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Skill Mismatch and Labor Market Institutions

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Skill Mismatch and Labor Market Institutions

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Abstract

This study examines the impact of skill mismatch on wages among Organisation for Economic Co-operation and Development (OECD) countries according to labor market regulations. If workers and firms find low matching quality due to imperfect information, they may search for better matches. In frictional labor markets, skill-mismatched workers are less likely to change jobs owing to the low possibility that another firm will hire them, and firms will not fire workers because of high firing costs. I show not only the impact of skill mismatch on wages by country but also the importance of labor market regulations. The results show that workers with skill surplus suffer from wage penalties, while workers with skill deficits enjoy wage premiums. Furthermore, I find that the higher the active labor market policy spending, the lower the impact of skill mismatch on wages. On the other hand, employment protection legislation and unemployment benefits do not affect the impact of skill mismatch on wages.

Keywords: Skill mismatch, Wage, Matching quality, Employment protection, Active labor market policy, Unemployment benefit

JEL classification: J31, J28, I26

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I. INTRODUCTION

Does the impact of skill mismatch on wages differ according to labor market regulations? Based on the matching quality theory, if workers and firms find low matching quality due to imperfect information, workers may suffer wage penalties, and firms may face low productivity. Labor turnover in a perfect competitive labor market could improve matching quality immediately. However, if there are search frictions, skill-mismatched workers are less likely to change jobs because of the low possibility of another firm hiring them, and firms will not fire workers owing to high firing costs, which means that there is scope to improve the efficiency of human capital allocation (Adalet McGowan and Andrews 2015; 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 difference in the impact of skill mismatch on wages by country and the kinds of labor market regulations associated with low productivity.

Jovanovic (1979), Mincer and Jovanovic (1979), Mortensen (1978), and others developed the theory of matching quality between workers and firms. This theory assumes that workers and firms possess imperfect information on their matching quality. This is considered an “experience good” (Nelson 1970) because workers and firms do not know their matching qualities at the time of hiring but only recognize them after the match. If workers find large search friction with their matching qualities in the market, they must accept their current jobs because it is difficult to find a better job, which leads to low productivity.

Empirical studies based on the matching quality theory show that 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 five 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 U.S. 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 well-matched workers. Guvenen et al. (2015) introduce two additional measures—overutilizing and underutilizing—to consider asymmetric effects of skill mismatch and show that overutilizing has a negative impact on wages, whereas underutilizing has no impact on wages.

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 U.S. Although they do not create a skill mismatch measure, they 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 U.S. 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.

As for multi-country analysis, using data of the Programme for the International Assessment of Adult Competencies (PIAAC), the Organisation for Economic Co-operation and Development (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 owing 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 skill mismatch on wages among the 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 underutilization lowers earnings by 4–16%, while overutilization 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, and likely yield 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 labor market regulation 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 regulation. 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 labor market regulations 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 regulations. There is much literature on the impact of a skill mismatch on wages; however, to the best of my knowledge, there are few studies examining the relationship between skill mismatch and wages according to labor market policies. To consider the asymmetric effect of overutilizing and underutilizing skills, I divide skill mismatch into skill surplus and skill deficit.[1] Skill deficit has received little attention in previous studies (McGuiness et al. 2018). I use three indicators capturing labor market regulation: Employment Protection Legislation (EPL); Active Labor Market Policy (ALMP) spending; and the unemployment benefit. The aim of EPL is to protect jobs, so labor market friction tends to be large. The aim of ALMP is to increase job-search efficiency, while unemployment benefit is considered a "passive" labor market policy (Martin 2015) because a high unemployment benefit does not provide an incentive to work. The results show that skill surplus (underutilization) has a negative impact on wages in most countries. In a few countries, skill deficit (overutilization) has a positive impact on wages. Furthermore, I find that the higher the ALMP spending, the smaller the absolute value of the impact of skill surplus and skill deficit on wages, though EPL and unemployment benefit do not relate to wages. These results suggest that ALMP spending may be related to failing efficient allocation of workers, while EPL and a high unemployment benefit are not. Thus, if policymakers spend on high ALMP, this may lead to an efficient labor market.

