analysis, policies are divided into two main categories. Policies mostly targeted on firms are gathered under the name 'demand side of skills' while policies dealing primarily with the available workforce in the labour market are referred to as policies from the 'supply side of skills'. A greater clarity in the analysis was thus expected from this distinction. The alternative measure of skill mismatch adopted in this thesis is based on the one developed by Perry et al. (2014). Perry et al. (2014) highlight the drawbacks of the measure used by Adalet McGowan and Andrews (2015b) (based on OECD, 2013), and constructed an alternative measure which is thus expected to give a more accurate picture of skill mismatch.

1.2 Research questions and structure of the thesis

Having all the above in mind, the main scientific questions to be analyzed in this paper are:

- What are the individual and job characteristics influencing the probability of being skill mismatched?
- What are the public policies associated with lower levels of skill mismatch?
- To what extent could these policies potentially reduce the level of skill mismatch?

Accordingly, this thesis proceeds as follows. Section 2 defines skill mismatch, highlights the adverse effects that it can trigger, introduces public policies and stresses out the importance of individual and firm characteristics when performing such an analysis. The data, the different measures of skill mismatch and the statistical model are outlined in section 3. Section 4 presents the results and the robustness checks and adds a distortion analysis. Section 5 discusses the results and the limitations of the study. Section 6 concludes.

2. Theoretical framework and literature review

2.1 Defining skill mismatch

Skill mismatch is defined as the mismatch for a certain worker between his/her current skills and the required skills for his/her job. This is the widely used definition of skill mismatch (OECD[1], Adalet McGowan and Andrews, 2015a and 2015b, Desjardins and Rubenson, 2011). Skill mismatch occurs when skills possessed by the workers exceed or do not meet the skills required at their workplace. Indeed, some people might be capable of handling more complex tasks with their skills being underused. These people are referred to as over-skilled. On the opposite, other people might lack the skills normally required for the job. These people are referred to as under-skilled. Over-skilled people and under-skilled people are thus mismatched. When people are neither over-skilled nor under-skilled, they are defined as well-matched.

This definition has several implications. First, skill mismatch can be a temporary phenomenon. One mismatched person at time t can become well-matched at time t+1 if he/she switches job to a more suited one or if the level of skills required to perform his/her tasks changes over time. Likewise, if this person increases her/his skills through additional education, training or else, he/she can move from mismatched to well-matched or the opposite. Finally, skills can also become obsolete because they are not used at the workplace or they are not upgraded.

As a result of this instability, Guvenen et al. (2015) found that workers choose their next occupations so as to reduce skill mismatch. Moreover, over the life cycle, workers become more aware of their true capacities and tend to consider more suitable careers.

This thesis focuses on skill mismatch rather than education mismatch. A great care must be taken as skill mismatch and education mismatch are two different measures (Green and McIntosh, 2007, Badillo-Amador and Vila, 2013). Several authors have thus highlighted the importance of focusing on the notion of skills when dealing with mismatch in the workplace (Dumartin, 1997, Krahn and Lowe, 1998, Ryan and Sinning, 2009). Papers with unclear distinction between education mismatch and skill mismatch were not considered in this literature review. Education mismatch refers to the general number of years of education required to perform a job. Even if data for the latter are easier to collect among the population, it doesn't give an exact picture of skill levels for three main reasons: 1) the education level doesn't necessarily account for its intrinsic quality. 2) As mentioned previously, skills can vary over the lifetime of a worker while education cannot, except if the individual is not done with his/her studies. 3) Skills give a more appropriate measure of a worker's current capabilities, especially for workers who have been done with their studies for a long time. On this matter, the recently published Programme for the International Assessment of Adult Competencies (PIAAC) dataset gives a new opportunity to obtain a direct measure of skill mismatch around the world.

[1] http://skills.oecd.org/hotissues/skillsmismatch.html

2.2 Consequences of skill mismatch on personal success and economic growth

Skill mismatch can have adverse effects at different levels.

2.2.1 Individual level: earnings, job satisfaction and human capital accumulation

At the individual level, skill mismatch can impact worker's earnings and job satisfaction. Allen and van der Velden (2001) found that skill mismatch has a strong negative effect on job satisfaction among the eleven European countries they observed. The same results were obtained by Cabral Vieira (2005) and Badillo-Amador and Vila (2013) respectively for the cases of Portugal and Spain. More important than considering skills alone, Desjardins and Rubenson (2011) found that one must consider whether high-skilled or low-skilled workers are well-matched or mismatched when trying to explain wages differentials.

Besides, workers who are mismatched accumulate human capital less efficiently than workers who are well-matched (Guvenen et al., 2015). Finally, skill mismatch is expected to lead to higher turnover costs as less-satisfied mismatched workers are more likely to search for more suitable jobs (Quintini, 2011), thus often lowering the incentives for both the firms and the workers to engage costs in on-the-job training (Varhaest and Omey, 2006).

2.2.2 Firm and country level: labour productivity, allocation of resources

Better and more adapted skills are expected to facilitate technology adoption (Benhabib and Spiegel, 2002). Consequently, skill mismatch can result in a slower adaptation to technological progress (OECD, 2012). Using PIAAC data, Adalet McGowan and Andrews (2015a) found that higher skill mismatch is associated with lower labour productivity through a less efficient allocation of resources.

The allocative efficiency theory is based on the idea that high productive and low productive firms coexist and draw from a common pool of skilled workers. Low productivity firms tend to have a high share of mismatched workers and thus trap resources. Therefore, high productivity firms have more trouble to attract this skilled labour force, resulting in an overall productivity loss. According to OECD (2012), lowering skill mismatch is associated with significant gains in allocative efficiency and would thus potentially explain a large part of cross-country differences in labour productivity.

For all these reasons, reducing skill mismatch seems to be an important matter. OECD[2] even considers skill mismatch as one of the main challenges that economies face. Adalet McGowan and Andrews (2015a) argue that the scope to improve the efficiency of human capital allocation is large. Furthermore, a large body of literature has highlighted the close relationship between allocation of human capital and aggregate productivity for the economy as a whole (Olley and Pakes, 1996, Hsieh and Kelenov, 2009, Bartelsman et al., 2013).

[2] http://skills.oecd.org/hotissues/skillsmismatch.html

According to Mavromaras et al. (2013), although skill mismatch can be influenced by temporary factors such as an unexpected imbalance between labour demand and labour supply due to an economic shock, skill mismatch seems to be a persistent phenomenon with long lasting cross-countries differences. As a result, wondering about the impact of public policies aiming at reducing it seems to be a topic of utmost importance.

2.2.3 Positive effects of skill mismatch?

Nevertheless, one can also argue that skill mismatch is not necessarily a bad thing if it is kept at a reasonably low level. For instance, firms in the adjustment process during the introduction of a new technology could take advantage of mismatched labour (Desjardins and Rubenson, 2011). Nevertheless, such argument seems to be relevant only in a short time perspective and is offset by the adverse effects of skill mismatch on labour productivity in the long run. Therefore, this analysis gives credit to the importance of reducing skill mismatch in our knowledge based economies and highlights the leading role of public policies to do so.

2.3 Policies

On this matter, several possible solutions seem to emerge. Skill mismatch can be addressed through a better adaptation to the available supply of skills in the labour force. Policies aiming at reducing frictions in the allocation of labour could thus solve mismatch issues. Desjardins and Rubenson (2011) stress out the importance of taking into consideration both the demand and the supply side of skills when dealing with skill mismatch. Both policies targeting the demand and the supply of skills can result in reducing skill mismatch. The demand side of skills is concerned with policies mostly targeted on firms while the supply side of skills mostly deals with the available workforce in the labour market. Though some of the following policies can be categorized both from the demand and supply of skills, this distinction is made in order to guarantee a greater clarity in the analysis. Note that all the following policies are covered by Adalet McGowan and Andrews (2015b), except entrepreneurship, investments in education and active market labour programmes that are added to the model.

2.3.1 Demand side of skills

- Firing regulations and use of fixed-term and temporary work contracts

Firms could decide to replace mismatched workers by workers more suited to the job. Brunello et al., (2007) found that higher levels of skill mismatch are expected in countries where it is more difficult to fire permanent employees. Likewise, a broader use of fixed-term and temporary work contracts can result in a reduction of mismatch by helping avoiding strong firing regulations (Adalet McGowan and Andrews, 2015b).

- Increasing the allocative efficiency

The allocative efficiency theory warns about the possibility of skilled workers being 'trapped' in inefficient firms. Indeed, higher barriers to firm exit would keep alive these low productive firms, thus maintaining the level of skill mismatch among the labour force. Acemoglu et al. (2013) show that optimal policies should aim at encouraging low productive firms to exit. Policies that penalize business failure could therefore be a hurdle for the reallocation of workers (Andrews and Cingano, 2014). Smooth bankruptcy legislation would thus be beneficial for the reallocation process. The smoothness of bankruptcy legislation could be measured by the comparative level of exit costs across countries.

Likewise, a higher managerial quality could lead to a decrease in skill mismatch through an increase in the efficiency of the allocation of workers. At the recruitment process, good managers could be better suited to hire the most suited applicants, they could create innovative processes in the adoption of new technologies and they could internally reallocate the mismatched workers in occupations for which they would be better suited (O'Leary et al., 2002).

Finally, a higher level of competition is expected to induce a reduction in skill mismatch through a greater market discipline and an improved allocation of talent (Pica and Rodriguez Mora, 2005). OECD[3] defines product market regulation as one of the main policy ingredients necessary to enhance competition.

- Flexibility of wage settings

When workers are over-skilled, their wages are substantially lower than the ones they could reasonably expect. Firms should theoretically adjust wages to counter balance the gap between the actual and the expected productivity of the mismatched workers. Therefore, a higher degree of flexibility in the setting of the wages with the possibility of bargaining would result in a reduction of skill mismatch in the workplace (Adalet McGowan and Andrews, 2015b). However, OECD (2014a) stresses that strong collective bargaining agreements result in lower wage differentials, therefore reducing the incentives of mismatched workers to look for ways to flee from their unsuited occupations.

- Entrepreneurship

Entrepreneurship could also be a channel to tackle skill mismatch. Low job satisfaction among talented mismatched workers, especially among over-skilled workers, could make them flee from their unsuited job and choose to shift towards entrepreneurship. Indeed, entrepreneurs are generally more satisfied with their jobs than non-entrepreneurs (Blanchflower and Oswald, 1998). Nascent entrepreneurship rates might thus be negatively correlated with the probability of being mismatched. If such argument holds, public policies supporting entrepreneurship would thus be expected to reduce levels of skill mismatch. To the best of my knowledge, this variable has not been empirically tested before.

[3] http://www.oecd.org/eco/growth/indicatorsofproductmarketregulationhomepage.htm

2.3.2 Supply side of skills

- Residential mobility

Residential mobility can be another important matter when dealing with skill mismatch as firms located in countries where residential mobility is high can choose from a larger pool of candidates when they are looking for suitable workforce. Residential mobility improves the allocation of human resources in the labour market (Henley, 1998). Andrews et al. (2011) found that residential mobility is positively correlated with worker reallocation rates. Inefficient housing market policies could create lock-in effects which would lower residential mobility. Therefore, policies in housing markets could reduce skill mismatch by increasing residential mobility (Van der Vlist et. al, 2002).

