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EFFECTS OF SKILL MISMATCHES ON WAGES BY LEVEL OF EMPLOYMENT PROTECTION[†]

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Abstract

This study examines the impact of a skill mismatch on wages among the Organisation for Economic Co-operation and Development member and partner countries according to employment protection legislation strictness. I propose a skill mismatch measure using occupation-level skill requirements combined with worker-level data. The results show that a skill mismatch usually has no impact on wages, except for workers in the Czech Republic, Greece, the Netherlands, New Zealand, and the Russian Federation, who suffer wage penalties, and workers in Chile, who enjoy wage premiums. Additionally, skill mismatches in countries with more job protection will likely have a high impact on wages.

Keywords: Skill mismatch, Wage, Matching quality, Employment protection

JEL Classification Code: J31 J28 I26

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I. INTRODUCTION

Does the impact of skill mismatch on wages differ according to employment protection legislation (EPL) strictness? If workers and firms find low matching quality due to imperfect information, workers may suffer a low wage penalty, and firms may face low productivity. Labor turnover in a perfect labor market could improve matching quality. However, in labor markets with strict EPL, skill-mismatched workers are less likely to change their jobs due to the low possibility that another firm hire them, and firms will not fire workers due to high firing costs, which means that matching quality will not improve (Bassanini and Garnero 2013; Gielen and Tatsiramos 2012; Boeri and Van Ours 2008; Gómez-Salvador et al. 2004). Thus, it is important to investigate the extent of the impact of skill mismatch on wages according to EPL.

Jovanovic (1979), Mincer and Jovanovic (1979), Mortensen (1978), and others develop the theory of matching quality between workers and firms. The theory assumes that workers and firms have imperfect information on their matching quality, which is considered an "experience good" (Nelson 1970) because workers and firms do not know their matching qualities at the time of hiring, but realize it after the match. If workers find that their matching qualities are low, they may suffer a wage penalty or may try to find a better job. However, the theory unambiguously predicts a negative effect of strict employment protection on labor market flows (Boeri and Van Ours 2008).

Empirical studies based on the matching quality theory show that a skill mismatch has a negative impact on wages. Fredriksson et al. (2015) and Guvenen et al. (2015) construct a skill mismatch measure by using the absolute value of the differences between workers' skills and required skills. Using Swedish data, Fredriksson et al. (2015) show that a one-standard deviation increase in skill mismatch lowers the entry wage by 1.2% for workers with at least 5 years of experience and has no impact on wages for inexperienced workers. Guvenen et al.

(2015) examine the effect of skill mismatch on wages in the US and construct a model that incorporates the persistence of the mismatch over the life cycle. Using a Mincer wage regression, they find that worst-matched workers earn 8.8% lower wages after 10 years of tenure compared to a well-matched worker.

Studies by Jackson (2013) and Woodcock (2015) represent another strand of the empirical literature based on the matching quality theory. Both investigate the impact of skill mismatch on labor market outcomes and employment mobility in the US. Although they do not create a skill mismatch measure, they instead estimate worker-firm matching effects using the mixed effect model. Woodcock (2015) shows that a skill mismatch between workers and firms explains 16% of the variation in the logarithm of earnings in the US. Jackson (2013) investigates whether a skill mismatch affects workers' productivity in North Carolina. Using students' achievements as teacher productivity, he estimates a teacher-school matching measure by the maximum likelihood random match effects model. The results suggest that an increase in matching quality increases workers' productivity.

Except for Fredriksson et al. (2015), these studies focus mostly the US, which has the least strict EPL among the Organisation for Economic Co-operation and Development (OECD) countries. In Sweden, which has slightly stricter EPL than the OECD average, the impact of skill mismatch Fredriksson et al. (2015) find may be also less than in countries with the strictest EPL.

As for multi-country analysis, using the Programme for the International Assessment of Adult Competencies (PIAAC) data, the OECD (2016) shows that a skill mismatch has a negative effect on wages in all countries analyzed. They construct a skill mismatch measure based on workers' subjective judgments. However, workers may not estimate the required skill precisely due to overconfidence or ignorance of the required skills. Furthermore, as the OECD (2016) points out, the measure is based on numeracy and literacy, while skill mismatch

according to workers' judgments may be more general. Allen et al. (2013) estimate the impact of a skill mismatch on wages among OECD countries. They define skill mismatch as "skill use relative to one's own skill level" and construct a skill mismatch measure using the frequency of skill use and skill level. They find that underskilling lowers earnings by 4–16% and overskilling raises earnings by around 10% in some countries. However, workers cannot use skills they do not gain, and thus, the frequency of using a skill does not imply the necessity to use it as well. These studies show that skill mismatch has a negative impact on wages in almost all countries analyzed, but their skill mismatch measures are problematic because they use a rough measure developed using 1-digit occupation codes. These measures are also subjective, which likely yields larger measurement errors for skill mismatch than an objective skill mismatch measure does. I overcome this problem by using objective occupational data based on 4-digit occupation codes.

In this study, I investigate the cross-national variation of the impact of cognitive skill mismatch on wages and how the impacts vary by EPL using data from the PIAAC and O*net. The PIAAC is conducted by 33 countries, so it enables an investigation of the impact of skill mismatch by labor market institution. O*net provides objective detailed skill-level requirements by occupation according to evaluation by professional job analysts.

This study contributes to the empirical literature on matching quality theory by considering EPL as a potential determinant of wages. I show not only the impact of a skill mismatch on wages, but also the importance of labor market institutions. There is much literature on the impact of a skill mismatch on wages; however, to the best of my knowledge, this is the first study to examine the relationship between skill mismatch and wages according to EPL strictness.[1] The results show that a skill mismatch has no impact on wages in most

[1] Gielen and Tatsiramos (2012) investigate the impact of job quality on a worker's quitting behavior and shows the relationship between post-quit behavior and wages by EPL. The

countries, which differs from results reported in previous studies. In a few countries, skill mismatched workers suffer a wage penalty, while in Chile, the only exception, workers enjoy a wage premium. Furthermore, the stricter the EPL is, the larger the impact of a skill mismatch on wages is. This suggests that labor markets tend to be inefficient with strict EPL. Thus, if policymakers impose strict EPL, this may come at the cost of an inefficient labor market.

The remainder of this paper proceeds as follows. Section 2 presents the theoretical background of the model and the empirical specification. Section 3 describes the data. Section 4 reports the empirical results. Section 5 concludes the paper.

II. THEORETICAL BACKGROUND AND MODEL

2.1. Model

In the absence of matching quality, the production function reduces to a simple Cobb-Douglas production function, which provides an output Q_{ijt}. Assume that worker i has productive characteristics, such as human capital and ability, indexed by $L_{it} > 0$. Firm j has productive characteristics, such as organizational capital and technology, represented by index $K_j > 0$.

$$Q_{ij} = \mu L_i^{\theta} K_j^{\psi} e_{ij} \tag{1}$$

Because I do not observe output prices or firms' compensation policies, I define a firm effect, $\psi \log K_j = y_j\alpha + \psi_j$, where y_i is a vector of observable firm characteristics that determine productivity, α a parameter vector, and ψ_j the idiosyncratic shock to the firm. Since workers' productivity may vary over time as they accumulate human capital, the worker-specific component of the logarithm of wages is $\theta \log L_i = x_i\beta + \theta_i$, where x_i is a vector of observable

current study differs in that it focuses on the direct relationship between skill mismatch and wages.

personal characteristics that determine productivity, β a parameter vector, and θ_i a worker effect that measures the returns to time-invariant characteristics (e.g., education). Hence, x_i is the portable component of a worker's wage, reflecting the market value of his/hers productive attributes.

I base the model that includes a matching quality term on Jackson (2013) and Woodcock (2015). While these authors assume that matching quality is unobservable, I assume that matching quality is observable with errors. When firm j employs worker i in occupation o with skill mismatch M_{ijo},

$$Q_{ij} = \mu L_i^{\theta} K_j^{\psi} M_{ijo}^{\phi} e_{ij} \tag{2}$$

where μ is a scale factor; θ, ψ, and ϕ are parameters; $M_{ijo} > 0$ is a skill mismatch shifter, and e_{ij} is an idiosyncratic productivity shock. One can interpret M_{ijo} as an index of the complementarity between workers' and firms' productive attributes. Following Guvenen et al. (2015) and Fredriksson et al. (2015), worker i has a skill set $\boldsymbol{S}_i^* = (S_{i1}^*, S_{i2}^*, \ldots, S_{in}^*)$, with S_i^* being the true value of the skills; however, workers and firms observe the worker's skill with noise, when workers and firms meet. Thus, I can measure skill mismatch by the location of the occupation and the worker. Let $S_{ik}^* = S_{ik} + \eta_{ik}$, with S_{ik} being the worker's skill as the worker and a firm observe, and η_{ik} being noise, where $\eta_{ik} \sim N(0,\sigma^2_{\eta ik})$. A firm j engaged in occupation o requires a skill set of $\boldsymbol{R_j}^* = (R_{jo1}^*, R_{jo2}^*, \ldots, R_{jon}^*)$. Therefore, I define skill mismatch as $\phi \log M_{ijo} = \phi * 1/n \Sigma^n_k |(S_{ik} + \eta_{ik}) - R_{jok}| = \phi * 1/n \Sigma^n_k |S_{ik} - R_{jok} + \eta_{ik}|$, which measures the component of wages due to skill mismatch. I give the precise explanation of the empirical measure below.