The remainder of this paper proceeds as follows. Section 2 presents the theoretical

[1] Hereinafter, skill mismatch refers to the sum of skill surplus and skill deficit.

background of the model and the empirical specifications. 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 $K_j > 0$.

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

where μ is a scale factor; θ and ψ are parameters, and e_{ij} is an idiosyncratic productivity shock.

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. 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 personal characteristics that determine productivity, β a parameter vector, and θ_i the idiosyncratic shock to a worker. Hence, x_i is the portable component of a worker's wage, reflecting the market value of his/her 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. When firm j employs worker i in occupation o with skill mismatch M_{ijo},

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

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 of $\boldsymbol{S}_i^*= (S_{i1}^*, S_{i2}^*, \ldots, S_{in}^*)$, 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} be the worker's skill. A firm j engaged in occupation o requires a skill set of $\boldsymbol{R_{jo}}= (R_{jo1}, R_{jo2}, \ldots, R_{jon})$. Therefore, I define skill mismatch as $|S_{ik} - \boldsymbol{R_{jo}}|$, which measures the component of wages due to skill mismatch. I give a 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_jQ_{ij} - w_{ij}. When workers 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

$$\begin{aligned}
\log w_{ij} &= \log \mu + \log \gamma_j p_j + \theta \log L_i + \psi \log K_j + \phi \log M_{ijo} + \log e_{ij} \\
&= \log \mu + \log \gamma_j p_j + x_i\beta + \theta_i + y_{ij}\alpha + \psi_j + \phi \log M_{ijo} + \log e_{ij} \\
&= \log \mu + x_t\beta + y_{ij}\alpha + \phi \log M_{ijo} + \theta_i + \psi_j + \log \gamma_j p_j + \log e_{ij.}
\end{aligned} \tag{3}$$

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.

2.2. Econometric Model

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

$$\log w_{ijo} = \gamma + \phi^{d} skill\_deficit_{ijo} + \phi^{s} skill\_surplus_{ijo} + x_i\beta + u_{ijo} \tag{4}$$

$$\begin{aligned}\log w_{ijoc} = \gamma + \phi^{d} skill\_deficit_{ijc} + \phi^{s} skill\_surplus_{ijoc} + \zeta^{d} skill\_deficit_{ijo} * policy_c \\ + \zeta^{s} skill\_surplus_{ijo} * policy_c + x_i\beta + \delta_i + u_{ijoc}\end{aligned} \tag{5}$$

where $skill\_deficit_{ijo}$ and $skill\_surplus_{ijo}$ are skill deficit and skill surplus, respectively, and $policy_c$ represents labor market regulation measures in country c. The skill mismatch measures I use here take 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, and dummy variables indicating that the individual is an immigrant and that the test language is the same as the respondent's native language. δ_i is a country-specific fixed effect. u_{ijo} is an idiosyncratic error term. First, I estimate Eq. (4) by country. Second, I estimate Eq. (5) by the fixed effect model because there are likely public policies and institutions related to skill mismatch other than labor market regulations.

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

III. DATA

3.1. PIAAC

OECD countries and their 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

[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, the 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.

technology-rich environments, and collects information on education, labor, and family background. For 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 skill score and available working history. Furthermore, the cross-national character of the data allows for an analysis of labor market regulations (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, 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

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[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 U.S. because information on occupation is not available.

occupational information for workers, human resource professionals, students, and so on. O*net covers 974 occupations in the U.S. and provides information about the importance of workers' knowledge, skills, and abilities for each occupation by integers from zero to six. I 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 on skills based on 6-digit occupation codes. The PIAAC uses International Standard Classification of Occupations (ISCO-08) occupational classifications, while O*net uses 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 U.S. workers, I apply the information to all countries because there are no detailed occupational data otherwise, to the best of my knowledge.

3.3. Labor market regulations

I adopt the measure of labor market regulations from the OECD.[6] Table 1 shows the labor market regulations by country. 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).[7] This indicator incorporates

[5] See the 2010 SOC x ISCO-08 crosswalk at http://www.bls.gov/soc/soccrosswalks.htm.
[6] See ALMP and unemployment benefit at https://stats.oecd.org/Index.aspx?datasetcode=SOCX_AGG.
[7] For details about the methodology to create the EPL indicators, see OECD (2014).