Andrews et al. (2011) noticed that strict tenant-landlord regulations reduce residential mobility by discouraging the supply of rental housing and by locking-in tenants. High transaction costs on property purchase are also expected to lower residential mobility (Oswald, 1999). The cost of obtaining a building permit can also negatively affect the housing supply (Caldera Sánchez and Johansson, 2011) and thus increase the level of skill mismatch (Adalet McGowan and Andrews, 2015b).

- Participation in lifelong learning

Skills can be updated and improved after being hired through the participation of lifelong learning, therefore reducing the gap between the skills expected by the firms and the current skills of the employees. Nijhof (2005) argues that a flexible skill formation system with different trajectories in the lifetime is essential in our knowledge based economies. Arulampalam et. al (2004) highlight the importance of focusing on the on-the-job skills acquisition through work-related training when dealing with mismatch inside the company. Indeed, Adalet McGowan and Andrews (2015b) found that higher participation rates to lifelong learning are associated with lower levels of skill mismatch.

- Investments in education

Braconier et al. (2014) set focus on the importance of capital accumulation through higher spending in education. Higher investments in education would thus not only increase the general level of skills among the population, but at least as importantly, lead to a better match with the labour market by following students in their job research, by improving negotiations between schools, firms and universities and reducing the gap between the studies and the job market. As a result, higher investments in education could therefore potentially result in a reduction of skill mismatch.

- Active market labour policies

Active market labour policies enlarge the potential pool of workers by helping the unemployed find work. Active labour market programmes (ALMP) help mobilize more fully each country's labour resources (OECD, 2014b). Therefore, countries which are largely involved in active market labour policies might experience lower levels of skill mismatch. Marsden et al. (2002) found that countries having relatively low expenditures in active labour programmes experience higher levels of mismatch in the labour market.

2.4 Summary table of expected policy effects according to previous theoretical and empirical evidence

	Demand side of skills						
Policy Factors	Firing regulations and use of temporary work contracts		Increasing the allocative efficiency			Flexibility of wage settings	Entrep.°
Policy variables tested	Employment protection legislation (Permanent)	Employment protection legislation (Fixed-term and temp. work contract)	Cost of closing a business	Managerial quality	Product market regulation	Coverage rate of collective bargaining agreements	Nascent entrepreneur. rates°
Expected effect on skill mismatch	↑	↑	↑	↓	↑	↑/↓	↓°

↑: Increases skill mismatch // ↓: Decreases skill mismatch // °: policy not empirically tested by Adalet McGowan and Andrews (2015b)

Table 2.1: Expected policy effects according to previous theoretical and empirical evidence for policies from the demand side of skills

	Supply side of skills					
Policy Factors	Residential mobility			Lifelong learning	Investments in education°	Active labour market programmes (ALMP)°
Policy variables tested	Transaction costs	Tenant-landlord regulation	Cost of obtaining a building permit	Participation to lifelong learning	Investments in education°	Public exp. in ALMP°
Expected effect on skill mismatch	↑	↑	↑	↓	↓°	↓°

↑: Increases skill mismatch // ↓: Decreases skill mismatch // °: policy not empirically tested by Adalet McGowan and Andrews (2015b)

Table 2.2: Expected policy effects according to previous theoretical and empirical evidence for policies from the supply side of skills

2.5 Individual and firm characteristics influencing skill mismatch

A large amount of literature has aimed at detecting which people are more prone to be mismatched. Allen et al. (2013) find that the probability of being over-skilled is larger for young people than older people. This can be due to the fact that young people have no or little work experience and thus start with temporary and/or low demanding jobs. On the opposite, older people can become under-skilled over the course of their career due to the obsolescence of skills.

Great care must be taken when analyzing the correlation between being a migrant and being mismatched. Visintin et al. (2015) conclude that the probability of being mismatched is higher for immigrants than for native workers. However, the country of origin and the country of residence largely influence this outcome. Nieto et al. (2014) find that there is no significant relationship between being mismatch and being a migrant in the European Union when considering immigrants from the European Union. Alternatively, immigrants from non-European Union countries are more likely to experience skill mismatch compared to native workers.

Some firm characteristics could also play a role in the emergence of skill mismatch. According to the literature, firm size has an ambiguous impact on skill mismatch. Quintini (2011) didn’t find any statistically significant relationship between skill mismatch and firm size while Allen et al. (2013) obtained a positive relationship only between over-skilling and firm size. An internal better managerial quality could also lead to a reduction of skill mismatch (Adalet McGowan and Andrews, 2015b).

3. Methodology

3.1 PIAAC Data

3.1.1 Overview

This thesis explores the database from the recent Programme for the International Assessment of Adult Competencies (PIAAC). PIAAC is an internationally harmonized test of cognitive skills which gives new opportunities to measure skill mismatch and to compare it across countries. The proficiency of a reasonably large share of adults aged between 16 and 65 from 22 OECD countries was assessed. On average, around 5 000 individuals were interviewed in each country.

This Programme has been conducted by the Organisation for Economic Co-operation and Development (OECD) in 2011 and 2012 and the results were published in late 2013. This Programme was renewed over the year 2014 and extended to a larger set of countries (33 countries). However, to this date, the results haven't been publicly published. Therefore, the results published in 2013 are used in this thesis.

The following countries took part in the survey: Austria, Belgium, Canada, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russia[4], Slovakia, Sweden, United Kingdom and United States of America[5].

PIAAC is a voluntary assessment performed from home. To the best of my knowledge, respondents did not get any financial compensation. Interviews were both conducted by phone and online. Respondents mostly used computers to perform the tests. If they couldn't use computers, tests were also implemented via pencil-and-paper.

3.1.2 Assessed skills

The range of assessed skills is wide. The interviewed people were asked a number of questions separated in two parts consisting of a background questionnaire (which is referred to as 'self-report') and proficiency tests in literacy, numeracy and problem solving in technology-rich environments. According to OECD (2013), the literacy assessment measures the '*ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential'* (p.61). The numeracy assessment tests the '*ability to access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life'* (p.61). Finally, the problem solving in technology rich environments assessment indicates the '*ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks'* (p.61).

[4] Gathered data for Russia do not include the population of the Moscow municipal area. Data for Russia thus represent the population of Russia excluding people living in Moscow and its close surroundings.

[5] Note that due to the unavailability of data for several individual and firm characteristics, the United States of America were later removed from my sample.

In the PIAAC dataset, skills were estimated using item-response-theory models (IRT) (Embretson and Reise, 2010). This means that the difficulty of each item is treated as information to be later incorporated in scaling items. Therefore, as the respondents worked on different sets of assessments items and they did not receive items covering every skill domain, their proficiency scores were derived from 10 plausible values (instead of one) for each skill domain (numeracy, literacy and problem solving in technology rich environments).

The self-report assessment includes two questions about the feeling that workers have about their current skills regarding their occupations. In the first one, respondents are asked if they feel that their skills could allow them to perform more demanding tasks than the ones required in their current job. In the second one, respondents are asked if they feel that they would need more training to be able to accurately perform their present tasks. A negative answer to these two questions would result in an individual being self-reported as well-matched.

3.1.3 Various measures of skill mismatch

Skill mismatch is an artificial measure. There are a number of different approaches to define and measure it, even when using the PIAAC dataset.

The first decision to make is to decide whether it is preferable to use numeracy, literacy or problem solving proficiency score. Perry et al. (2014) use numeracy scores as they argue that numeracy skills are most likely to be comparable between countries. Allen et al. (2013) argue that numeracy skill mismatches appear to more efficiently explain earnings differentials than literacy skills. On the opposite, Adalet McGowan and Andrews (2015a and 2015b) set their focus on literacy scores. Desjardins et Rubenson (2011) argue that literacy skills are getting more significant in our knowledge based economies as written and coded information is increasing.

In any measure of skill mismatch, the main idea is to define specific proficiency scores thresholds for each occupation in each country. If the assessed skills of the worker are higher/lower than the up/down threshold, the individual is defined as mismatched, respectively over-skilled and under-skilled. Otherwise, the individual is defined as well-matched.

Adalet McGowan and Andrews (2015a and 2015b) used a measure of skill mismatch based on a method developed in OECD (2013). Their measure uses the *self-report* questionnaire and the mean of the 10 plausible values. Perry et al. (2014) criticize this measure and highlight its drawbacks.[6]

They thus define their own alternative measure based on two characteristics: the absence of use of the self-report and the use of the 10 plausible values.

Using the self-report when calculating the thresholds for each occupation can be biased for two reasons: 1) reporting oneself as mismatched is subjective while being mismatched is not. 2) Only a low fraction of workers self-report themselves as being well-matched (only 3.48% of

[6] For a more detailed description of these two measures, further information can be found in the part A of the appendix section.

respondents in Germany for instance). Perry et al. (2014)'s alternative measure of skill mismatch thus avoids these issues by only relying on purely assessed skills. Cut-off points at 1.5 SD from the mean value of proficiency scores for the *entire* set of respondents are thus calculated for each occupation in each country.

Secondly, the use of the *mean* of the 10 plausible values is questionable because the associated standard errors are not considered in the analysis. The uncertainty in the measure of skills is thus not accounted for. Therefore, Perry et al. (2014) consider the 10 plausible values alone in their analysis, instead of the mean of the 10 plausible values.

For these reasons, though the use of cut-off points at 1.5 SD of the mean is arbitrary, such as was the choice of the 5^{th} and 95^{th} percentile in Adalet McGowan and Andrews (2015a and b)'s measure, Perry et al. (2014)'s alternative method is expected to give a more trustworthy picture of skill mismatch.

3.1.4 Measure of skill mismatch used in the analysis

The measure used in this thesis is thus based on Perry et al. (2014)'s alternative measure and only focusses on proficiency scores in literacy.

Besides, the 2-digit occupation codes are chosen in this analysis. The 2-digit occupation codes divide the whole labour force into around 50 different categories of occupations while the 1-digit occupation codes only refer to 10 different categories of occupations. For instance, *technicians and associate professionals* are grouped together in the 1-digit occupation level (occupation n°3) while these people are divided into *science and engineering professionals* (occupation n°31), *health associate professionals* (occupation n°32), *business and administration associate professionals* (occupation n°33), *legal, social, cultural and related professionals* (occupation n°34) and *information and communications technicians* (occupation n°35) in the 2-digit occupation level. Using 2-digit occupation codes gives a more accurate picture of skill mismatch in the labour force. Indeed, using 1-digit occupation codes would have implied that the level of skills required was the same in some similar, albeit different, occupations.

However, data for the decomposition at the 2-digit occupation level were absent for Austria, Canada, Estonia and Finland. Therefore, these countries were not considered in the analysis. Using 2-digit occupation codes also strongly increased computational efforts.