Assume that firms face price p_j for their output, normalized to have mean one. The worker maximizes w_{ij} and the firm maximizes $p_j Q_{ij} - w_{ij}$. When employees of firm j have bargaining strength γ_j and there is no outside option, the bargaining solution is $w_{ij} = \gamma_j p_j Q_{ij}$. Taking the

logarithms, I have

$$\log w_{ij} = \log \mu + \log p_j\gamma_j + \theta \log L_i + \psi \log K_j + \phi \log M_{ijo} + \log e_{ij}$$
$$= \log \mu + x_i\beta + \theta_i + y_{ij}\alpha + \psi_j + \log p_j\gamma_j + \phi * 1/n\Sigma^n{}_k \mid S_{ik} - R_{jk} + \eta_{ik} \mid + \log e_{ij}$$
$$= \log \mu + x_i\beta + y_{ij}\alpha + \phi * 1/n\Sigma^n{}_k \mid S_{ik} - R_{jk} + \eta_{ik} \mid + \theta_i + \psi_j + \log p_j\gamma_j + \log e_{ij.} \quad (3)$$

The logarithm of wage is additively separable in worker-, firm-, and match-specific components. They measure the relative wage differences due to productivity differences between workers, firms, and matches due to product market conditions, as p_j reflects.

Empirically, I can control θ_i and ψ_j using information about workers and firms, but I do not directly observe a worker's true skill nor the worker's skill that the worker and firms observe. Instead, I use PIAAC test scores, which are noisy signals about their true skills. Furthermore, I do not observe η_{ik}, which may correlate with an idiosyncratic productivity shock.

2.2. Econometric Model

To conduct the empirical analysis, I rewrite Eq. (3) as follows:

$$\log w_{ijo} = \gamma + \phi skill\_mismatch_{ijo} + x_i\beta + y_{jo}\alpha + \theta_i + u_{ijo} \quad (4)$$

where $skill\_mismatch_{ijo}$ is skill mismatch. The skill mismatch measure I use here takes positive values, and there is no skill mismatch when it takes the value of zero. x_i is a vector of individual characteristics, including average numeracy and literacy scores, tenure, tenure squared, experience, and experience squared. y_{jo} is a vector of firm and occupation characteristics, such as the number of employees, and dummy variables for occupation and industry. θ_i is a time-invariant-worker-specific determinant, such as education. u_{ij} is an error term, which I can decompose into the noise of skill mismatch and an idiosyncratic error. Thus, u_{ijo} may correlate with $skill\_mismatch_{ijo}$. This equation estimates the coefficients on skill mismatch by ordinary

least squares (OLS), which are biased toward to zero due to the noise. Therefore, I estimate Eq. (4) by not only OLS, but also with an instrumental variable (IV) estimation.

In countries with less strict EPL, skill mismatched workers will move to new jobs with higher wages or be fired. Thus, I expect a low or zero impact of skill mismatch on wages. On the other hand, in those with strict EPL, I expect that skill mismatched workers will be less likely to quit their job because workers may have difficulties finding better jobs due to the low possibility of hiring. In this case, the effect of a skill mismatch on wages is ambiguous. First, skill mismatched workers have to accept lower wages because they have no choice but stay in their current job, which means that a skill mismatch has a negative impact on wages. Second, negative skill mismatched workers can enjoy a wage premium if the worker has higher relative bargaining power, Mcgowan and Andrews (2015) points out. Thus, ϕ can be negative or positive.

III. DATA

3.1. PIAAC

OECD countries and its partners in 24 countries conducted the PIAAC survey between 2011 and 2012 in the first round and in nine countries between 2014 and 2015 in the second round.[2] The samples in each country contain around 5,000 adults aged between 16 and 65. The PIAAC assesses adults' numeracy, literacy, and problem-solving skills in technology-rich environments, and collects information on education, labor, and family background. For

[2] The participating countries are as follows:

- Round 1 (2011–2012): Australia, Austria, Belgium (Flanders), Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), and the United States.
- Round 2 (2014–2015): Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia, and Turkey.

problem-solving skills the survey tests respondents who can use computers, so there are no available scores for individuals who do not use computers. Therefore, I exclude this score from the analysis. The survey measures numeracy and literacy scores by 10 plausible values calculated using item response theory, which is represented using a 500-point scale.[3] The main virtue of the PIAAC is that I can obtain a cognitive skills score and available working history. Furthermore, the cross-national character of the data allows for an analysis of labor market institutions (Levels et al. 2014). However, I cannot examine all countries in the PIAAC because some information, such as wages and occupation, are missing. The remaining countries for analysis are Belgium (Flanders), Chile, the Czech Republic, Denmark, France, Greece, Israel, Italy, Japan, Korea, Lithuania, the Netherlands, New Zealand, Norway, Poland, the Russian Federation, Slovak Republic, Slovenia, Spain, and the United Kingdom (England and Northern Ireland).[4]

3.2. O*net

O*net, constructed by the U.S. Department of Labor, provides the primary source of occupational information for workers, human resource professionals, students, and so on. O*net covers 974 occupations in the US and provides information about the importance of workers' knowledge, skills, and abilities for each occupation by integers from zero to six. I

[3] The numeracy and literacy domains are defined according to the OECD (2013), as follows.

- Numeracy: the ability to access, use, interpret, and communicate mathematical information and ideas to engage in and manage the mathematical demands of a range of situations in adult life. To this end, numeracy involves managing a situation or solving a problem in a real context by responding to mathematical content/information/ideas represented in multiple ways.
- Literacy: 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. Literacy encompasses a range of skills from decoding written words and sentences to comprehending, interpreting, and evaluating complex texts.

[4] Note that the Russian Federation's wage data do not compare well with those available from other sources (OECD 2016). I exclude the US because information on occupation, wages, and education is not available.

consider this information objective because professionals with acknowledged expertise in the areas of occupational analysis and assessment research and development developed O*net. I construct skill mismatch measures by occupation because O*net provides information about skills based on 6-digit occupation codes. The PIAAC uses International Standard Classification of Occupations (ISCO-08) occupational classifications, while O*net classifies occupations based on the 2010 Standard Occupational Classification (SOC). Therefore, I use the crosswalk between the 2010 SOC and ISCO-08 for matching.[5] Since a few ISCO-08 occupational classifications do not appear in the SOC, I drop them from the analysis. Though O*net represents US workers, I apply the information to all countries because there are no detailed occupational data otherwise, to the best of my knowledge.

3.3. EPL Strictness

I adopt the measure of EPL from the OECD. I use the EPL indicator for regulations on individual dismissals of workers with regular contracts because it is the most relevant for workers with indefinite contracts (Gielen and Tatsiramos 2012).[6] This indicator incorporates three aspects of dismissal protection: procedural inconveniences, notice periods and severance pay, and difficulty of dismissal (OECD 2014). The indicator is measured on a 0-6 scale, with higher values representing stricter regulation. Table 1 shows the EPL indicators by country. The countries with the least strict EPL are the United Kingdom, New Zealand, and Japan; those with the strictest EPL are the Czech Republic, the Russian Federation, and the Netherlands.

3.4. Skill-Mismatch Measure

I construct the skill mismatch measure as follows:

[5] See the 2010 SOC x ISCO-08 crosswalk at http://www.bls.gov/soc/soccrosswalks.htm.
[6] For details about the methodology to create the EPL indicators, see OECD (2014).

$$skill\_mismatch_{io} = \frac{1}{2}\sum_{k}^{2} |score_{ik} - requiredskill_{ok}| \quad (5)$$

where $skill\_mismatch_{io}$ is the skill mismatch of worker i in occupation o, $score_{ik}$ is worker i's score for skill k (numeracy or literacy), and $required\_skill_{ok}$ is the required level of skill k for occupation o. I use equally weighted numeracy and literacy scores because their correlation is very high.[7]

Based on the Defense Manpower Data Center, P.T.D. (2009), Table 2 shows the list of skills from O*net that apply to the PIAAC's numeracy and literacy skills. Based on Guvenen et al. (2015) and Yamaguchi (2012), I first estimate the required skills for occupation o. I standardize each importance score from O*net to one. Second, I conduct a principal component analysis according to numeracy and literacy, sum the first principal component of each importance score, and convert the numeracy and literacy skills required in an occupation into percentile ranks among occupations. Third, I convert the PIAAC scores to percentile ranks by numeracy and literacy. I define the skill mismatch by the difference between the PIAAC score and required skill level, and the average numeracy and literacy skill mismatches, which means that I weight the numeracy and literacy skill mismatches equally. Finally, I normalize the defined skill mismatch so its standard deviation is equal to one by country.

Furthermore, to consider the asymmetric effects of a positive and negative skill mismatch, I construct two skill mismatch measures following Guvenen et al. (2015). I separate the skill mismatch measure into a positive (overskilled) and negative (underskilled) skill mismatch, defined respectively as follows:

$$positive\_skill\_mismatch_{ijo} = \Sigma_k \max[score_{ik} - required\_skillj_{ok}, 0] \quad (7)$$

[7] The correlation coefficients in each country range from 0.81-0.93.

and

$$negative\_skill\_mismatch_{ijo} = \Sigma_k \, |\min[score_{ik} - required\_skill_{jok}, 0]|. \quad (8)$$

Both variables take positive values because I take the absolute value in Eq. (8); thus, a negative coefficient indicates a wage penalty. I normalize these skill mismatch measures so their standard deviations are equal to one by country.