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. 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.

ALMPs contain social expenditures other than education, aimed at the improvement of the beneficiaries' prospects of finding gainful employment or to otherwise increase their earning capacity (OECD 2019). The classification of the ALMP is as follows: (1) Public employment services (PES) and administration; (2) Training; (3) Employment incentives; (4) Sheltered and supported employment and rehabilitation; (5) Direct job creation; (6) Start-up incentives.[8] Data on ALMP spending refer to 2010. I use the ALMP measure for spending per head, at current prices and current purchasing power parity-corrected denominated in U.S. dollars.

As a "passive labor market policy" indicator in contrast to ALMP, I use unemployment benefits (UB). UB offers replacement income to unemployed people. Thus, UB would increase the reservation wage, and people may stay on unemployment longer. UB include unemployment compensation and severance pay. I use this measure for spending per head, at current prices and current purchasing power parity-corrected denominated in U.S. dollars.

3.4. Skill Mismatch Measure

Based on the Defense Manpower Data Center, P.T.D. (2009), Table 2 shows the list

[8] See OECD (2019) for more details.

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

$$skill\_surplus_{ijo} = \Sigma_k \max[score_{ik} - required\_skill_{jok}, 0] \quad (6)$$

and

$$skill\_deficit_{ijo} = \Sigma_k |\min[score_{ik} - required\_skill_{jok}, 0]|. \quad (7)$$

where $skill\_surplus_{ijo}$ is the skill surplus of worker *i* in occupation *o*, $skill\_deficit_{ijo}$ is the skill deficit of worker *i* in occupation *o*, $score_{ik}$ is worker *i*'s score for skill *k* (numeracy or literacy), and $required\_skill_{jok}$ is the required level of skill *k* for occupation *o*. I use equally weighted numeracy and literacy scores because their correlation is very high.

Both variables take positive values because I take the absolute value in Eq. (7); thus, a negative coefficient indicates a wage penalty. Finally, I normalize these skill mismatch measures, so their standard deviations are equal to one by country.

3.5. Descriptive statistics

I select prime age (between age 25 and 59) 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 U.S. dollars to account for cross-national differences. I exclude the top and bottom 1% to avoid outliers in the wage distribution. Descriptive statistics and sample selection are shown in Table A1 and A2.

Figure 1 shows the distribution of skill surplus and deficit. The former appears as positive values, while the latter appears as negative values. In most countries, the mean of skill mismatch is slightly larger than zero, except in Chile and Israel, meaning that firms in these countries are not likely to fully utilize workers' skills. The mean values of skill deficit in Chile and Israel are the highest, indicating that many workers in these countries lack the skills to perform their jobs.

Figure 2 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, and dummy variables indicating that the individual is an immigrant and that the test language is the same as the respondent's native language. The graphs show that a skill surplus has a negative relationship with wages and that a skill deficit has a positive relationship with wages; therefore, the skill mismatch may have an asymmetric impact on wages.

IV. EMPIRICAL RESULTS

4.1. Country by country analysis

As a step to document the difference in the impact of skill mismatch on the logarithm of hourly wages, I estimate Eq. (4) by country using OLS. The estimated results are shown in Figure 3. As expected in Figure 2 (a) and (b), skill surplus has a negative impact on wages, while skill surplus has a positive impact on wages. The effect of skill surplus ranges from -0.03 to -0.15. However, for Chile and Greece, skill surplus has statistically no impact on wages because of the small size of the coefficients. On the other hand, a skill deficit has a statistically significant positive impact on wages for Denmark, France, Japan, Korea, Slovenia, Spain, and the United Kingdom. The effect of skill deficit ranges from 0.02 to -0.11. The results show that workers with skill surplus tend to suffer from wage penalty in most countries and that workers with skill deficit tend to enjoy wage premium in some counties, which means firms pay too high wages to workers with skill deficit. The results suggest that the impacts of skill surplus and skill deficit on wage vary by country.