As being well-matched or mismatched refers to subjects being currently working, respondents who were not currently working or whose occupation was not stated (at the 2-digit decomposition of occupations level) were removed from the sample.

Note that this thesis uses 1.2 standard deviation (SD) as a threshold and not 1.5 SD as Perry et al. (2014) did in their study. Indeed, using 1.5 SD thresholds gives mean levels of skill mismatch of around 10% across OECD countries while using 1.2 SD thresholds increases the measured levels of skill mismatch to around 20%. This was thus more coherent with the levels of skill mismatch that Adalet McGowan and Andrews (2015b) obtained with their measure based on OECD (2013). In the robustness checks section, these results are compared to the ones that would have been obtained with the original 1.5 SD thresholds in order to ensure the consistency of this choice.

Besides, as some policy indicators either partially covered several effects at the same time or were highly correlated, only one policy is tested at a time, like Adalet McGowan and Andrews (2015b) did in their study. This also has the advantage to always test each policy on the largest number of countries for which data for this policy are available. However, in the robustness checks section, several sensitivity tests are performed with, as far as it was possible, the introduction of multiple low correlated policies.

3.2 Data for policy variables

Data for the different policy variables come from a wide variety of sources.

3.2.1 Demand side of skills

- Firing regulations and use of fixed-term and temporary work contracts

The OECD Employment Protection Legislation (EPL) database[7] has relevant cross-country indicators for these issues. The indicator for the '*protection of permanent workers against individual and collective dismissals'* could therefore be a proxy of the strictness of firing restrictions while the indicator for the *'regulation on temporary forms of employment'* measures the strictness of regulation on the use of fixed-term and temporary work contracts. The first indicator ranges between 1.62 for the United Kingdom and 2.98 for Germany with a mean of 2.45 while the second indicator ranges between 0.54 for the United Kingdom and 3.75 for France with a mean of 2.06. Data refer to 2013 and were available for all the countries in the sample.

- Increasing the allocative efficiency

Lower barriers to firm exit could result in a reduction of skill mismatch by releasing 'trapped' mismatched workers in the labour force. Barriers to exit are represented in the model by the comparative level of exit costs across countries. Data come from World Bank, Doing Business Indicators[8] and measure the national average cost of insolvency proceedings as a percentage of the value of the estate. This indicator ranges between 1.0 in Norway to 22.0 in Italy with a mean of 8.94. Data refer to 2014 and were available for all the countries in the sample.

Pica and Rodriguez Mora (2005) showed that a higher level of competition could induce a reduction in skill mismatch through a greater market discipline and an improved allocation of talent. Data for product market regulation are collected from the OECD database[9]. OECD[10] defines product market regulation as one of the two main policy ingredients (with effective

[7] http://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm
[8] http://www.doingbusiness.org/data/exploretopics/resolving-insolvency
[9] http://www.oecd.org/eco/growth/indicatorsofproductmarketregulationhomepage.htm
[10] http://www.oecd.org/eco/growth/indicatorsofproductmarketregulationhomepage.htm

antitrust framework) necessary to enhance competition. Data for economy-wide indicators of policy regimes were available for 2008 and 2013. The indicator for product market regulation ranges between 0.96 in Netherlands to 2.69 in Russia with a mean of 1.57. Data refer to 2013 and were available for all the countries in the sample.

The measure of managerial quality is directly derived from the PIAAC dataset. This thesis used Adalet McGowan and Andrews (2015b)'s method for measuring managerial quality. Respondents who answered YES to the question: '*Are you managing employees in your current work?*' (variable D_Q08A in the dataset) are selected. Then, the mean of literacy proficiency scores for each occupation (at the 2-digit level) is calculated in each country to get a proxy for managerial quality. Indeed, literacy skills seemed the most adequate measure, as literacy skills are the most usual qualities required for managers. Data were available for all the countries in the sample. Contrary to the other policy variables, the indicator of managerial quality is thus not an aggregate measure at the country level but a measure at the 2-digit decomposition of occupations level. Each occupation (at the 2-digit level) in each country was thus assigned a certain level of managerial quality.

- Flexibility of wage settings

A higher degree of flexibility in the setting of wages with the possibility of bargaining would result in a reduction of skill mismatch in the workplace (Adalet McGowan and Andrews, 2015b). Such argument could be measured with the coverage rate of collective bargaining agreements. This coverage rate is calculated as the percentage of workers who are covered by collective agreements regardless of whether or not they belong to a trade union. The source of the data is Visser (2013)'s calculation based on OECD estimates. This indicator ranges between 10.0% in Korea and 96.0% in Belgium with a mean of 59.10%. Data refer to 2011 and were available for all countries in the sample except Russia.

- Entrepreneurship

The Global Entrepreneurship Monitor (GEM) has a national indicator of nascent entrepreneurship rates[11]. This indicator measures the percentage of the population aged 15-64 who are currently involved in setting a business they will own or co-own. This indicator ranges between 2.26% in Japan and 5.30% in the United Kingdom with a mean of 3.56%. Data refer to 2012 and were available for all countries in the sample except the Czech Republic and Slovakia.

Note that descriptive statistics and correlation tables for the policies of the demand side of skills are provided in the tables B1, E1 and E3 of the appendix section.

[11] http://www.gemconsortium.org/data/key-indicators

3.2.2 Supply side of skills

- Residential mobility

Several factors can influence residential mobility and thus indirectly have an impact on skill mismatch.

Andrews et al. (2011) found that strict tenant-landlord regulations reduce residential mobility by discouraging the supply of rental housing and by locking-in tenants. They created an indicator for the strictness of tenant-landlord regulations in the private rental market. Their indicator is based on the ease of tenant eviction, the tenure security and the extent of the deposit requirements. The indicator for the strictness of tenant-landlord regulations ranges between 1.99 in Norway and 4.33 in Sweden with a mean of 2.67. Data were available for all countries in the sample except Russia. Data refer to 2009 and were constructed by relying on replies to the OECD Housing Questionnaires.

High transaction costs are expected to lower residential mobility (Oswald, 1999). Andrews et al. (2011) measured average national transaction costs of purchasing property for the buyer as percentage of the property value. This indicator ranges between 2.22 in Denmark and 14.78 in Belgium with a mean of 7.81. Data refer to 2009 and were available for all countries in the sample except Russia.

The cost of obtaining a building permit can also affect the house supply. Adalet McGowan and Andrews (2015b) argue that the elasticity of housing supply is negatively correlated with the average number of days to obtain a building permit, and thus with residential mobility (Caldera Sánchez and Johansson, 2011). The cost of obtaining a building permit is represented in the model in terms of average number of days. Data come from World Bank, Doing Business Indicators[12]. Data range between 28 days in Korea and 286 days in Slovakia with a mean of 165 days. Data refer to 2014 and were available in all countries in the sample.

- Participation in lifelong learning

I used the Eurostat database[13] to obtain a measure of the importance of lifelong learning. Eurostat[14] defines lifelong learning as '*all learning activities undertaken throughout life after the initial education with the aim of improving knowledge, skills and competences, within personal, civic, social or employment-related perspectives*'. The participation rate to an education or training during the last four weeks prior to the interview was thus measured. Therefore, the participation rate in lifelong learning was collected for the countries present in the sample. Data range between 2.8% in Slovakia and 31.2% in Denmark with a mean of 11.65%. Data refer to 2009 and were available in all countries in the sample except Japan, Korea and Russia.

[12] http://www.doingbusiness.org/data/exploretopics/dealing-with-construction-permits
[13] http://ec.europa.eu/eurostat/statistics-explained/index.php/Lifelong_learning_statistics
[14] http://ec.europa.eu/eurostat/cache/metadata/en/trng_lfs_4w0_esms.htm

- Investments in education

Data for investments in education were collected from the OECD database[15,16] and the indicator used in this thesis was calculated as the sum of the public and private spending on primary to non-tertiary education and on tertiary education as percentage of the gross domestic product for the countries present in the sample. The purpose of this sum was to get rid of the bias that could arise from diversity in fee levels across countries. This sum for primary to non-tertiary education ranges between 2.30% in Russia and 4.70% in Denmark with a mean of 3.58% while the sum for tertiary education ranges between 0.90% in Italy and 2.30% in Korea with a mean of 1.45%. Data refer to 2012 and were available in all countries in the sample except the investments in tertiary education for Denmark.

- Active market labour policies

Data regarding the active market labour policies come from the OECD database[17]. They refer to the level of public expenditures in active labour programmes as a percentage of the gross domestic product. This indicator ranges between 0.21% in Japan and 1.85% in Denmark with a mean of 0.69%. Data refer to 2012 and were available for all the countries in the sample except Russia and the United Kingdom.

Note that descriptive statistics and correlation tables for the policies of the supply side of skills are provided in the tables B1, E2 and E3 of the appendix section.

[15] https://data.oecd.org/eduresource/public-spending-on-education.htm#indicator-chart
[16] https://data.oecd.org/eduresource/private-spending-on-education.htm#indicator-chart
[17] http://www.oecd.org/employment/emp/employment-outlook-statistical-annex.htm

3.3 Empirical Analysis

The impact of several public policies on skill mismatch is tested. The first step of the analysis is to test which are the important individual and firm characteristics that matter when trying to explain skill mismatch. The dependent variable is whether a person is well-matched or mismatched. In the second step of the analysis, variables related to public policies are introduced to test their impact on skill mismatch.

3.3.1 Importance of individual and firm characteristics

A binomial logit specification is used to measure the influence of several individual and firm characteristics on the probability of being skill mismatched. In this analysis, the logit specification models the probability of the positive outcome 'being skill mismatched' given a set of regressors including the different individual and firm characteristics (model (a)). The dependent variable is the binary variable *mismatched* which is equal to 1 if the individual is defined as mismatched and 0 if the individual is defined as well-matched according to the results obtained from the alternative measure of skill mismatch.

The model is thus as follows:

$$\text{logit mismatched}_{i,f} = \alpha_1 + \alpha_2 * I_i + \alpha_3 * F_f + \varepsilon_{i,f} \qquad \text{(a)}$$

The index *i* represents the observed individual i and the index *f* represents the firm in which this individual *i* is currently working. The vector I_i represents the individual characteristics of the individual *i*. The individual characteristics include age, marital status, migrant status, gender and level of education. The vector F_f represents the characteristics of the firm in which the individual *i* is currently working. The firm characteristics include the size of the firm, the contract type and if the firm is a private firm (compared to a public firm/non-governmental organization). Standard errors are inherently clustered in all the regressions performed throughout the thesis and country fixed effects are also introduced in the model at this stage.

3.3.2 Introduction of policy variables

In this second stage of the analysis, policy indicators are introduced to test the impact of public policies on the probability of being mismatched. Again, a binomial logit specification is used with the binary variable *mismatched* as dependent variable. Individual and firm characteristics are now used as control variables and policy indicators are used as 'main' independent variables.