Because skill mismatch measures are observed with errors, the coefficients of the skill mismatch measures may suffer from attenuation biases. As such, I estimate Eq. (4) by instrumental variable estimation. The instrumental variable for *skill_mismatch* I use here is:

$$\widehat{skill\_mismatch}_{ij} = skill\_mismatch_{ij} - \widetilde{skill\_mismatch}_j \quad (6)$$

where $\widetilde{skill\_mismatch}_j$ is the average skill mismatch for workers across occupations and countries. The instrumental variables for positive- and negative- skill mismatch are:

$$\widehat{positive\_skill\_mismatch}_{ij} = positive\_skill\_mismatch_{ij} - \widetilde{positive\_skill\_mismatch}_j \quad (7)$$

and

$$\widehat{negative\_skill\_mismatch}_{ij} = negative\_skill\_mismatch_{ij} - \widetilde{negative\_skill\_mismatch}_j, \quad (8)$$

where $\widetilde{positive\_skill\_mismatch}_j$ and $\widetilde{negative\_skill\_mismatch}_j$ are the average positive and negative skill mismatches for workers across occupations and countries, respectively.

3.5. Data

I select male workers employed full time with permanent contracts to concentrate on people who are highly attached to the labor force. I define wage as purchasing power parity-corrected hourly earnings (including bonuses) denominated in US dollars to account for cross-national differences. I exclude the top and bottom 1% to avoid outliers in the wage distribution. Tenure is the number of years working for the same employer and experience is the number of years of paid work during a lifetime.

Table 3 shows the descriptive statistics. The average values of skill mismatch range between 1.3 – 1.6, with the Netherlands and Greece representing the highest and lowest values in the range, respectively. Most countries have a higher mean positive skill mismatch than negative skill mismatch, except Chile and Israel, meaning that firms in these countries are not likely to fully utilize workers' skills. Norway has the highest mean value of positive skill mismatch, at 1.16, while Chile has the lowest, at 0.55. The mean values of negative skill mismatch in Chile and Israel are the highest, at 0.86 and 0.79, respectively, indicating that many workers in these countries lack the skills to perform their jobs. The mean value of negative skill mismatch in the Czech Republic is the lowest, at 0.34. The average PIAAC scores by country are around 45-59, with Chile and the Netherlands representing the lowest and highest scores, respectively. The average years of tenure are 11 years, with the longest in Slovenia and the shortest in Russian Federation. The Appendix describes the sample selection by country.

Figure 1 shows the relationship between the residuals of log wages and skill mismatch measures by country. I obtain the residuals of log wages by regressing log wages on the PIAAC score, experience, experience squared, tenure, tenure squared, and dummy variables for industries, occupation, education, immigrants. The graphs show that a skill mismatch has a slightly negative relationship with wages, except for Chile. Therefore, the skill mismatch may

have a small negative impact on wages. In Chile, skill mismatched workers seem to enjoy a wage premium.

IV. EMPIRICAL RESULTS

Table 4 presents the results for the logarithm of hourly wages. The OLS estimators tend to be smaller than the instrumental variable estimators in most countries are, but the difference between the magnitudes of the OLS estimator and those of the instrumental variable estimators is small. Thus, the biases due to measurement errors are not serious.

In the IV results, the coefficient of skill mismatch is negative and largest in the Russian Federation, which indicates that a one-standard deviation increase in skill mismatch lowers wages by about 12%. The coefficient of skill mismatch is negative and the second largest in Lithuania, Greece, the Czech Republic, New Zealand, and the Netherlands, which indicates that a one-standard deviation increase in skill mismatch lowers wages by about 3-5%. For Belgium, Denmark, France, Italy, Japan, Norway, Poland, Slovenia, and Spain, the coefficients of skill mismatch range from about 0.003 to about 0.04, are negative and small, and statistically insignificant due to the small coefficients. In contrast, the coefficient for Chile is positive and statistically significant, indicating that a one-standard deviation in skill mismatch increases wages by about 6%, which means that skill mismatched workers in Chile enjoy a wage premium. For Israel, Korea, the Slovak Republic, and the United Kingdom, the coefficients of skill mismatch range from 0.05 to 0.02, are positive and small, and statistically insignificant. To clarify the differences in the impacts of a skill mismatch on wages, Figure 2 shows the relationship between the coefficients of skill mismatch and the EPL indicator. The figure shows a slightly negative relationship between the impact of a skill mismatch and the EPL indicator, suggesting that under strict EPL, skill mismatched workers are likely to suffer a serious wage

penalty.[8]

Table 5 presents the results of the impact of positive and negative skill mismatches on the logarithm of hourly wages. The OLS estimators tend to be smaller than the instrumental variable estimators in most countries are.

From the IV analysis, the coefficients of positive skill mismatch are the largest in absolute values in the Russian Federation. The coefficient for the Russian Federation is negative and significant, which implies that a one-standard deviation increase in positive skill mismatch lowers wages by 14%. The coefficients for the Czech Republic, France, the Netherlands, New Zealand, Slovenia, and Spain are negative and statistically significant. For these countries, the effect ranges from -0.02 to -0.06, which means that a one-standard deviation increase in skill mismatch lower wages by about 2 – 6%. For Belgium, Chile, Greece, Israel, Lithuania, Poland, and the United Kingdom, the effects are negative and statistically insignificant. For Denmark, Italy, Japan, Korea, Norway, and the Slovak Republic, the effect is positive and statistically insignificant. Figure 3 shows the relationship between the impact of a positive skill mismatch and the EPL indicator. The graph suggests that positive skill mismatched workers are likely to suffer serious wage penalties as the EPL becomes stricter.

Recall that a negative skill mismatch is a positive number; thus, the negative coefficient implies that an increase in negative skill mismatch lowers wages. For Greece and Japan, the coefficients are -0.06 and -0.09, respectively, and statistically significant, meaning that negative skill mismatched workers in these countries suffer a wage penalty of 6-9%. For Belgium, the Czech Republic, Denmark, Italy, Lithuania, the Netherlands, New Zealand, Norway, Poland, the Russian Federation, and the Slovak Republic, the coefficients are negative, but statistically insignificant. For Chile and Slovenia, the coefficients are 0.14 and 0.06, and statistically significant, indicating that negative skill mismatched workers in these countries

[8] Note that this relationship should not be interpreted as a causal effect of the EPL indicator.

enjoy a wage premium of 6-14%. The coefficients in France, Israel, Korea, Spain, and the United Kingdom are positive and statistically insignificant. Figure 4 shows the relationship between the impact of a negative skill mismatch and the EPL indicator. The figure demonstrates the slightly negative relationship and suggests that a negative skill mismatch does not correlate with the EPL indicator because negative skill mismatched workers may suffer a wage penalty or enjoy a wage premium due to the frictional labor market.

In summary, the results show that workers in most countries do not suffer a wage penalty, which differs from results reported in prior studies. However, skill mismatched workers in a few countries, such as the Czech Republic, Greece, the Netherlands, New Zealand, and the Russian Federation, suffer a wage penalty, while skill mismatched workers in Chile enjoy higher wages than well-matched workers do. When I decompose the skill mismatch measure into positive and negative skill mismatch, positive skill mismatched workers suffer a serious wage penalty. Negative skill mismatched workers in Greece and Japan suffer from wage penalty, while those in Chile and Slovenia enjoy a wage premium, implying that negative skill mismatched workers remain with their employers because the firms would not fire them due high firing costs. Furthermore, I find a negative relationship between the effects of a skill mismatch and a positive skill mismatch on wages and the EPL level. This finding suggests that in countries with high EPL, positive skill mismatched workers are likely to suffer a wage penalty. However, the effects of a negative skill mismatch on wages do not seem to have any relationship because this mismatch has both positive and negative effects on wages. Hence, if policymakers decide to impose strict EPL to protect employees, it is possible that the legislation will prevent the efficient allocation of skill mismatched workers.

V. CONCLUSION

I investigate the extend of the cross-national variation in the relationship between wages and skill mismatch by EPL strictness. According to the theory of matching quality, workers and firms cannot fully observe workers' skills due to imperfect information, so a skill mismatch emerges at the time of hiring. They eventually learn about the skill over time. In labor markets with less friction, workers change their jobs. However, in labor markets with more friction, workers have difficulty finding better jobs and firms pay high firing costs. These frictions make workers stay in their current jobs, and workers cannot eliminate the skill mismatch. Thus, a skill mismatch would be a source of labor market inefficiency, so skill mismatched workers are likely to suffer a wage penalty due to low productivity or to enjoy a higher wage premium than well-matched workers are.

Estimating a wage equation, I find that skill mismatch has no impact on wages in most countries. In the Czech Republic, Greece, the Netherlands, New Zealand, and the Russian Federation, a skill mismatch has a negative impact on wages, and the magnitude of the impact increases as EPL becomes stricter. The exception is that skill mismatched workers in Chile enjoy a wage premium. When I decompose the skill mismatch measure into positive and negative skill mismatched, I find that positive skill mismatched workers are likely to suffer a wage penalty, and its magnitude is larger as EPL becomes stricter. However, negative skill mismatched workers in Chile and Slovenia are likely to enjoy wage premium, and those in Greece and Japan are likely to suffer a wage penalty. There is no relationship between the impact of negative skill mismatch on wages and EPL strictness.