4.2. Pooled countries analysis

I next investigate the relationship between skill mismatch, labor market regulations, and wages. Table 3 shows the estimation results consisting of Eq. (5), using EPL, ALMP, and UB as labor market regulations. The positively estimated coefficient on the interaction term between skill mismatch and labor market regulations implies that skill mismatched workers tend to earn higher wages than well-matched workers under stricter EPL, higher ALMP spending, and higher UB. First, the results show that workers with skill surplus suffer from wage penalties and that workers with skill deficit enjoy wage premiums. A one-standard-deviation increase in skill surplus lowers wages by about 7%, while the same in skill deficit increases wages by about 6%. The impacts of labor market regulations on skill mismatch slopes are heterogeneous across regulations. The estimated coefficients of the interaction term between skill mismatch and EPL suggest that EPL has no impact on wages for each one-standard-deviation increase in skill surplus and skill deficit. By contrast, the estimated coefficients of the interaction term between skill mismatch and ALMP spending suggest that a 100-dollar increase in ALMP spending is associated with a 0.3 percentage point wage increase for each one-standard-deviation increase in skill surplus and that a 100-dollar increase in ALMP spending is associated with a 0.3 percentage point lower wage increase for each one-standard deviation increase in skill deficit. The estimated coefficients of the interaction term between skill mismatch and UB suggest that UB has no impact on wages. The results suggest that ALMP can explain the differences in the impact of skill mismatch on wages. Furthermore, the results show that ALMP spending has an impact on wages such that ALMP offsets the impact of skill mismatch on wages even though the impact is very small.

In summary, the results show that the impacts of skill mismatch vary by country. Workers with skill surplus tend to suffer from wage penalties, while those with skill deficit in Denmark, France, Japan, Korea, Slovenia, Spain, and the United Kingdom enjoy wage premiums. These differences in results can partly explain ALMP spending. Higher ALMP spending tends to offset wage penalties for workers with skill surplus and wage premiums for workers with skill deficits, meaning that workers with skill surplus can earn higher wages, and firms do not have to pay higher wages to workers with skill deficits.

ALMP targets various groups such as young people, older workers, lower skilled workers, and the unemployed and have various types of spending. The result in Table 3 does not reveal which type of ALMP spending has the most impact on wages for an increase in skill mismatch. Therefore, I estimate Eq. (5) by type of ALMP spending. Analysis of the various ALMP spending produces an interesting pattern of results (Table 4). Spending for training and employment incentives have significant positive interactions with the return to skill surplus. That is, countries with higher spending for training and employment incentives have systematically higher return to skills on the labor market. For example, the estimate in column (2) suggests that a 100-dollar increase in spending for training is associated with a one percentage point wage increase for each one-standard-deviation increase in skill surplus. By contrast, spending for PES and administration, sheltered and supported employment and rehabilitation, startup incentives, and direct job creation is not significantly related to differences in the return to skill surplus across countries. As for skill deficit, PES and administration, training and sheltered and supported employment and rehabilitation have significant negative interactions with the return to skill deficit. Spending for startup incentives and direct job creation is not significantly related to differences in return to skill deficit. The results suggest that spending to directly encourage workers to work has an impact on skill mismatch.

V. CONCLUSION

I investigate the extent of the cross-national variation in the relationship between wages and skill mismatch by labor market regulation. According to the theory of matching quality, workers and firms cannot fully observe workers' skills because of 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 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, and skill mismatched workers are likely to suffer wage penalties owing to low productivity or to enjoy higher wage premiums than well-matched workers.

Estimating a wage equation, I find that workers with skill surplus suffer from wage penalties in most countries. Workers with skill deficits in Denmark, France, Japan, Korea, Slovenia, Spain, and the United Kingdom tend to enjoy wage premiums. Spending on ALMP partly explains the difference in the results by country, and higher ALMP spending offsets wage penalty and wage premium. However, EPL and UB have no impact on wage. Thus, spending to directly encourage workers to work is likely to have an impact on skill mismatch.