The model is thus as follows:

$$\text{logit mismatched}_{i,f,c} = \beta_1 + \beta_2 * I_i + \beta_3 * F_f + \beta_4 * P_c + \mu_{i,f,c} \qquad \text{(b)}$$

The vectors I_i and F_i still represent respectively the individual characteristics and the firm characteristics and are used in this model (b) as the set of control variables. The vector P_c represents the policy variables tested in the model. As these policies are measured at the national level, country fixed effects are removed from the model.

4. Empirical results

This section explores the results obtained from models (a) and (b). In the first part of the analysis, results about the individual and firm characteristics determining the probability for an individual of being mismatched are reported. These characteristics are later defined as control variables for the main part of the analysis when introducing the different policy indicator variables. The associated reduction of the probability of being mismatched when reducing/increasing the selected policy indicator from the level of the least favorable country ('worst student in the class' country) to the mean level across the countries analyzed in the study (all other the variables being measured at the mean value) is also later calculated in order to have a better understanding of the magnitude of the impact of each policy and in an attempt to compare these impacts.

4.1 Individual and firm characteristics

	Skill mismatch	**Over-skilled**	**Under-skilled**
Dependent variable	mismatched = 1 if mismatched and 0 otherwise	over-skilled = 1 if over-skilled and 0 otherwise	under-skilled = 1 if under-skilled and 0 otherwise
Single	0.005 (0.008)	0.005 (0.006)	-0.000 (0.011)
Female	-0.025*** (0.005)	-0.021*** (0.003)	-0.003 (0.005)
Immigrant	0.079*** (0.011)	-0.048*** (0.011)	0.093*** (0.009)
Age 25-34	0.023** (0.011)	-0.014* (0.008)	0.035*** (0.011)
Age 35-44	-0.001 (0.012)	-0.020 (0.013)	0.019 (0.013)
Age 45-54	-0.007 (0.012)	-0.048** (0.020)	0.045* (0.024)
Age 55 or more	0.023 (0.026)	-0.083*** (0.026)	0.082*** (0.030)
Upper Secondary	-0.066*** (0.013)	0.048*** (0.012)	-0.070*** (0.009)
Post Secondary-non-tertiary	-0.022 (0.020)	0.104*** (0.010)	-0.093*** (0.012)
Tertiary	-0.053*** (0.015)	0.097*** (0.011)	-0.119*** (0.007)
Firm size: 11-50	-0.000 (0.011)	-0.001 (0.009)	0.000 (0.005)
Firm size: 51-250	0.000 (0.008)	-0.000 (0.007)	-0.001 (0.004)
Firm size: 251-1000	-0.006 (0.009)	-0.004 (0.007)	-0.003 (0.008)
Firm size: 1000+	0.029*** (0.010)	0.025*** (0.006)	-0.006 (0.008)
Fixed contract	0.004 (0.007)	0.003 (0.009)	0.001 (0.005)
Temporary contract	0.021*** (0.007)	0.003 (0.010)	0.016** (0.007)
Private	-0.006 (0.004)	0.002 (0.006)	-0.010* (0.005)
Pseudo-R^2	0.010	0.045	0.058
Number of observations	49263	49263	49263

*Table 4.1: Estimates from the logit regression of model (a). Values are marginal effects and standard errors are in parentheses. The number of stars denotes the statistical significance: *** at the 1% level, ** at the 5% level and * at the 10% level.*

Table 4.1 reports the results obtained from model (a). The coefficients are the marginal effects which represent the average impact across the countries in the sample of a unit change in the observed explanatory variable on the probability of being skill mismatched.

This impact is relative to the excluded individual which would be here a young married male, non-immigrant with low education attainment and employed with an indefinite contract in a small firm from the public sector or in a non-governmental organization. Indeed, such individual is obtained when all the included variables are equal to zero.

The results from model (a) show that females are less likely to be mismatched than men. This result is mostly supported by the fact that females are less likely to be over-skilled (column 2). Indeed, no statistically significant relationship was obtained between gender and under-skilling. The same results were obtained by Adalet McGowan and Andrews (2015b) in their study. These results are in line with what Quintini (2011) found using another dataset. This result is contrary to the common assumption that women would be *more* likely to be over-skilled because they would put a higher focus on their family life, as Adalet McGowan and Andrews (2015b) point out in their paper.

Immigrants are more likely to be mismatched (column 1). It even seems to represent one of the most important factors of mismatch. Columns 2 and 3 show that this result is driven by the fact that immigrants are more likely to be under-skilled and less likely to be over-skilled. This result must be interpreted with caution because of the variety of the migrant population. The language barrier and the low or maladapted skills of a part of the migrant population could explain the higher likelihood of being under-skilled. On the opposite, well-educated or experienced immigrants could suffer from the non-recognition of their past working experience and diplomas obtained in their home countries. However, it seems that the latter argument is offset by the first argument over the entire migrant population. The low share of immigrants in the sample makes further analysis of the migrant case thorny. Note that again, these results are in line with the results found by Adalet McGowan and Andrews (2015b).

The results from model (a) are consistent with the theory of obsolescence of skills, as age seems positively correlated with under-skilling and negatively correlated with over-skilling with statistically significant relationships for people aged 45-54 and people older than 55. However, contrary to Adalet McGowan and Andrews (2015b), my results didn’t justify the assumption that skill mismatch decreases with age. Indeed, the relationship between age and skill mismatch was statistically non-significant, except for people between 25 and 34 who seem to be the most affected by skill mismatch along with people over 55, though the relationship was statistically non-significant. Higher skill mismatch for people over 55 could be explained again by the obsolescence of skills and the difficulties of finding a suited job when being close to retirement.

The results from model (a) about the level of education attainment are in line with the assumption that the higher the level of education attainment, the lower the probability of being under-skilled and the higher the probability of being over-skilled, with the most important effect for the people with tertiary education. The same type of results were found by Adalet McGowan and Andrews (2015b).

As Adalet McGowan and Andrews found in their study (2015b), the relationship between firm size and skill mismatch is unclear. Workers in large firms are more likely to be mismatched. A result that is driven by the fact they are significantly more likely to be over-skilled, which is in line with what Allen et al. (2013) found in their study. As Adalet McGowan and Andrews (2015b) point out, this might be due to the fact that large firms are more likely to anticipate future skills needs and thus could keep over-skilled workers in order to use their skills in a later time.

Contrary to what Adalet McGowan and Andrews (2015b) found in their study, my results show that the use of temporary contracts was roughly positively correlated with skill mismatch. A result that is mostly supported by a higher probability of being under-skilled (column 3), which could be explained by the fact that some temporary missions might be more often performed by workers who haven't had the time to be properly trained for their tasks, due to the temporary aspect of their job.

Finally, note that the r-squared statistics turned out to be low. Similar r-squared statistics were found by Adalet McGowan and Andrews (2015b) in their study. These low r-squared statistics could be mostly explained by the model simplicity compared to the real-life high complexity of this social phenomenon and the still low numbers of observations. Besides, the r-squared statistics are significantly higher when analyzing over-skilling (column 2) or over-skilling (column 3) compared to skill mismatch as a whole (column 1). My opinion on this matter is that, as the results show, most of the individual and firm characteristics variables seem to have opposite effects on under-skilling and over-skilling (for example, higher level of education seems to be positively related to over-skilling and negatively related to under-skilling). Therefore, when analyzing the impact of these variables on skill mismatch as a whole, these opposite effects might partly offset each other, leading to lower levels of r-squared statistics.

4.2 Effect of policy variables

Policy indicators are then introduced to test the impact of public policies on the probability of being mismatched. Policy variables are added one at a time to model (a), resulting in model (b). Remember that the control variables include age, marital status, migrant status, gender, level of education, size of the firm, contract type and firm type. Coefficients for the control variables are not reported for the sake of brevity. Indeed, including policy variables didn’t have any significant impact on the coefficients of the control variables for which the results were broadly consistent with the ones obtained from model (a).

4.2.1 Demand side of skills

Results are reported in Table 4.2.

	Demand side of skills						
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise						
Policy Factors	Firing regulations and use of temporary work contracts		Increasing the allocative efficiency			Flexibility of wage settings	Entrepreneurship
Policy variables used	EPL (Permanent)	EPL (Fixed-term and temp. work cont.)	Cost of closing a business	Managerial quality	Product market regulation	Coverage rate of coll. barg. agr.	Nascent entrepreneurship rate
Effect on skill mismatch	0.0217*** (0.0078)	0.0045 (0.0037)	0.0018*** (0.0004)	-0.0000 (0.0001)	0.0250*** (0.0059)	-0.0001 (0.0001)	-0.0053** (0.0021)
Pseudo R^2	0.010	0.010	0.010	0.010	0.011	0.09	0.011
Number of observations	49263	49263	49263	47878	49263	47697	44108
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	Yes	No	No	No

*Table 4.2: Estimates from the logit regression of model (b) for the policy variables from the demand side of skills. Values are marginal effects and standard errors are in parentheses. The number of stars denotes the statistical significance: *** at the 1% level, ** at the 5% level and * at the 10% level.*

- Entrepreneurship[18]

Nascent entrepreneurship rates turned out to be negatively correlated with the probability of being mismatched. Countries where a larger share of the population is involved in starting a business experience on average lower levels of skill mismatch. This gives some support to the argument that entrepreneurship could be a solution for tackling skill mismatch by giving the possibility to current mismatched workers to flee from their unsuited jobs. Increasing the nascent entrepreneurship rate from the country where it is at the lowest level (Japan) to the mean level across the countries present in the analysis is associated with a reduction of the probability of being mismatched of 0.75%.

[18] Further discussion on the relationship between entrepreneurship and skill mismatch can be found in the part C of the appendix section.

- Firing regulations and use of fixed-term and temporary work contracts

The results from model (b) show that more stringent firing regulations for permanent employees result in higher levels of mismatch. Indeed, stringent firing regulations imply that it is hard for employers to fire potentially mismatched workers when trying to adapt to the available labour force, thus keeping a high level of mismatch within the firm. Reducing the level of employment protection legislation for permanent workers from the most restrictive country (Germany) to the mean level across the countries present in the analysis is associated with a reduction of the probability of being mismatched of 1.24%.

However, no statistically significant relationship was found between the stringency of the employment protection legislation for the use of fixed-term and temporary work contracts and skill mismatch. Besides, most of the multiple policy tests performed in the robustness checks section resulted in a statistically non-significant effect of this policy. Nevertheless, reducing the level of employment protection legislation for the use of fixed-terms and temporary work contracts from the most restrictive country (France) to the mean level across the countries present in the analysis is associated with a reduction of the probability of being mismatched of 0.78%.

This thus only partially supports the result obtained by Adalet McGowan and Andrews (2015b) which showed that policies dealing with employment protection legislation for permanent workers seem to be better suited than policies dealing with employment protection legislation for the use of fixed-term and temporary work contracts when aiming at reducing skill mismatch.

- Increasing the allocative efficiency

According to the literature, a higher degree of competition was expected to result in a lower level of mismatch through an increase in allocative efficiency. As explained earlier, lower barriers to exit and lower product market regulations were thus potential solutions to reduce mismatch in the workplace.