However, this study does not answer some remaining questions. It does not clarify the causal relationship between EPL strictness and the impact of a skill mismatch on wages due to lack of sufficient variation. Thus, further work is needed to understand the extent that EPL prevents efficient labor market allocation.

REFERENCES

Allen, J., Levels, M., and Van Der Velden, R. "Skill Mismatch and Skill Use in Developed Countries: Evidence from the PIAAC Study." *ROA Research Memoranda* 017, 2013.

Bassanini, A., and Garnero, A. "Dismissal Protection and Worker Flows in OECD Countries: Evidence from Cross-Country/Cross-Industry Data." *Labour Economics*, 21, 2013, 25–41. https://doi.org/10.1016/j.labeco.2012.12.003

Boeri, T., Van Ours, J., 2008. The Economics of Imperfect labour market. Princeton University Press.

Defense Manpower Data Center, P.T.D. "ASVAB Technical Bulletin No. 2 CAT-ASVAB Forms 3 and 4," 2009.

Fredriksson, P., Hensvik, L., and Skans, O. N. "Mismatch of Talent: Evidence on Match Quality, Entry Wages and Job Mobility." *Instigute for Evaluation of Labour Market and Education Policy,* Working Paper, 2015.

Gielen, A. C., and Tatsiramos, K. "Quit Behavior and the Role of Job Protection." *Labour Economics*, 19(4), 2012, 624–632. https://doi.org/10.1016/j.labeco.2012.05.002

Gómez-Salvador, R., Messina, J., and Vallanti, G. 2004. "Gross Job Flows and Institutions in Europe." *Labour Economics*, 11(4), 469–485. https://doi.org/10.1016/j.labeco.2004.02.006

Guvenen, F., Kuruşçu, B., Tanaka, S., and Wiczer, D. "Multidimensional Skill Mismatch." *National Bureau of Economic Research*, Working Paper No. 21376, 2015. https://doi.org/10.1017/CBO9781107415324.004

Jackson, C. K. "Match Quality, Worker Productivity, and Worker Mobility: Direct Evidence from Teachers." *Review of Economics and Statistics,* 95(4), 2013, 1096–1116. https://doi.org/10.1162/REST_a_00339

Jovanovic, B. “Job Matching and the Theory of Turnover.” *Journal of Political Economy*, 87(5), 1979, 972–990.

Levels, M., Van Der Veldeny, R., and Alleny, J. “Educational Mismatches and Skills: New Empirical Tests of Old Hypotheses.” *Oxford Economic Papers*, 66(4), 2014, 959–982. https://doi.org/10.1093/oep/gpu024

Mcgowan, M. A., and Andrews, D. “Skill Mismatch and Public Policy in OECD Countries.” OECD Economics Department Working Papers 1210, 2015. https://doi.org/10.1787/5js1pzw9lnwk-en

Mincer, J., and Jovanovic, B. “Labor mobility and wages.” *National Bureau of Economic Research*, Working Paper No 357, 1979.

Mortensen, D. T. “Specific Capital and Labor Turnover.” *The Bell Journal of Economics*, 9(2), 1978, 572–586. https://doi.org/10.2307/3003599

Nelson, P. “Information and Consumer Behavior.” *Journal of Political Economy*, 78(2), 1970, 311–329.

OECD. “Protecting Jobs, Enhancing Flexibility: A New Look at Employment Protection Legislation,” in *OECD Employment Outlook 2013*, 2013, 65–126. https://doi.org/10.1787/empl_outlook-2013-6-en

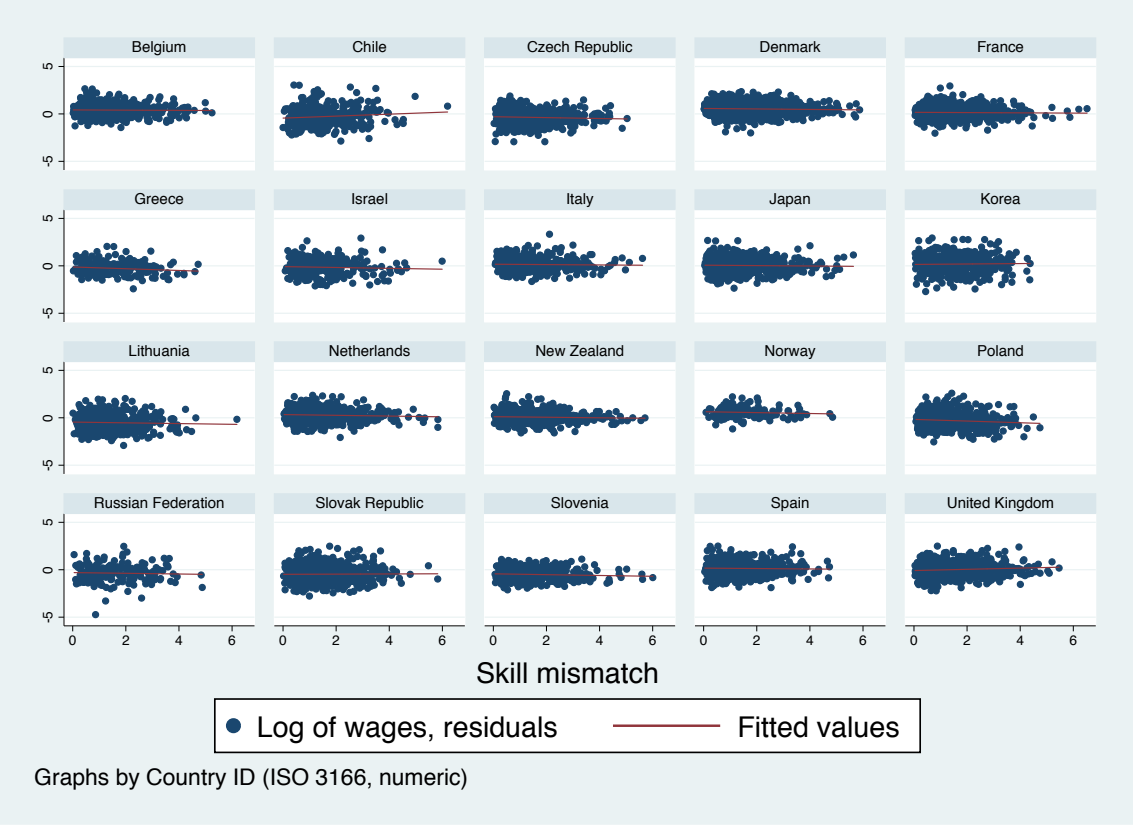
OECD. “Calculating Summary Indicators of Epl Strictness: Methodology.”, 2014.

OECD. “Skills Matter. Further Results from the Survey of Adult Skills.” *OECD Skills Studies*, 2016. https://doi.org/10.1787/23078731

Woodcock, S. D. “Match effects.” *Research in Economics*, 69(1), 2015, 100-121 . https://doi.org/10.1016/j.rie.2014.12.001

Yamaguchi, S. “Tasks and Heterogeneous Human Capital.” *Journal of Labor Economics*, 30(1), 2012, 1–53. https://doi.org/10.1086/662066

Figure 1: Relationship between hourly wages and skill mismatches



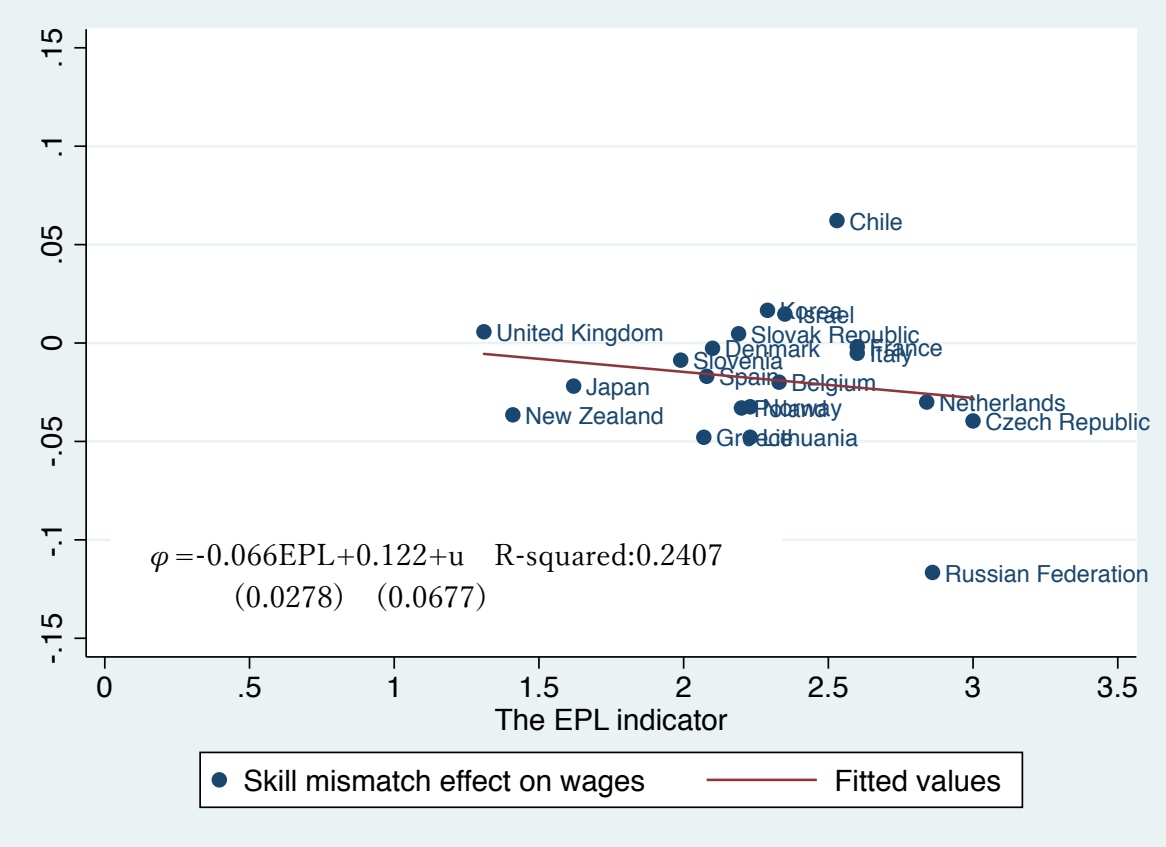
Source: PIAAC and O*net

Notes: Hourly wages denominated in U.S. Dollars. Male regular workers only.