However, this study does not answer the remaining question. It does not clarify the causal relationship between labor market regulations and the impact of a skill mismatch on wages due to insufficient variation. Thus, further work is needed to understand the extent to which labor market regulations prevent efficient labor market allocation.

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TABLE 1

Labor market regulations by country

	EPL	ALMP	ALMP						Unemployment Benefit
			PES and Administration	Training	Employment incentives	Sheltered and supported employment and rehabilitation	Direct job creation	Start-up incentives	
Belgium	2.33	62.20	80.1	62.20	76.5	52.4	29.6	1.4	1209.33
Chile	2.53	30.90	3.5	30.90	1.3	0.00	9.0	0.0	3.06
Czech Republic	3.00	10.80	29.5	10.80	13.3	21.1	11.3	1.2	202.63
Denmark	2.10	274.60	167.7	274.60	132.5	276.1	0.00	0.00	0.00
France	2.60	132.30	107.9	132.30	23.6	38.1	70.3	19.0	564.62
Greece	2.07	5.10	3.0	5.10	30.0	0.0	0.0	27.1	241.85
Israel	2.35	24.30	10.0	24.30	1.3	3.8	-	5.0	241.85
Italy	2.60	50.20	37.1	50.20	51.3	0.00	1.8	6.7	466.06
Japan	1.62	11.40	19.7	11.40	42.4	1.7	25.3	0.2	91.22
Korea	2.29	-	4.5	-	6.2	4.5	57.3	0.2	88.76
Lithuania	2.23	-	16.1	-	17.5	3.2	9.6	0.00	-
Netherlands	2.84	57.00	164.0	57.00	60.9	198.3	0.00	-	650.78
New Zealand	1.41	38.50	36.6	38.50	7.3	15.5	68.8	0.8	148.33
Norway	2.23	125.50	73.7	125.50	4.7	99.9	2.7	1.3	280.80
Poland	2.20	7.30	18.8	7.30	43.7	43.7	7.5	20.4	44.87
Slovak Republic	2.19	1.30	24.2	1.30	23.6	8.3	3.4	19.4	75.72
Slovenia	1.99	14.60	29.6	14.60	24.8	0.00	35.3	15.4	217.52
Spain	2.08	62.30	51.6	62.30	84.6	26.0	30.3	36.9	1025.29
United Kingdom	1.31	1.31	111.6	6.00	4.3	2.2	13.2	0.7	136.73

Source: OECD, OECD SOCX Database
Note: The EPL Indicators for PIAAC Round 2 countries (Chile, Greece, Israel, Lithuania, New Zealand, and Slovenia) are for 2014, and others are for 2011. Other indicators are for 2010.

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, P.T.D. (2009)

TABLE 3

What accounts for differences in return to skill mismatch across countries?

Dependent variable: log of hourly wage	(1)	(2)	(3)
Labor market regulations	EPL	ALMP	UB
Skill Surplus	-0.0775***	-0.0751***	-0.0688***
	(0.0248)	(0.0076)	(0.0090)
Skill Deficit	0.0600**	0.0659***	0.0531***
	(0.0241)	(0.0076)	(0.0114)
Skill surplus×Labor market regulations×10	0.0380	0.0003***	0.00002
	(0.0117)	(0.0001)	(0.0002)
Skill deficit×Labor market regulations×10	-0.0223	-0.0003***	0.0001
	(0.0104)	(0.0001)	(0.0003)
Country Fixed Effect	Yes	Yes	Yes
R-squared	0.2869	0.2854	0.2902
No. of Countries	19	15	18
No. of Observations	12,798	10,404	12,316

Source: PIAAC, O*net, OECD

Note: This table shows the estimation results of the fixed effect model consisting of Eq. (5). I do not report the estimates of the constant term or the coefficients of PIAAC score, years of education, and dummy variables indicating that the test language is the same as the native language of the respondent or that parents are immigrants. Standard errors clustered by each country are in parentheses.

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

TABLE 4

What accounts for differences in return to skill mismatch across countries?