The results from model (b) show that higher barriers to exit (represented by the cost of closing a business calculated as the national average cost of insolvency proceedings as a percentage of the value of the estate) are indeed positively correlated with skill mismatch. High barriers to exit would thus imply that mismatched workers could be 'trapped' in low productive firms. Reducing the level of costs of closing a business from the most restrictive country (Italy) to the mean level is associated with a reduction of the probability of being mismatched of 2.49%.

The relationship between managerial quality (calculated at the 2-digit decomposition of occupations level) and skill mismatch turned out to be statistically non-significant. The non-significance of the result might be a consequence of the imprecision of this measure. Indeed, at the 2-digit decomposition of occupations level, the number of 'managers' in a cell occupation (at the 2-digit level) / country can be very low and thus not give a sufficiently efficient image of the real managerial quality associated to this occupation. Another explanation could be the use of literacy proficiency scores to define managerial quality. Numeracy proficiency scores or problem solving proficiency scores for defining managerial quality might have given other results.

The level of product market regulation turned out to be positively correlated with the probability of being mismatched. This is in line with the theory stating that a lower level of product market regulation enhances competition and results in a reduction of skill mismatch through a greater market discipline and an improved allocation of talent (Pica and Rodriguez Mora, 2005). Reducing the level of product market regulation from the most restrictive country (Russia) to the mean level is associated with a reduction of the probability of being mismatched of 3.03%.

- Flexibility of wage settings

Contrary to what Adalet McGowan and Andrews (2015b) found, the results from model (b) highlighted a statistically non-significant influence of the coverage rate of collective bargaining agreements on skill mismatch. One explanation is that the two opposite effects of strong collective bargaining agreements would offset each other. Indeed, if Adalet McGowan and Andrews (2015b) argued that firms should theoretically adjust wages to deal with skill mismatch, OECD (2014a) stressed that strong collective bargaining agreements result in lower wage differentials, therefore reducing the incentives of mismatched workers to look for ways to flee from mismatch. Besides, the coefficient obtained was close to zero. Reducing the coverage rate of collective bargaining agreements from the country where it is the highest (Belgium) to the mean level of the countries present in the analysis is associated with a reduction of the probability of being mismatched of 0.28%.

4.2.2 Supply side of skills

Results are reported in Table 4.3.

	Supply side of skills						
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise						
Policy Factors	Residential mobility			Lifelong learning (LLL)	Investments in education		Active labour market programmes (ALMP)
Policy variables used	Trans. costs	Tenant-land. regulations	Cost of obt. a build. per.	Particip. LLL	From primary to non-ter.	In tertiary	Public expenditures in ALMP
Effect on skill mismatch	0.0020*** (0.0007)	0.0060 (0.0064)	0.0001* (0.0000)	-0.0012*** (0.0004)	-0.0155*** (0.0034)	-0.0228* (0.0119)	-0.0142*** (0.0044)
PseudoR²	0.011	0.010	0.010	0.011	0.010	0.010	0.011
Nb. Obs.	47697	47697	49263	41695	49263	45074	43625
Control var.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country f. e.	No	No	No	No	No	No	No

*Table 4.3: Estimates from the logit regression of model (b) for the policy variables from the supply side of skills. Values are marginal effects and standard errors are in parentheses. The number of stars denotes the statistical significance: *** at the 1% level, ** at the 5% level and * at the 10% level.*

- Investments in education

The results from model (b) showed that both overall investments in primary to non-tertiary and in tertiary education seem to be negatively correlated with the probability of skill mismatch. Both results were statistically significant. Increasing the sum of public and private investments on primary to non-tertiary education from the country where they are at the lowest level (Russia) to the mean policy value is associated with a reduction of mismatch of 2.20% while increasing the sum of public and private investments on tertiary education from the country where they are at the lowest level (Italy) to the mean policy value is associated with a reduction of mismatch of 1.34%.

- Active market labour policies

As expected, higher public expenditures in active market labour policies were negatively correlated with the probability of being mismatched. Increasing the level of public expenditures (measured as a percentage of the gross domestic product) in active market labour policies from the minimum level (Japan) to the mean level across countries analyzed in the study is associated with a reduction of skill mismatch of 0.73%.

- Residential mobility

Three main housing policies aiming at improving residential mobility are tested in this thesis and were expected to indirectly result in a reduction of the probability of being mismatched. These policies are the transaction costs, the stringency of tenant-landlord regulations and the cost of obtaining a building permit. Among these three policies, the transaction costs and the cost of obtaining a building permit turned out to be statistically significant with the expected positive signs while no statistically significant relationship was found for the stringency of tenant-landlord regulations.

Reducing the level of transaction costs from the most restrictive country (Belgium) to the mean level is associated with a reduction of skill mismatch of 1.50%. Reducing the stringency of tenant-landlord regulations from the most restrictive country (Sweden) to the mean level is associated with a reduction of skill mismatch of 1.04%. Finally, reducing the cost of obtaining a building permit from the most restrictive country (Slovakia) to the mean level is associated with a reduction of skill mismatch of 1.19%.

Besides, most of the tests performed in the following robustness checks sections turned out to again show no statistically significant relationship for the stringency of tenant-landlord regulations. Therefore, my results indeed justify the importance of policies increasing residential mobility, but to a lesser extent than what Adalet McGowan and Andrews (2015b) found in their study.

- Participation in lifelong learning

Participation in lifelong learning turned out to be negatively correlated with the probability of being mismatched. Countries with higher participation rates in lifelong learning experience on average lower levels of skill mismatch which is both consistent with the theory and with the results obtained by Adalet McGowan and Andrews (2015b). Increasing the share of the population involved in lifelong learning from the minimum level (Slovakia) to the mean level across countries is associated with a reduction of skill mismatch of 1.18%.

4.2.3 Summary table of potential reduction of skill mismatch

Public policy		% decrease in skill mismatch
Demand side of skills	EPL permanent	1.24
	EPL fixed-term and temporary^	0.78^
	Cost of closing a business	2.49
	Product Market Regulation	3.03
	Coverage rate of collective bargaining agreements^	0.28^
	Nascent entrepreneurship rates	0.75
Supply side of skills	Transaction costs	1.50
	Tenant-landlord regulations^	1.04^
	Cost of obtaining a building permit	1.19
	Lifelong learning	1.18
	Investments in education (primary to non-tertiary)	2.20
	Investments in education (tertiary)	1.34
	Public expenditures in ALMP	0.73

^: policy statistically non-significant in the main model

Table 4.4: Estimated decrease in skill mismatch from reducing the selected policy from the least favorable country ('worst student in the class' country) to the mean value

4.3 Distortion analysis of skill mismatch

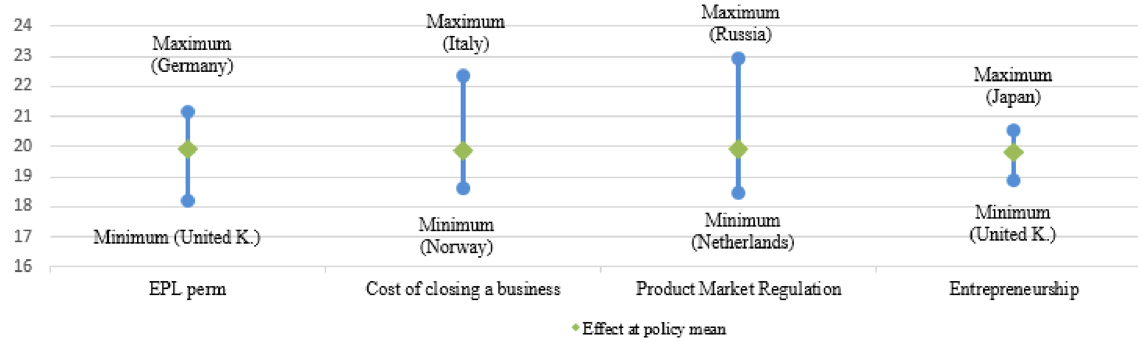

Fig. 4.1: Probability of skill mismatch: distortion from sample maximum and sample minimum to the policy mean for the statistically significant policies from the demand side of skills

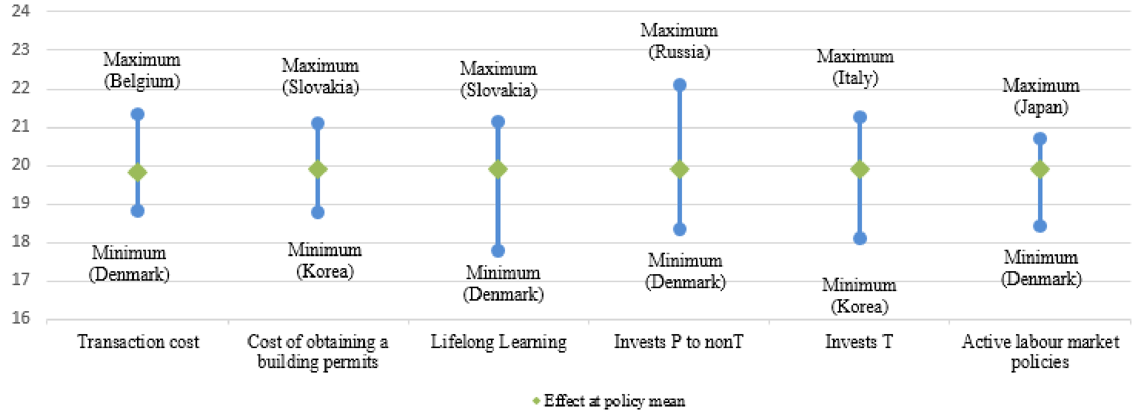

Fig. 4.2: Probability of skill mismatch: distortion from sample maximum and sample minimum to the policy mean for the statistically significant policies from the supply side of skills

The graphs in figures 4.1 and 4.2 represent the total distortion between the country with the most favorable policy environment regarding skill mismatch for the selected policy and the country with the least favorable policy environment, all the control variables being measured at the mean value. This set of graphs is thus an attempt to compare the potential effects of policy variables. The scope of distortion of skill mismatch seems to be particularly large (more than 3.5%) between the most and the least favorable countries for the cost of closing business, the level of product market regulation and the level of investments in the primary to non-tertiary education. On the opposite, the scope of distortion of skill mismatch seems low (less than 2.5%) for the nascent entrepreneurship rate, the level of transactions costs, the cost of obtaining a building permit and the level of public expenditures in active labour market policies.

Nevertheless, these results must be interpreted with caution as they don't take into account that some policies might be 'easier' to improve than others. Besides, these graphs might be influenced by the presence of potential country outliers in terms of policy environment. At first sight, potential country outliers can be detected as the countries for which the distance to the mean is the highest. This can be seen on the graphs for the policies for which the 'up' distortion (distortion above the mean) and 'low' distortion (distortion below the mean) are disproportionate. Further tests regarding the dependence on potential country outliers are performed in the robustness checks section.