Residuals of log wages obtained by regressing log wages on PIAAC score, experience, experience squared, tenure, tenure squared, and dummy variables for industry, occupation, education, and immigrant.

The top and bottom 1% of the hourly wages are dropped.

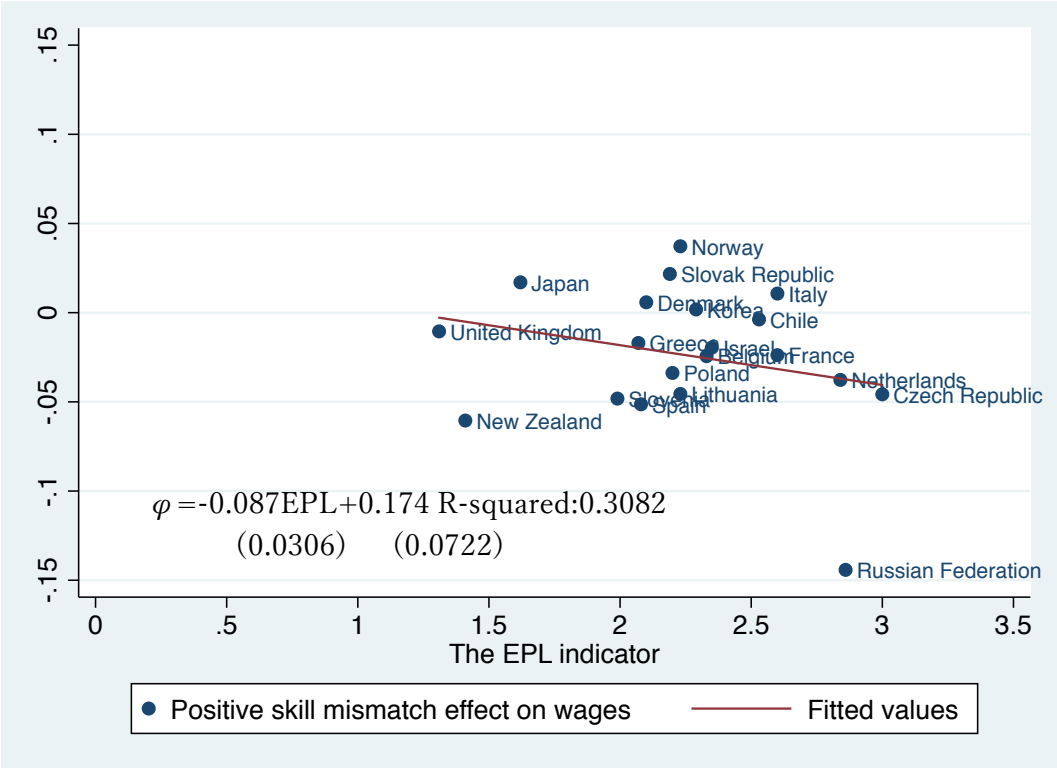
Figure 2: Effect of skill mismatch on wages by EPL indicator



Source: PIAAC, O*net, and OECD

Note: The regression is weighted by the inverse of the variance of the point estimates. Standard errors are in parentheses.

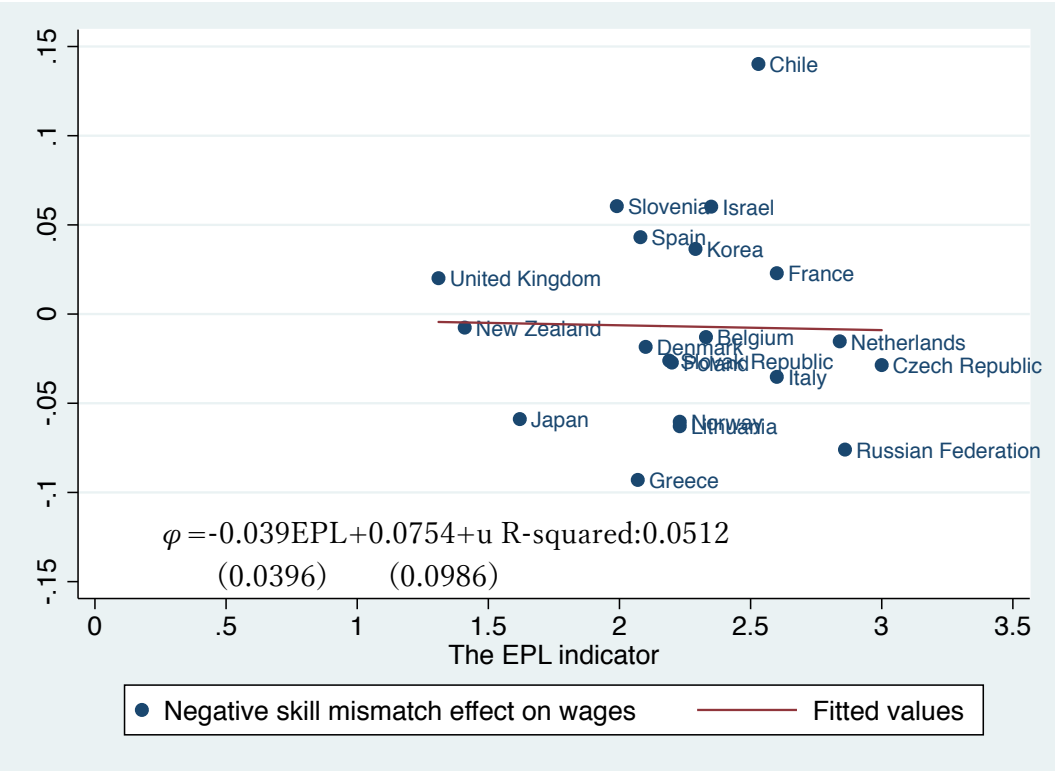
Figure 3: Effect of positive skill mismatch on wages by EPL indicator



Source: PIAAC, O*net and OECD

Note: The regression is weighted by the inverse of the variance of the point estimates. Standard errors are in parentheses.

Figure 4: Effect of positive-skill mismatch on wages by EPL indicator



Source: PIAAC, O*net, and OECD

Note: The regression is weighted by the inverse of the variance of the point estimates. Standard errors are in parentheses.

Table 1: EPL indicators by country

Belgium	2.33
Chile	2.53
Czech Republic	3.00
Denmark	2.10
France	2.60
Greece	2.07
Israel	2.35
Italy	2.60
Japan	1.62
Korea	2.29
Lithuania	2.23
Netherlands	2.84
New Zealand	1.41
Norway	2.23
Poland	2.20
Russian Federation	2.86
Slovak Republic	2.19
Slovenia	1.99
Spain	2.08
United Kingdom	1.31

Source: OECD

Note: Indicators for PIAAC Round 2 countries (Chile, Greece, Israel, Lithuania, New Zealand, and Slovenia) are for 2014, and others are for 2011.

Table 2: List of skills

Literacy composite	
Inductive Reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
Written Comprehension	The ability to read and understand information and ideas presented in writing.
Oral Comprehension	The ability to listen and understand information and ideas presented through spoken words and sentences.
Reading Comprehension	Understanding written sentences and paragraphs in work-related documents.
English Language	Knowledge of the structure and content of the English language including the meaning and spelling of words, rules of composition, and grammar
Math Composite	
Deductive Reasoning	The ability to apply general rules to specific problems to produce answers that make sense.
Inductive Reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
Written Comprehension	The ability to read and understand information and ideas presented in writing.
Number Facility	The ability to add, subtract, multiply, or divide quickly and correctly.
Mathematical Reasoning	The ability to choose the right mathematical methods of formulas to solve a problem.
Information Ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).
Mathematics skill	Using mathematics to solve problems.