All in all, my results were consistent both in terms of statistical significance and signs with Adalet McGowan and Andrews (2015b) in the main analysis for all the policies jointly tested except the managerial quality, the stringency of tenant-landlord regulations, the employment protection legislation for the use of fixed-term and temporary work contracts and the coverage rate of collective bargaining agreements for which my results didn't show any statistically significant relationship. Note also that I didn't get any policy with both statistically significant results and opposite effect compared to what Adalet McGowan and Andrews (2015b) found in their study. The three main policies that I added in my model, which were nascent entrepreneurship rates, investments in education and public expenditures in active market labour programmes, turned out to be statistically significant with the expected effects.

4.4 Robustness checks

In order to check the consistency of the results obtained in the main analysis, several sensitivity tests were performed.

As explained earlier, the threshold of 1.2 SD used in the measure of skill mismatch might seem arbitrary. The robustness of the results was thus tested when using 1.5 SD thresholds, as it is the case in Perry et al. (2014), for the policies which turned out to be statistically significant in the main analysis. As reported in tables D1 and D2 of the appendix section, the results were broadly robust with this new threshold. The nascent entrepreneurship rate, which was statistically significant at the 5% level in the main model, the level of investments in tertiary education, which were statistically significant at the 10% level in the main model, and the employment protection legislation for permanent workers lost their statistical significance. However, these three variables turned out to be robust to most of the multiple policy models tested.

Indeed, the robustness of the results was also tested by including multiple policy variables at the same time. Given the high correlation between the different policy variables (tables E1, E2 and E3 of the appendix section), policies from the demand and supply sides at the same time were introduced, as far as it was possible. Note that as some countries are missing for certain policy variables, using multiple policy variables thus often reduces the considered sample. The results reported in the table F1 of the appendix section show that the results were broadly robust to the ones obtained from the main analysis. Indeed, the tenant-landlord regulations, the employment protection legislation for the use of fixed-term and temporary work contracts and the coverage rate of collective bargaining agreements turned out to be statistically non-significant in most of the models in which they were introduced, which thus again weakens the impact that Adalet McGowan and Andrews (2015b) gave to these three variables.

Finally, the robustness of my results was tested by removing the most restrictive country and the least restrictive country for each policy tested. Note that again this technique reduces the number of considered countries. Results are reported in table G1. All of the statistically significant policies from the main analysis turned out to remain statistically significant, except the investments in tertiary education which was thus given partial support throughout this robustness checks section.

4.5 Summary tables of results

	Demand side of skills						
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise						
Policy Factors	Firing regulations and use of temporary work contracts		Increasing the allocative efficiency			Flexibility of wage settings	Entrepreneurship
Policy variables used	Employment protection legislation (Permanent)	Employment protection legislation (Fixed-term and temp. work cont.)	Cost of closing a business	Manageri al quality	Product market regulation	Coverage rate of collective bargaining agreements	Nascent entrepreneurship rate
Main model	↑***	↑	↑***	↓	↑***	↓	↓**
Model with different threshold	↑	o	↑***	o	↑***	o	↓
Multiple policy model	↑***	↑	↑***	o	↑***/**/*	↓	↓**/.
Non dep. on country outliers	↑**/*	↑	↑***	o	↑***	↓	↓*

↑: increases skill mismatch // ↓: decreases skill mismatch // o: not tested // The number of stars denotes the statistical significance.

Table 4.5: Summary of results from the main analysis and the robustness checks for policies from the demand side of skills

	Supply side of skills						
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise						
Policy Factors	Residential mobility			Lifelong learning (LLL)	Investments in education		Active labour market programmes (ALMP)
Policy variables used	Trans. Costs	Tenant-land. reg.	Cost of obt. a build. per.	Particip. LLL	From primary to non-ter.	In tertiary	Public expenditures in ALMP
Main model	↑***	↑	↑*	↓***	↓***	↓*	↓***
Model with different threshold	↑**	o	↑**	↓***	↓***	↓	↓***
Multiple policy model	↑**/*	↑	↑*	↓***	↓***	↓**	↓*/.
Non dep. on country outliers	↑**	↑*/.	↑**/*	↓***	↓***	↓***/.	↓***/*

↑: increases skill mismatch // ↓: decreases skill mismatch // o: not tested // The number of stars denotes the statistical significance.

Table 4.6: Summary of results from the main analysis and the robustness checks for policies from the supply side of skills

<table>
<tr><th></th><th></th><th>Adalet McGowan and Andrews (2015b)</th><th>Mauriès (2016)</th></tr>
<tr><td rowspan="5">Methodology</td><td>Skill mismatch measure</td><td>Adalet McGowan and Andrews (2015b) based on OECD (2013)</td><td>Mauriès (2016) based on Perry et al. (2014)</td></tr>
<tr><td>Number of countries in the sample</td><td>22</td><td>17</td></tr>
<tr><td>Decomposition of occupations level</td><td>1-digit</td><td>2-digit</td></tr>
<tr><td>Proficiency scores analyzed</td><td>Literacy</td><td>Literacy</td></tr>
<tr><td rowspan="11">Individual and firm characteristics</td><td>Marital status</td><td>Slight over-skilling among bachelors</td><td>No statistically significant relationship</td></tr>
<tr><td>Gender</td><td colspan="2">Lower probability of being mismatched/over-skilled among women</td></tr>
<tr><td>Migrant status</td><td colspan="2">Lower probability of being over-skilled and higher probability of being mismatched/under-skilled among immigrants</td></tr>
<tr><td rowspan="2">Age</td><td colspan="2">Age negatively correlated with over-skilling and positively correlated with under-skilling</td></tr>
<tr><td>Skill mismatch decreases with age</td><td>Higher probability of being mismatched among the youth (25-34) (significant) and the elders (age 55 or more) (non-significant)</td></tr>
<tr><td rowspan="2">Education attainment</td><td colspan="2">Education attainment negatively correlated with under-skilling and positively correlated with over-skilling</td></tr>
<tr><td>Higher probability of being mismatched with a tertiary attainment</td><td>Lower probability of being mismatched with a upper-secondary/tertiary attainment</td></tr>
<tr><td>Firm size</td><td colspan="2">Higher probability of being mismatched/over-skilled in large firms (1000 employees and more)</td></tr>
<tr><td>Contract type</td><td>No statistically significant relationship</td><td>Higher probability of being mismatched/under-skilled for workers with temporary contracts</td></tr>
<tr><td>Firm type</td><td>Lower probability of being mismatched/over-skilled in the public sector</td><td>Slight under-skilling in the public sector</td></tr>
<tr><td rowspan="7">Policies from the demand side of skills*</td><td>EPL (permanent)</td><td colspan="2">Lower levels of skill mismatch in countries with smooth regulations on the firing of permanent workers</td></tr>
<tr><td>EPL (fixed-term and temp. work. cont.)</td><td>Lower levels of skill mismatch in countries with smooth legislation on fixed-term and temporary work contracts</td><td>No statistically significant relationship</td></tr>
<tr><td>Cost of closing a business</td><td colspan="2">Lower levels of skill mismatch in countries with low cost of closing a business</td></tr>
<tr><td>Managerial quality</td><td>Managerial quality negatively correlated with skill mismatch</td><td>No statistically significant relationship</td></tr>
<tr><td>Product market regulation</td><td colspan="2">Lower levels of skill mismatch in countries with smooth product market regulations</td></tr>
<tr><td>Coverage rate of collective bargaining agreements</td><td>Lower levels of skill mismatch in countries with low coverage rate of collective bargaining agreements</td><td>No statistically significant relationship</td></tr>
<tr><td>Nascent entrepreneurship rate</td><td>Not tested</td><td>Lower levels of skill mismatch in countries with high nascent entrepreneurship rates</td></tr>
<tr><td rowspan="7">Policies from the supply side of skills*</td><td>Trans. Costs</td><td colspan="2">Lower levels of skill mismatch in countries with low transaction costs</td></tr>
<tr><td>Tenant-land. reg.</td><td>Lower levels of skill mismatch in countries with smooth tenant-landlord regulations</td><td>No statistically significant relationship</td></tr>
<tr><td>Cost of obt. a build. per.</td><td colspan="2">Lower levels of skill mismatch in countries with low costs of obtaining a building permit</td></tr>
<tr><td>Particip. LLL</td><td colspan="2">Lower levels of skill mismatch in countries with high participation in lifelong learning</td></tr>
<tr><td>Public expenditures in ALMP</td><td>Not tested</td><td>Lower levels of skill mismatch in countries with high public expenditures in ALMP</td></tr>
<tr><td>Investments from primary to non-ter. education</td><td>Not tested</td><td>Lower levels of skill mismatch in countries with high investments in primary to non-tertiary education</td></tr>
<tr><td>Investments in tertiary education</td><td>Not tested</td><td>Lower levels of skill mismatch in countries with high investments in tertiary education</td></tr>
</table>

*Note: no distinction between the demand and supply sides of skills is made in Adalet McGowan and Andrews (2015b)

Table 4.7: Summary table of the comparison between Adalet McGowan and Andrews (2015b) and Mauriès (2016)

5. Limitations of the study and sustainability aspects

5.1 Limitations of the study

Some limitations of the study can be highlighted.

Firstly, the analysis only relied on proficiency scores in literacy. Results in numeracy and problem solving were thus not covered in this study. Though one could expect that the results obtained from literacy proficiency scores might be highly correlated with the results obtained from the other two proficiency areas, the choice of the observed proficiency scores might influence the results regarding the policy variables.

When the policy variables were introduced, the probability of being mismatched was analyzed without any distinction between over-skilling and under-skilling. Indeed, this thesis had the aim to explore the impact of public policies on skill mismatch as a whole. Some policies might reduce over-skilling but at the same enhance under-skilling, or the other way around. In that case, it would be thorny to give any conclusion on the real efficiency of such policies for the population as a whole.

The way the respondents performed the tests seems to be also questionable as the motivation that they had making the test can influence the results. However, such motivation argument seems hard to measure. Further background information on the process of the test might strengthen the analysis. Likewise, one can wonder about the overall reliability of the PIAAC dataset. Indeed, the collection of data and the potential differences in the selection process across countries might have a substantial impact on the results obtained in this analysis.

Besides, people are heterogeneous both within (diversity of the population) and across countries (influence of different historical, cultural and cultural norms and backgrounds). Therefore, it seems to be a thorny challenge to attempt to capture skill mismatch both in a national and international context. As a result, other geographical aspects could also be taken into account, such as the type of country (Mediterranean, North European, Central European, Asian…), the population density and the location (urban, suburban or rural area).

Most of the policy indicators used in this analysis are proxies meant to represent public policies which were expected to have an impact on skill mismatch. Therefore, the choice of the indicators may have influenced the outcome. This can also explain why some of the tested policies didn’t give any statistically significant results. Besides, this thesis relied, as far as possible, on indicators measured around the years when the PIAAC was conducted (between 2011 and 2012). However, some indicators were not available for these years, which made the analysis rely on older or more recent measures (2009, 2010, 2013, 2014). Furthermore, as in any cross-country database, reliability of the indicators measured in several countries can be also questioned.

The 2-digit decomposition of occupations level was chosen in this study. The results thus relied on 17 countries, which can be considered as a low number of countries. Note that the upcoming wave of results from PIAAC will consider more countries, increasing the number of countries to 33.

No particular attention has been given to the potentially positive effects of skill mismatch in the empirical part of this thesis. Indeed, as presented in the literature review, one might argue that a skill surplus might be valuable, especially in the short run. Over-skilled workers today might be a valuable resource for technical change tomorrow. Therefore, one might wonder about the price that society would be willing to pay to be able to adapt to technological change.

In regard to this matter, although this was not the argument given in my analysis, one might think that higher investments in education could potentially create non-necessary over-educated workers, which could form an over-skilled workforce in the labor market. Nevertheless, two question remain regarding this issue: i) Do higher investments in education necessarily create more over-educated workers? ii) How high is the correlation between over-education mismatch and over-skilling? Few papers have attempted to deal with both education mismatch and skill mismatch at the same time. Indeed, recent years have seen a shift in the focus of mismatch from education mismatch to skill mismatch. Furthermore, these few papers seem to conclude that these two types of mismatch are different and that the link between the two is not straightforward (Desjardin and Rubenson, 2011). Besides, most of them were performed only at the national level (Ame et al. 2013, Di Pietro and Urwin, 2006). Due to the limited scope of this thesis and the choice of analyzing skill mismatch alone, these two questions were thus mostly left uncovered in this analysis.

Finally, note that this thesis has attempted to highlight the policies which seem to be efficient at reducing skill mismatch and to give an insight into the different impacts that they can have on skill mismatch. However, this thesis didn’t attempt to determine how ‘flexible’ public policies are, as some policies might be easier to ‘correct’ than others.

5.2 Sustainability aspects

This thesis mostly focusses on the social and economic pillars of sustainability. Skills are at the core of our modern knowledge based economies and therefore their appropriate use is fundamental. Indeed, as described earlier, reducing skill mismatch seems to be of utmost importance to promote economic growth and development. Having the right people at the right job thus covers several advantages including higher job satisfaction, lower (costly) turnover and a higher individual productivity often associated with corresponding wage increases. Following the allocative efficiency theory, a lower share of skill mismatched workers would shrink the share of low productive firms and increase the overall productivity in the country. This surplus in productivity linked with a higher national competitiveness, would thus be expected to result in creation of jobs and an increase in the wealth and economic performance of the country. However, it might be interesting to note that the regional picture could be less obvious. Specific regions could take advantage of this improved allocation of talent at the expense of others, specifically if one assumes that they draw from a common pool of workers. Nevertheless, such theoretical argument is out of the scope of this thesis and the interested reader can refer to the already existing body of work on this topic.

Environmental aspects are broadly left uncovered as this thesis doesn’t seem to have any particular impact on environmental issues.

6. Conclusion and suggestions for future research

This thesis has explored the impact of public policies on skill mismatch.

The general idea was that skill mismatch is often described to trigger a large set of adverse effects (Allen and van der Velden, 2001, Cabral Vieira, 2005, Mavromaras et al., 2013), leading to substantial loss in productivity (Adalet McGowan and Andrews, 2015a). The presence of long-lasting cross-country differences could thus imply that a favorable policy environment seems to be an important matter when tackling skill mismatch.

Using the last wave of data from the Programme for the International Assessment of Adult Competencies and policy variables from different sources, results show that policies targeted on firms and policies dealing with the available workforce can result in a reduction of skill mismatch levels with various impacts. Most of the results were consistent both with the theory and the empirical literature. Lower levels of skill mismatch are thus expected for countries with smooth regulations on the firing of permanent workers. Policies increasing the allocative efficiency also seem to be associated with a reduction of skill mismatch and a higher participation in lifelong learning seems to efficiently reduce the gaps between the skills of the workers and the skills required for his/her job. However, contrary to Adalet McGowan and Andrews (2015b), policies regulating the use of fixed-term and temporary work contracts turned out to have no or little impact on skill mismatch. The same type of relationship was found regarding the flexibility of wage settings which thus doesn't seem to be an efficient solution when aiming at reducing skill mismatch. Besides, the importance of housing policies increasing residential mobility was verified but to a lesser extent than what Adalet McGowan and Andrews (2015b) found in their study, with only around half of the tested housing policies which turned out to be statistically significant. New to the literature, high investments in education, higher public expenditures on active market labour policies and a strong focus on entrepreneurship seem be associated with lower levels of skill mismatch.

Other policy variables might be tested and added to the model. Nevertheless, some policies might be hard to measure due to the absence of reliable data necessary to such a cross-country analysis. Further research could also be done on the flexibility of the public policies that seem to be efficient at reducing skill mismatch. Indeed, the purpose of this thesis was to test the impact of public policies on skill mismatch, thus highlighting policies which seem to be efficient at reducing the shares of skill mismatched workers in the society. However, this thesis didn't try to deal with the easiness of 'correcting' such policies. Further attention should be drawn to the measure of the actual associated productivity gains associated with a reduction of skill mismatch. Finally, alternative analysis could focus on the potentially beneficial effects of skill mismatch, an original area of research that has mostly been uncovered by the scientific community.

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Appendices

A. Further information on the two measures of skill mismatch

- Adalet McGowan and Andrews (2015b)'s measure

Adalet and McGowan (2014)' measure is constructed in the following way: people who *self-report* themselves as well-matched are kept. These people have answered 'No' to the following two questions: 'Do you feel that your skills are not challenged enough in your current job?' (variable F_Q07A in the PIAAC dataset) and 'Do you feel that you need more training to cope with your present duties?' (variable F_Q07B in the PIAAC dataset). From the proficiency scores of these self-reported well-matched people, the 5^{th} and 95^{th} percentile thresholds are calculated for each occupation in each country.

Bandwidths using these thresholds are then created and tested on the entire set of respondents. For each respondent, the average of the 10 plausible values is tested. Only one mismatch variable per person is thus created. If the average of the 10 plausible values is lower than the 5^{th} percentile threshold, the individual is defined as under-skilled. If the average of the 10 plausible values is higher than the 95^{th} percentile threshold, the individual is defined as over-skilled.

- Perry et al. (2014)'s measure

Perry et al. (2014)' measure is constructed in the following way: average skill levels and standard deviations (SDs) are calculated for the *entire* set of respondents for each occupation in each country.

Then, bandwidths using +-1.5 SD are created. For each respondent, the 10 plausible values are tested one by one and are associated with -1 if they are lower than $\text{mean}_{\text{occup,country}} - 1.5{*}\text{SD}_{\text{occup,country}}$ (under-skilled), +1 if they are higher than $\text{mean}_{\text{occup,country}} + 1.5{*}\text{SD}_{\text{occup,country}}$ (over-skilled) or 0 if they lie between $\text{mean} - 1.5{*}\text{SD}_{\text{occup,country}}$ and $\text{mean} + 1.5{*}\text{SD}_{\text{occup,country}}$ (well-matched). 10 skill mismatch variables per person are thus created. Finally, the average of these 10 skill mismatch variables is used to define if the respondent is well-matched or mismatched.

For a deeper comparison of the two measures, I advise the reader to refer to Perry et al. (2014)'s article which primarily focused on the measures of skill mismatch:

Perry, A., S. Wiederhol and D.A. Ackerman-Piek (2014), How Can Skill Mismatch be Measured? New Approaches with PIAAC, Methods, data, analyses, Vol. 8(2), pp. 137-174.

B. Descriptive statistics

Public policy		Mean	Standard deviation	Minimum	Maximum
Demand side of skills	EPL permanent	2.45	0.37	1.62	2.98
	EPL fixed-term and temporary	2.06	0.90	0.54	3.75
	Cost of closing a business	8.94	5.99	1.00	22.00
	Product Market Regulation	1.57	0.38	0.96	2.69
	Coverage rate of collective bargaining agreements	59.10	29.46	10.00	96.00
	Nascent entrepreneurship rates	3.56	0.89	2.26	5.30
	Barriers to entrepreneurship °	1.89	0.36	1.31	2.65
	Governmental support (i) °	2.75	0.37	2.11	3.52
	Governmental support (ii) °	2.53	0.38	1.71	3.30
Supply side of skills	Transaction costs	7.81	3.70	2.22	14.78
	Tenant-landlord regulations	2.67	0.62	1.99	4.33
	Cost of obtaining a building permit	165.12	72.13	28.00	286.00
	Lifelong learning	11.65	8.59	2.80	31.20
	Investments in education (primary to non-tertiary)	3.58	0.74	2.30	4.70
	Investments in education (tertiary)	1.45	0.33	0.90	2.30
	Public expenditures in ALMP	0.69	0.44	0.21	1.85

°: Entrepreneurship policies added in the discussion of the part C of the appendix

Table B1: Descriptive statistics of the policy variables

Mismatch type	Mean	Standard deviation	Minimum	Maximum
Under-skilling (1.2 SD)	10.60	0.89	9.21	12.84
Over-skilling (1.2 SD)	9.87	1.22	8.11	11.89
Skill mismatch (1.2 SD)	20.47	1.29	18.96	22.88
Under-skilling (1.5 SD)	6.50	0.64	5.20	8.07
Over-skilling (1.5 SD)	4.62	0.85	3.16	6.57
Skill mismatch (1.5 SD)	11.12	0.77	9.71	12.81

Table B2: Descriptive statistics of skill mismatch

C. Discussion on the relationship between entrepreneurship and skill mismatch

As presented in my main analysis, higher nascent entrepreneurship rates seem to be associated with lower levels of skill mismatch, thus supporting the idea that a reduction of skill mismatch could partially be triggered by mismatched (unsatisfied) workers choosing to shift towards more satisfying entrepreneurial activities, leading to a reduction of the overall level of skill mismatch. Indeed, as the PIAAC dataset gives a static image of skill mismatch, measuring the actual nascent entrepreneurship rates seems to be the most accurate indicator when dealing with entrepreneurship. However, one can argue that the level of national barriers to entrepreneurship and the direct measure of governmental support for entrepreneurship might more accurately cover the relationship between entrepreneurship and skill mismatch. The argument there is that lower national barriers to entrepreneurship and higher governmental support for entrepreneurship might not be necessarily associated with higher actual entrepreneurship rates.

However, these two points were tested in order to get a clearer understanding of the potential link between entrepreneurship and skill mismatch.

Data for the measure of barriers to entrepreneurship are collected from the OECD database[19]. Koske et al. (2015) have calculated an index for the barriers to entrepreneurship based on measures of various characteristics including the complexity of regulatory procedures and the administrative burdens on startups. Data refer to 2008 and were available for all countries in the sample. The National Expert Survey (NES) from the Global Entrepreneurship Monitor[20] (GEM) has two indicators of the direct measure of governmental support and policies regarding entrepreneurship. The first one (i) deals with the *extent to which entrepreneurship is considered by the governments as a relevant economic issue* while the second one (ii) measures the extent to which *taxes or regulations are either size-neutral or encourage new and SMEs.* Data refer to 2012 and were available for all countries except the Czech Republic.