Source: Defense Manpower Data Center (2009)

Table 3: Descriptive statistics

	Belgium		Chile		Czech Republic		Denmark	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Log hourly earnings including bonuses	3.0596	0.3524	2.2077	0.6280	2.1854	0.3840	3.2103	0.3281
Skil mismatch	1.3927	0.9208	1.4675	0.9822	1.5407	1.0241	1.4486	0.9922
Positive skill mismatch	0.8936	0.9372	0.5500	0.9082	1.1192	1.0157	0.9246	1.0133
Negative skill mismatch	0.4901	0.8351	0.8617	0.9823	0.3421	0.6653	0.4760	0.8050
Average skill score	56.8047	8.8522	44.8164	9.5456	56.4255	7.1779	56.6389	8.7161
Tenure	12.4424	9.6555	11.6212	8.3303	9.8030	7.5147	9.4942	8.5709
Experience	23.0724	10.5075	22.3105	11.6974	21.8645	10.7307	24.5254	11.6070
Number of observations	771		363		631		1,535	
	France		Greece		Israel		Italy	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Log hourly earnings including bonuses	2.7600	0.3544	2.3878	0.4418	2.6930	0.5926	2.7652	0.4295
Skil mismatch	1.4359	0.9391	1.6451	1.0986	1.4316	0.9606	1.5500	1.0158
Positive skill mismatch	0.7463	0.9412	0.9652	1.0852	0.6153	1.0050	1.0130	1.0765
Negative skill mismatch	0.6973	0.9771	0.6332	1.0653	0.7932	0.9074	0.4772	0.8200
Average skill score	52.9721	9.3709	52.0470	8.5475	55.1417	9.7264	51.5991	8.9014
Tenure	12.3304	9.6243	12.3690	6.8489	11.8337	8.2359	12.7441	8.6837
Experience	22.5004	11.1873	21.5430	8.6703	22.7493	11.3382	22.0721	10.0423
Number of observations	1,111		187		338		424	
	Japan		Korea		Lithuania		Netherlands	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Log hourly earnings including bonuses	2.7477	0.5036	2.8566	0.5474	1.9668	0.5116	3.1254	0.4024
Skil mismatch	1.4122	1.0310	1.5121	0.8990	1.4630	0.9383	1.2730	0.9351
Positive skill mismatch	1.0493	1.0300	0.8919	0.9181	0.9593	0.9448	0.7648	0.9231
Negative skill mismatch	0.4781	0.9854	0.6332	1.0032	0.4090	0.7458	0.5869	0.9114
Average skill score	58.9024	7.7908	55.5221	6.9518	53.5526	8.2698	58.9999	8.3245
Tenure	11.7707	9.2486	8.4150	7.4995	11.0526	7.0630	11.7763	8.8948
Experience	23.0380	11.7234	16.6576	9.3979	23.9177	9.7087	23.1841	11.1140
Number of observations	664		588		490		868	
	New Zealand		Norway		Poland		Russian Federation	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Log hourly earnings including bonuses	2.9393	0.4005	3.2173	0.3391	2.2198	0.4874	1.4634	0.6890
Skil mismatch	1.3221	0.9457	1.5476	0.9757	1.4237	0.8778	1.5853	1.0859
Positive skill mismatch	0.7052	0.9381	1.1552	0.9985	0.8753	0.8807	1.0685	1.1107
Negative skill mismatch	0.7014	0.9965	0.4397	0.9624	0.5778	1.0169	0.4143	0.7656
Average skill score	56.3518	9.7995	55.0025	8.6871	53.8727	8.3309	55.6493	7.3386
Tenure	10.8411	8.0501	9.9041	7.8120	10.9694	8.3823	7.1650	5.6875
Experience	22.6004	12.6516	22.5849	11.3962	20.7164	11.0936	20.2188	11.1100
Number of observations	669		143		503		183	
	Slovak Republic		Slovenia		Spain		United Kingdom	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Log hourly earnings including bonuses	2.1239	0.4956	2.1388	0.3780	2.6971	0.4521	2.9182	0.4760
Skil mismatch	1.5164	0.9442	1.4660	0.9923	1.3818	0.9329	1.4658	0.9840
Positive skill mismatch	1.0189	0.9275	0.8317	1.0153	0.7959	0.9660	0.8806	0.9914
Negative skill mismatch	0.4371	0.8690	0.5746	0.8481	0.5566	0.8244	0.5798	0.9658
Average skill score	56.2735	6.9746	50.5737	9.1813	53.1054	8.7881	56.3609	8.9621
Tenure	10.0923	7.3397	13.3999	7.9323	12.2939	8.5074	9.7482	8.0753
Experience	22.5777	10.5522	23.4191	9.4383	22.3286	10.5542	23.3752	11.9839
Number of observations	646		448		614		915	

Source: PIAAC and O*net

Note: See 2.2 for the definition of skill mismatch.

Male regular workers only.

Table 4: Wage regression with skill mismatch

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Belgium		Chile		Czech Republic		Denmark		France	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Skill mismatch	-0.0193	-0.0199	0.0623**	0.0622**	-0.0336*	-0.0396**	-0.0073	-0.0027	0.0001	-0.0019
	(0.0129)	(0.0132)	(0.0315)	(0.0312)	(0.0176)	(0.0186)	(0.0077)	(0.0080)	(0.0083)	(0.0086)
PIAAC score (Average)	0.0053***	0.0053***	0.0143***	0.0143***	0.0032	0.0036	0.0044***	0.0042***	0.0055***	0.0055***
	(0.0017)	(0.0017)	(0.0048)	(0.0045)	(0.0032)	(0.0031)	(0.0010)	(0.0010)	(0.0012)	(0.0012)
Tenure	0.0077*	0.0077**	-0.0171	-0.0171	0.0181***	0.0179***	0.0050**	0.0050**	0.0051	0.0051*
	(0.0040)	(0.0039)	(0.0139)	(0.0130)	(0.0068)	(0.0066)	(0.0025)	(0.0025)	(0.0031)	(0.0030)
Tenure squared*1/1000	-0.0505	-0.0506	0.7501**	0.7502**	-0.3815**	-0.3773**	-0.0784	-0.0796	-0.0184	-0.0181
	(0.1121)	(0.1084)	(0.3774)	(0.3530)	(0.1931)	(0.1855)	(0.0672)	(0.0661)	(0.0832)	(0.0812)
Experience	0.0203***	0.0203***	0.0020	0.0020	-0.0044	-0.0043	0.0231***	0.0231***	0.0170***	0.0170***
	(0.0046)	(0.0045)	(0.0119)	(0.0111)	(0.0065)	(0.0062)	(0.0032)	(0.0032)	(0.0035)	(0.0034)
Experience squared	-0.0003***	-0.0003***	-0.0000	-0.0000	0.0000	0.0000	-0.0003***	-0.0003***	-0.0002***	-0.0002***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	2.3879***	2.0280***	1.6693***	1.1579***	1.0293***	1.7593***	2.7659***	2.6111***	1.7053***	1.6543***
	(0.1211)	(0.1438)	(0.4961)	(0.2854)	(0.2596)	(0.2210)	(0.1363)	(0.0940)	(0.1356)	(0.1196)
R-squared	0.4579	0.4578	0.5419	0.5419	0.4459	0.4457	0.4609	0.4607	0.4992	0.4992
Observations	771		363		631		1,535		1,111	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Greece		Israel		Italy		Japan		Korea	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Skill mismatch	-0.0687**	-0.0479*	0.0086	0.0147	-0.0118	-0.0052	-0.0250	-0.0219	0.0073	0.0166
	(0.0302)	(0.0264)	(0.0311)	(0.0294)	(0.0227)	(0.0228)	(0.0218)	(0.0228)	(0.0247)	(0.0253)
PIAAC score (Average)	-0.0018	-0.0019	0.0124***	0.0125***	0.0051	0.0049	0.0089***	0.0087***	0.0095***	0.0092***
	(0.0054)	(0.0047)	(0.0031)	(0.0029)	(0.0032)	(0.0030)	(0.0032)	(0.0031)	(0.0035)	(0.0034)
Tenure	-0.0028	-0.0008	0.0039	0.0040	-0.0067	-0.0067	0.0281***	0.0282***	0.0177*	0.0177**
	(0.0223)	(0.0189)	(0.0152)	(0.0142)	(0.0086)	(0.0081)	(0.0074)	(0.0071)	(0.0093)	(0.0089)
Tenure squared*1/1000	-0.0198	-0.0780	0.0848	0.0818	0.3289	0.3309	-0.3811*	-0.3830*	-0.0078	-0.0088
	(0.6570)	(0.5518)	(0.3905)	(0.3630)	(0.2288)	(0.2155)	(0.2032)	(0.1962)	(0.3231)	(0.3100)
Experience	0.0474*	0.0457**	0.0373**	0.0374***	0.0201*	0.0202*	0.0171***	0.0170***	0.0252***	0.0252***
	(0.0268)	(0.0233)	(0.0150)	(0.0140)	(0.0121)	(0.0113)	(0.0064)	(0.0062)	(0.0097)	(0.0093)
Experience squared	-0.0007	-0.0007	-0.0006**	-0.0006**	-0.0003	-0.0003	-0.0003**	-0.0003**	-0.0005*	-0.0005**
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Constant	1.7709***	2.0765***	1.0154***	1.0032***	2.3772***	2.2614***	2.4749***	2.5477***	1.5268***	1.4212***
	(0.4476)	(0.3975)	(0.3740)	(0.3459)	(0.4486)	(0.3885)	(0.2873)	(0.2832)	(0.3029)	(0.2645)
R-squared	0.4713	0.4693	0.5116	0.5115	0.4259	0.4257	0.4562	0.4562	0.3838	0.3836
Observations	187		338		424		664		588	

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
	Lithuania		Netherlands		New Zealand		Norway		Poland	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Skill mismatch	-0.0650**	-0.0479*	-0.0340**	-0.0300**	-0.0351**	-0.0365**	-0.0299	-0.0324	-0.0221	-0.0330
	(0.0263)	(0.0263)	(0.0137)	(0.0144)	(0.0141)	(0.0143)	(0.0341)	(0.0288)	(0.0251)	(0.0254)
PIAAC score (Average)	0.0116***	0.0107***	0.0066***	0.0065***	0.0082***	0.0082***	0.0034	0.0036	0.0063*	0.0066**
	(0.0037)	(0.0036)	(0.0018)	(0.0018)	(0.0018)	(0.0017)	(0.0040)	(0.0034)	(0.0033)	(0.0032)
Tenure	-0.0049	-0.0043	-0.0010	-0.0010	-0.0009	-0.0009	0.0175	0.0174	0.0075	0.0077
	(0.0109)	(0.0104)	(0.0043)	(0.0042)	(0.0052)	(0.0050)	(0.0133)	(0.0111)	(0.0102)	(0.0097)
Tenure squared*1/1000	0.2205	0.2055	0.1096	0.1108	0.1333	0.1336	-0.4219	-0.4210	-0.0911	-0.0962
	(0.2931)	(0.2787)	(0.1087)	(0.1058)	(0.1244)	(0.1198)	(0.4142)	(0.3463)	(0.2764)	(0.2634)
Experience	-0.0026	-0.0035	0.0199***	0.0199***	0.0209***	0.0209***	0.0031	0.0031	0.0099	0.0097
	(0.0109)	(0.0104)	(0.0048)	(0.0047)	(0.0051)	(0.0049)	(0.0128)	(0.0107)	(0.0091)	(0.0087)
Experience squared	-0.0001	-0.0000	-0.0002**	-0.0002**	-0.0003***	-0.0003***	-0.0000	-0.0000	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Constant	3.1993***	2.7690***	1.8466***	2.0610***	1.7777***	2.0518***	3.4379***	2.6321***	0.9770*	1.0066*
	(0.5421)	(0.3439)	(0.2148)	(0.2306)	(0.1287)	(0.1548)	(0.4229)	(0.2364)	(0.5519)	(0.5254)
R-squared	0.3872	0.3865	0.5014	0.5013	0.5210	0.5210	0.5533	0.5533	0.4428	0.4425
Observations	490		868		669		143		503	
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
	Russian Federation		Slovak Republic		Slovenia		Spain		United Kingdom	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Skill mismatch	-0.1044*	-0.1166**	0.0171	0.0047	-0.0123	-0.0087	-0.0082	-0.0169	0.0026	0.0057
	(0.0598)	(0.0562)	(0.0212)	(0.0219)	(0.0149)	(0.0150)	(0.0186)	(0.0194)	(0.0166)	(0.0169)
PIAAC score (Average)	0.0154*	0.0159*	0.0147***	0.0155***	0.0070***	0.0069***	0.0063**	0.0064***	0.0087***	0.0087***
	(0.0093)	(0.0081)	(0.0033)	(0.0033)	(0.0021)	(0.0020)	(0.0026)	(0.0025)	(0.0020)	(0.0020)
Tenure	0.0608**	0.0607***	0.0078	0.0079	0.0136	0.0135*	0.0112*	0.0113*	0.0033	0.0033
	(0.0260)	(0.0228)	(0.0090)	(0.0087)	(0.0086)	(0.0081)	(0.0067)	(0.0064)	(0.0065)	(0.0063)
Tenure squared*1/1000	-0.9002	-0.8772	-0.1987	-0.2020	-0.1731	-0.1697	0.0252	0.0206	0.0700	0.0690
	(0.8612)	(0.7560)	(0.2480)	(0.2383)	(0.2359)	(0.2239)	(0.1810)	(0.1726)	(0.1812)	(0.1764)
Experience	-0.0300	-0.0293	0.0054	0.0054	0.0016	0.0018	0.0110*	0.0109*	0.0346***	0.0346***
	(0.0243)	(0.0212)	(0.0082)	(0.0079)	(0.0094)	(0.0089)	(0.0062)	(0.0060)	(0.0053)	(0.0052)
Experience squared	0.0001	0.0001	-0.0002	-0.0002	-0.0000	-0.0000	-0.0002	-0.0002	-0.0006***	-0.0006***
	(0.0005)	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	0.6036	1.4457**	0.4619	1.2287***	2.2675***	2.0228***	1.9257***	1.4725***	1.5805***	1.4368***
	(0.9563)	(0.6043)	(0.3642)	(0.3575)	(0.2938)	(0.2700)	(0.1999)	(0.1760)	(0.1877)	(0.1728)
R-squared	0.4502	0.4500	0.3485	0.3481	0.4221	0.4221	0.5093	0.5091	0.5723	0.5723
Observations	183		646		448		614		915	

Notes: All estimates are weighted by sampling weights.

The dependent variable is the log of monthly wages including bonuses.

All regressions include dummy variables for industry, occupation, number of employees, education, and immigrants.

Robust standard errors are in parentheses.

***p<0.01, ** p < 0.05, * p < 0.1.

Table 5: Wage regression with positive and negative skill mismatch

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Belgium		Chile		Czech Republic		Denmark		France	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Positive skill mismatch	-0.0226	-0.0244	0.0222	-0.0038	-0.0469**	-0.0458**	-0.0088	0.0058	-0.0107	-0.0238*
	(0.0162)	(0.0172)	(0.0437)	(0.0413)	(0.0213)	(0.0225)	(0.0103)	(0.0111)	(0.0116)	(0.0130)
Negative skill mismatch	-0.0138	-0.0129	0.1061**	0.1402***	0.0054	-0.0286	-0.0052	-0.0184	0.0142	0.0229
	(0.0173)	(0.0176)	(0.0468)	(0.0499)	(0.0347)	(0.0410)	(0.0134)	(0.0151)	(0.0141)	(0.0141)
PIAAC score (Average)	0.0054***	0.0056***	0.0189***	0.0230***	0.0054	0.0036	0.0045***	0.0028*	0.0072***	0.0086***
	(0.0021)	(0.0021)	(0.0066)	(0.0064)	(0.0039)	(0.0039)	(0.0014)	(0.0015)	(0.0017)	(0.0018)
Tenure	0.0077*	0.0077**	-0.0162	-0.0154	0.0180***	0.0179***	0.0050**	0.0051**	0.0051	0.0051*
	(0.0040)	(0.0039)	(0.0140)	(0.0131)	(0.0068)	(0.0066)	(0.0025)	(0.0025)	(0.0031)	(0.0030)
Tenure squared*1/1000	-0.0508	-0.0514	0.7246*	0.7021**	-0.3741*	-0.3774**	-0.0783	-0.0804	-0.0222	-0.0246
	(0.1118)	(0.1080)	(0.3794)	(0.3540)	(0.1925)	(0.1847)	(0.0672)	(0.0661)	(0.0832)	(0.0813)
Experience	0.0202***	0.0202***	0.0011	0.0003	-0.0042	-0.0043	0.0231***	0.0231***	0.0169***	0.0168***
	(0.0047)	(0.0045)	(0.0120)	(0.0114)	(0.0064)	(0.0062)	(0.0032)	(0.0032)	(0.0035)	(0.0034)
Experience squared	-0.0003***	-0.0003***	0.0000	0.0000	0.0000	0.0000	-0.0003***	-0.0003***	-0.0002***	-0.0002***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	2.5730***	2.0218***	-0.0101	0.9599***	2.0710***	1.7599***	2.9385***	2.6776***	1.8763***	1.5325***
	(0.1491)	(0.1482)	(0.4167)	(0.2954)	(0.3233)	(0.2470)	(0.1563)	(0.1081)	(0.1552)	(0.1340)
R-squared	0.4579	0.4578	0.5438	0.5424	0.447	0.4457	0.4609	0.4597	0.5	0.4994
Observations	771		363		631		1,535		1,111	
ard errors in parentheses	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
* p<0.05, * p<0.1	Greece		Israel		Italy		Japan		Korea	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Positive skill mismatch	-0.0563	-0.0170	-0.0108	-0.0196	-0.0054	0.0107	-0.0254	0.0170	-0.0060	0.0018
	(0.0415)	(0.0375)	(0.0375)	(0.0407)	(0.0280)	(0.0295)	(0.0290)	(0.0320)	(0.0334)	(0.0378)
Negative skill mismatch	-0.0908*	-0.0930**	0.0338	0.0602	-0.0281	-0.0352	-0.0156	-0.0589**	0.0246	0.0365
	(0.0494)	(0.0461)	(0.0541)	(0.0559)	(0.0425)	(0.0441)	(0.0268)	(0.0296)	(0.0346)	(0.0343)
PIAAC score (Average)	-0.0045	-0.0073	0.0153***	0.0177***	0.0034	0.0018	0.0084*	0.0024	0.0120**	0.0123**
	(0.0068)	(0.0064)	(0.0052)	(0.0057)	(0.0044)	(0.0046)	(0.0044)	(0.0047)	(0.0049)	(0.0052)
Tenure	-0.0007	0.0036	0.0047	0.0055	-0.0072	-0.0075	0.0281***	0.0285***	0.0174*	0.0173*
	(0.0223)	(0.0192)	(0.0151)	(0.0141)	(0.0090)	(0.0085)	(0.0074)	(0.0071)	(0.0093)	(0.0089)
Tenure squared*1/1000	-0.0817	-0.2068	0.0550	0.0281	0.3481	0.3675	-0.3812*	-0.3865**	0.0061	0.0086
	(0.6604)	(0.5674)	(0.3889)	(0.3633)	(0.2427)	(0.2310)	(0.2032)	(0.1956)	(0.3267)	(0.3131)
Experience	0.0456*	0.0420*	0.0374**	0.0375***	0.0207*	0.0214*	0.0171***	0.0168***	0.0248**	0.0247***
	(0.0265)	(0.0233)	(0.0150)	(0.0139)	(0.0122)	(0.0114)	(0.0064)	(0.0062)	(0.0098)	(0.0095)
Experience squared	-0.0007	-0.0006	-0.0006**	-0.0006**	-0.0003	-0.0003	-0.0003**	-0.0003**	-0.0004*	-0.0004**
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Constant	2.9449***	2.2816***	0.9111**	0.8158**	2.9425***	2.3471***	2.6934***	2.8528***	1.0647***	1.3335***
	(0.5975)	(0.4353)	(0.3973)	(0.3832)	(0.4974)	(0.4053)	(0.3362)	(0.3253)	(0.3499)	(0.2843)
R-squared	0.4726	0.469	0.5124	0.5118	0.4265	0.4257	0.4562	0.4518	0.3844	0.3842
Observations	187		338		424		664		588	