	Other entrepreneurship related indicators		
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise		
Policy variables used	Barriers to entrepreneurship (2008)	GVT support (i), 2012	GVT support (ii), 2012
Effect on skill mismatch	0.0180** (0.0087)	0.0022 (0.0077)	-0.0220*** (0.0059)
Pseudo R^2	0.010	0.010	0.010
Number of observations	49263	46755	46755
Control variables	Yes	Yes	Yes
Country fixed effects	No	No	No

*Table C1: Estimates from the logit regression of model (b) for the other entrepreneurship related indicators. Values are marginal effects and standard errors are in parentheses. Coefficients for the control variables are not reported for the sake of brevity. The number of stars denotes the statistical significance: *** at the 1% level, ** at the 5% level and * at the 10% level.*

[19] http://www.oecd.org/eco/growth/indicatorsofproductmarketregulationhomepage.htm
[20] http://www.gemconsortium.org/data/key-indicators

Results reported in table C1 show that countries where the barriers to entrepreneurship are low seem to experience lower levels of skill mismatch. This result is partially supported by the direct measure of governmental support to entrepreneurship.

This analysis thus gives a more elaborate and somehow less clear-cut interpretation of the impact of entrepreneurship on skill mismatch.

D. Results with the 1.5 SD thresholds

	Demand side of skills			
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise			
Policy Factors	Firing regulations	Increasing the allocative efficiency		Entrepreneurship
Policy variables used	Employment protection legislation (Permanent)	Cost of closing a business	Product market regulation	Nascent entrepreneurship rate
Effect on skill mismatch	0.0083 (0.0069)	0.0013*** (0.0005)	0.0230*** (0.0070)	-0.0024 (0.0037)
Pseudo R^2	0.017	0.017	0.017	0.019
Number of observations	49263	49263	49263	44108
Control variables	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	No

*Table D1: Estimates from the logit regression of model (b) with the 1.5 SD thresholds for the measure of skill mismatch for the policy variables from the demand side of skills which were statistically significant with the 1.2 thresholds. Values are marginal effects and standard errors are in parentheses. Coefficients for the control variables are not reported for the sake of brevity. The number of stars denotes the statistical significance: *** at the 1% level, ** at the 5% level and * at the 10% level.*

	Supply side of skills					
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise					
Policy Factors	Residential mobility		Lifelong learning (LLL)	Investments in education		Active labour market programmes (ALMP)
Policy variabl es used	Trans. costs	Cost of obt. a build. per.	Participation in LLL	From primary to non-ter.	In tertiary	Public exp. in ALMP
Effect on skill mismat ch	0.0012** (0.0005)	0.0001** (0.0000)	-0.0010*** (0.0003)	-0.0098*** (0.0028)	-0.0117 (0.0085)	-0.0155*** (0.0037)
Pseudo R^2	0.017	0.017	0.019	0.017	0.014	0.018
Nb. Obs.	47697	49263	41695	49263	45074	43625
Contro l var.	Yes	Yes	Yes	Yes	Yes	Yes
Countr y f. e.	No	No	No	No	No	No

*Table D2: Estimates from the logit regression of model (b) with the 1.5 SD thresholds for the measure of skill mismatch for the policy variables from the supply side of skills which were statistically significant with the 1.2 thresholds. Values are marginal effects and standard errors are in parentheses. Coefficients for the control variables are not reported for the sake of brevity. The number of stars denotes the statistical significance: *** at the 1% level, ** at the 5% level and * at the 10% level.*

E. Correlation tables for the policy indicators

Demand side of skills						
	EPL permanent	EPL fixed-term and temporary^	Cost of closing a business	Product Market Regulation	Coverage rate of collective bargaining agreements^	Nascent entrepreneurship rates
EPL permanent	1.00					
EPL fixed-term and temporary^	0.53	1.00				
Cost of closing a business	0.13	0.18	1.00			
Product Market Regulation	0.17	0.36	0.28	1.00		
Coverage rate of collective bargaining agreements^	0.68	0.40	-0.10	-0.19	1.00	
Entrepreneurship	-0.61	-0.47	0.11	-0.35	-0.33	1.00

^: policy statistically non-significant in the main model

Table E1: Correlation matrix for the policy indicators from the demand side of skills

Supply side of skills							
	Transaction costs	Tenant-landlord regulations^	Cost of obtaining a build. permit	Lifelong learning	Investments education primary to non-tertiary	Investments education tertiary	Public expenditures in ALMP
Transaction costs	1.00						
Tenant-landlord regulations^	0.41	1.00					
Cost of obtaining a building permit	0.59	0.13	1.00				
Lifelong Learning	-0.69	-0.02	-0.77	1.00			
Invest. ed. primary to non-ter	-0.32	-0.24	-0.63	0.69	1.00		
Invest. ed. tertiary	-0.43	-0.36	-0.65	0.78	0.30	1.00	
Public expenditures in ALMP	-0.18	0.40	-0.37	0.86	0.67	-0.26	1.00

^: policy statistically non-significant in the main model

Table E2: Correlation matrix for the policy indicators from the supply side of skills

Demand and supply sides of skills							
	Transaction costs	Tenant-landlord reg.^	Cost of obtaining a building permit	Lifelong learning	Invest. ed. primary to non-tertiary	Invest. ed. tertiary	Public exp. in ALMP
EPL permanent	0.61	0.52	0.35	-0.35	-0.22	-0.62	0.28
EPL fixed-term and temporary^	0.54	0.30	0.26	-0.41	0.08	-0.37	-0.06
Cost of closing a business	0.36	0.29	0.58	-0.65	-0.60	-0.47	-0.33
Product Market Regulation	0.18	0.26	0.25	-0.45	-0.44	-0.24	-0.24
Coverage rate of collective bargaining agreements^	0.42	0.56	0.13	0.32	0.30	-0.41	0.69
Entrepreneur.	-0.19	-0.23	-0.29	0.03	0.17	0.64	-0.23

^: *policy statistically non-significant in the main model*

Table E3: Correlation matrix for the policy indicators from both the demand and supply sides of skills

F. Multiple policy models

	Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise										
Demand side of skills	EPL perm.		0.0295 *** (0.0074)							0.0199 *** (0.0099)	
	EPL temp.					0.0008 (0.0027)			0.0037 (0.0025)		
	Cost clos.bus.	0.0015 *** (0.0005)								0.0013 *** (0.0004)	
	PMR		0.0287 *** (0.0100)		0.0170 * (0.0093)	0.0212 *** (0.0050)		0.0273 *** (0.0069)			0.0197 ** (0.0091)
	Col. bar.						-0.0001 (0.0001				
	N. entrep.	-0.00511 ** (0.0022)		-0.0012 (0.0047)							-0.0060 ** (0.0026)
Supply side of skills	Trans. Costs	0.0009 * (0.0005)		0.0013 * (0.0007)	0.0014 ** (0.0007)		0.0016 * (0.0008)				
	Ten.-Lan. Reg.							0.0031 (0.0059)	0.0007 (0.0041)		
	Cos. buil. permit							0.0001 * (0.0000)			
	Lifelong learning										-0.0010 *** (0.0003)
	Inv. pri. to non-ter.						-0.0121 *** (0.0043)		-0.0147 *** (0.0044)		
	Inv. ter.					-0.0210 ** (0.0086)					
	ALMP		-0.0104 * (0.0063)	-0.0085 * (0.0047)	-0.0078 (0.0050)					-0.0099 * (0.0051)	
Number of observations		42542	43625	38470	43625	45074	47697	47697	47697	43625	36540
Pseudo R²		0.11	0.10	0.11	0.10	0.10	0.10	0.10	0.10	0.11	0.012
Control variables		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects		No	No	No	No	No	No	No	No	No	No

*Table F1: Estimates from the logit regression of model (b) when including several policy variables at a time. Original model with the 1.2 SD threshold. Values are marginal effects and standard errors are in parentheses. Coefficients for the control variables are not reported for the sake of brevity. The number of stars denotes the statistical significance: *** at the 1% level, ** at the 5% level and * at the 10% level.*

G. Influence of potential country outliers

	Demand side of skills		**Supply side of skills**	
	Dependent variable: mismatched = 1 if individual is mismatched and 0 otherwise			
Countries tested	All available except the most restrictive	All available except the least restrictive	All available except the most restrictive	All available except the least restrictive
	Employment protection legislation (permanent)		Transaction costs	
Effect on skill mismatch	0.0178** (0.0086)	0.0201* (0.0115)	0.0023** (0.0010)	0.0022** (0.0008)
Pseudo R^2	0.010	0.010	0.010	0.009
Number of observations	46190	45191	45071	43508
	Employment protection legislation (temporary work)		Tenant-landlord regulations	
Effect on skill mismatch	0.0054 (0.0053)	0.0017 (0.0040)	0.0159* (0.0082)	0.0041 (0.0062)
Pseudo R^2	0.009	0.010	0.010	0.010
Number of observations	45913	45191	45299	44923
	Cost of closing business		Cost of obtaining a building permit	
Effect on skill mismatch	0.0018*** (0.0005)	0.0017*** (0.0004)	0.0001* (0.0000)	0.0001** (0.0000)
Pseudo R^2	0.011	0.010	0.011	0.010
Number of observations	47442	46489	46616	46472
	Product market regulation		Participation in lifelong learning	
Effect on skill mismatch	0.0283*** (0.0073)	0.0228*** (0.0080)	-0.0013*** (0.0004)	-0.0019*** (0.0004)
Pseudo R^2	0.011	0.010	0.012	0.010
Number of observations	47697	46237	39048	37506
	Coverage rate of collective bargaining agreements		Investments in education, primary to non-tertiary	
Effect on skill mismatch	-0.0001 (0.0001)	-0.0000 (0.0001)	-0.0155*** (0.0042)	-0.0163*** (0.0041)
Pseudo R^2	0.010	0.010	0.011	0.009
Number of observations	45071	44906	47697	45074
	Nascent entrepreneurship rates		Investments in education, tertiary	
Effect on skill mismatch	-0.0073* (0.0040)	-0.0024* (0.0014)	-0.0200 (0.0130)	-0.0421*** (0.092)
Pseudo R^2	0.010	0.010	0.010	0.010
Number of observations	40937	40036	43253	42283
	--		Public expenditures in active labour market programmes	
Effect on skill mismatch	--	--	-0.0161*** (0.0053)	-0.0184* (0.0102)
Pseudo R^2	--	--	0.010	0.009
Number of observations	--	--	40454	39436

*Table G1: Estimates from the logit regression of model (b) with one policy variable at a time when removing the most restrictive country and the least restrictive country. Values are marginal effects and standard errors are in parentheses. Coefficients for the control variables are not reported for the sake of brevity. The number of stars denotes the statistical significance: *** at the 1% level, ** at the 5% level and * at the 10% level.*