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
	Lithuania		Netherlands		New Zealand		Norway		Poland	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Positive skill mismatch	-0.0562	-0.0456	-0.0414**	-0.0377**	-0.0415**	-0.0605***	0.0288	0.0372	-0.0179	-0.0338
	(0.0369)	(0.0385)	(0.0176)	(0.0187)	(0.0203)	(0.0211)	(0.0835)	(0.0702)	(0.0336)	(0.0350)
Negative skill mismatch	-0.0946**	-0.0629	-0.0189	-0.0153	-0.0244	-0.0076	-0.0605	-0.0604	-0.0229	-0.0272
	(0.0417)	(0.0475)	(0.0176)	(0.0202)	(0.0176)	(0.0176)	(0.0471)	(0.0377)	(0.0280)	(0.0275)
PIAAC score (Average)	0.0084	0.0090*	0.0070***	0.0071***	0.0084***	0.0107***	-0.0044	-0.0051	0.0054	0.0061
	(0.0052)	(0.0054)	(0.0022)	(0.0024)	(0.0025)	(0.0023)	(0.0093)	(0.0077)	(0.0045)	(0.0044)
Tenure	-0.0053	-0.0046	-0.0010	-0.0010	-0.0008	-0.0004	0.0159	0.0159	0.0075	0.0076
	(0.0109)	(0.0104)	(0.0043)	(0.0042)	(0.0052)	(0.0050)	(0.0136)	(0.0113)	(0.0102)	(0.0097)
Tenure squared*1/1000	0.2499	0.2223	0.1090	0.1099	0.1324	0.1199	-0.3970	-0.3972	-0.0895	-0.0952
	(0.2923)	(0.2796)	(0.1089)	(0.1058)	(0.1237)	(0.1191)	(0.4193)	(0.3494)	(0.2768)	(0.2633)
Experience	-0.0021	-0.0032	0.0199***	0.0199***	0.0209***	0.0209***	0.0019	0.0019	0.0100	0.0097
	(0.0109)	(0.0104)	(0.0048)	(0.0047)	(0.0051)	(0.0049)	(0.0126)	(0.0105)	(0.0091)	(0.0086)
Experience squared	-0.0001	-0.0000	-0.0002**	-0.0002**	-0.0003***	-0.0003***	0.0000	0.0000	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Constant	1.7916***	2.8637***	1.8292***	2.0475***	1.9238***	1.9559***	3.4653***	2.9063***	0.8228	1.0235*
	(0.3301)	(0.4189)	(0.2215)	(0.2356)	(0.1714)	(0.1681)	(0.5207)	(0.2993)	(0.5958)	(0.5372)
R-squared	0.389	0.3881	0.5014	0.5014	0.521	0.5196	0.5566	0.5565	0.443	0.4427
Observations	490		868		669		143		503	

	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
	Russian Federation		Slovak Republic		Slovenia		Spain		United Kingdom	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Positive skill mismatch	-0.1319*	-0.1442**	0.0403	0.0217	-0.0367*	-0.0482**	-0.0464**	-0.0514**	-0.0072	-0.0200
	(0.0694)	(0.0655)	(0.0299)	(0.0325)	(0.0197)	(0.0207)	(0.0219)	(0.0216)	(0.0252)	(0.0278)
Negative skill mismatch	-0.0502	-0.0760	-0.0260	-0.0261	0.0331	0.0605**	0.0657**	0.0431	0.0120	0.0269
	(0.1112)	(0.0956)	(0.0261)	(0.0274)	(0.0265)	(0.0283)	(0.0286)	(0.0321)	(0.0236)	(0.0255)
PIAAC score (Average)	0.0182*	0.0180*	0.0114***	0.0128***	0.0115***	0.0140***	0.0130***	0.0119***	0.0101***	0.0120***
	(0.0102)	(0.0095)	(0.0043)	(0.0046)	(0.0031)	(0.0032)	(0.0029)	(0.0029)	(0.0031)	(0.0033)
Tenure	0.0632**	0.0624***	0.0084	0.0083	0.0140*	0.0142*	0.0113*	0.0115*	0.0030	0.0026
	(0.0272)	(0.0238)	(0.0090)	(0.0087)	(0.0085)	(0.0080)	(0.0067)	(0.0064)	(0.0065)	(0.0064)
Tenure squared*1/1000	-0.9751	-0.9264	-0.2143	-0.2141	-0.1776	-0.1786	0.0234	0.0181	0.0770	0.0865
	(0.9030)	(0.7878)	(0.2491)	(0.2386)	(0.2322)	(0.2183)	(0.1825)	(0.1731)	(0.1822)	(0.1787)
Experience	-0.0296	-0.0289	0.0057	0.0056	0.0013	0.0013	0.0129**	0.0124**	0.0348***	0.0351***
	(0.0243)	(0.0212)	(0.0083)	(0.0079)	(0.0094)	(0.0089)	(0.0061)	(0.0059)	(0.0053)	(0.0052)
Experience squared	0.0001	0.0000	-0.0002	-0.0002	-0.0000	-0.0000	-0.0002*	-0.0002*	-0.0006***	-0.0006***
	(0.0005)	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	-0.8181	1.3510*	1.3714***	1.3524***	1.9160***	1.6866***	1.3411***	1.2669***	2.4413***	1.3295***
	(1.2602)	(0.6896)	(0.4002)	(0.3832)	(0.3430)	(0.2967)	(0.2170)	(0.1857)	(0.2283)	(0.1952)
R-squared	0.451	0.4506	0.3509	0.3504	0.4267	0.4252	0.5197	0.519	0.5726	0.5721
Observations	183		646		448		614		915	

Notes: All estimates are weighted by sampling weights.

The dependent variable is the log of monthly wages including bonuses.

All regressions include dummy variables for industry, occupation, number of employees, education, and immigrants.

Robust standard errors are in parentheses.

***p<0.01, ** p < 0.05, * p < 0.1.

Appendix

Table A1: Sample selection

	Belgium	Chile	Czech Republic	Denmark	France	Greece	Israel
All male respondents	2,700	2,198	2,769	3,430	3,615	2,220	2,790
Test score is available	2,467	2,189	2,756	3,382	3,590	2,214	2,686
Regular workers	1,359	823	1,114	1,679	1,969	527	802
Skill mismatch infromation is available	1,315	809	1,108	1,652	1,847	485	750
Wage is available	1,263	769	990	1,601	1,792	395	646
Experience is available	1,262	568	986	1,599	1,792	336	472
All information is available	771	363	631	1,535	1,111	187	338
	Italy	Japan	Korea	Lithuania	Netherlands	New Zealand	Norway
All male respondents	2,235	2,517	3,102	2,033	2,545	2,667	2,655
Test score is available	2,220	2,468	3,092	2,004	2,501	2,613	2,557
Regular workers	929	1,518	976	1,016	1,296	1,215	1,633
Skill mismatch infromation is available	850	1,501	963	958	1,286	1,063	201
Wage is available	724	1,433	954	923	1,232	1,047	201
Experience is available	724	1,430	953	705	1,231	766	201
All information is available	424	664	588	490	868	669	143
	Poland	Russian Federation	Slovak Republic	Slovenia	Spain	United Kingdom	
All male respondents	4,733	1,344	2,706	2,616	2,964	3,737	
Test score is available	4,733	1,344	2,697	2,592	2,929	3,693	
Regular workers	1,171	434	1,079	1,125	1,037	1,698	
Skill mismatch infromation is available	1,149	372	1,046	1,108	1,020	1,288	
Wage is available	1,038	317	963	934	940	1,238	
Experience is available	1,033	313	961	874	940	1,238	
All information is available	503	183	646	448	614	915	

Source: PIAAC and O*net