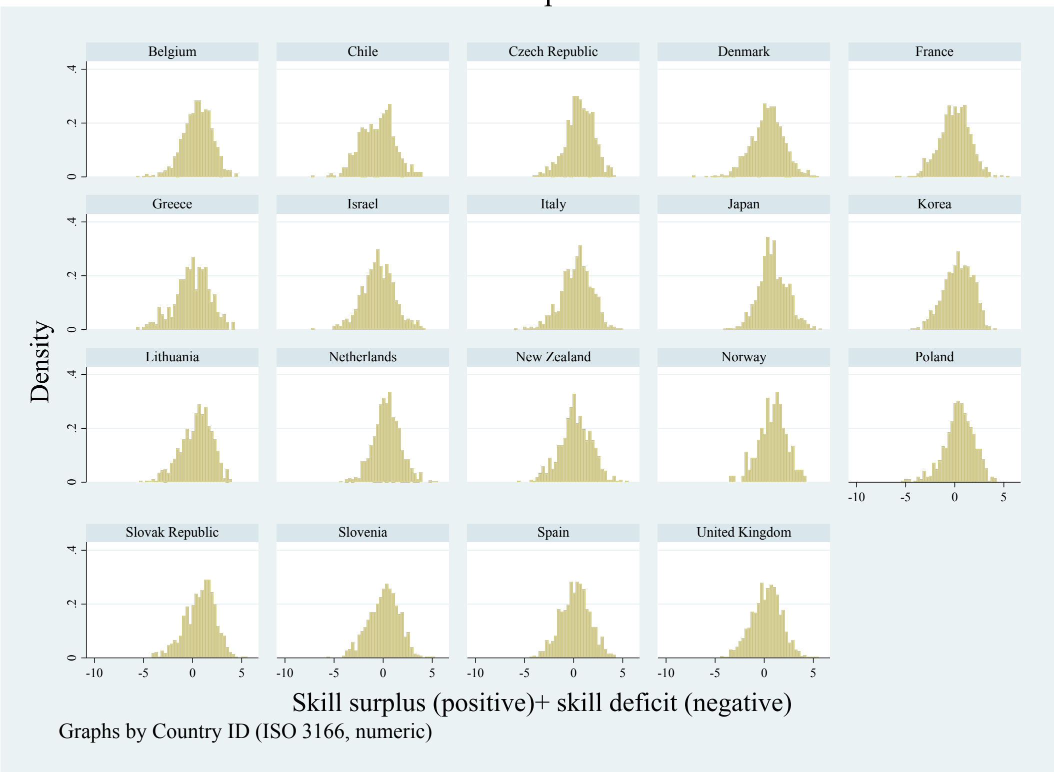
Dependent variable: log of hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Labor market regulations	PES and administration	Training	Employment incentives	Sheltered and supported employment and rehabilitation	Startup incentive	Direct job creation
Skill Surplus	-0.0735***	-0.0780***	-0.0659***	-0.0724***	-0.0837***	-0.0608***
	(0.0102)	(0.0076)	(0.0083)	(0.0072)	(0.0089)	(0.0093)
Skill Deficit	0.0677***	0.0594***	0.0493***	0.0630***	0.0608***	0.0526***
	(0.0096)	(0.0081)	(0.0121)	(0.0075)	(0.0084)	(0.0094)
Skill surplus×Labor market regulations×10	0.0006	0.0012**	0.0032***	0.0005	-0.0019	-0.0034
	(0.0014)	(0.0004)	(0.0010)	(0.0008)	(0.0040)	(0.0022)
Skill deficit×Labor market regulations×10	-0.0021**	-0.0010***	-0.0016	-0.0016***	0.0080	0.0003
	(0.0009)	(0.0003)	(0.0017)	(0.0004)	(0.0067)	(0.0018)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.2876	0.2930	0.2838	0.2879	0.2880	0.2887
No. of Countries	19	17	18	19	19	16
No. of Observations	12,798	11,523	11,981	12,798	12,798	11,221

Source: PIAAC, O*net, OECD

Note: This table shows the estimation results of the fixed effect model consisting of Eq. (5). I do not report the estimates of the constant term or the coefficients of PIAAC score, years of education, and dummy variables indicating that the test language is the same as the native language of the respondent or that parents are immigrants. Standard errors clustered by each country are in parentheses.

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

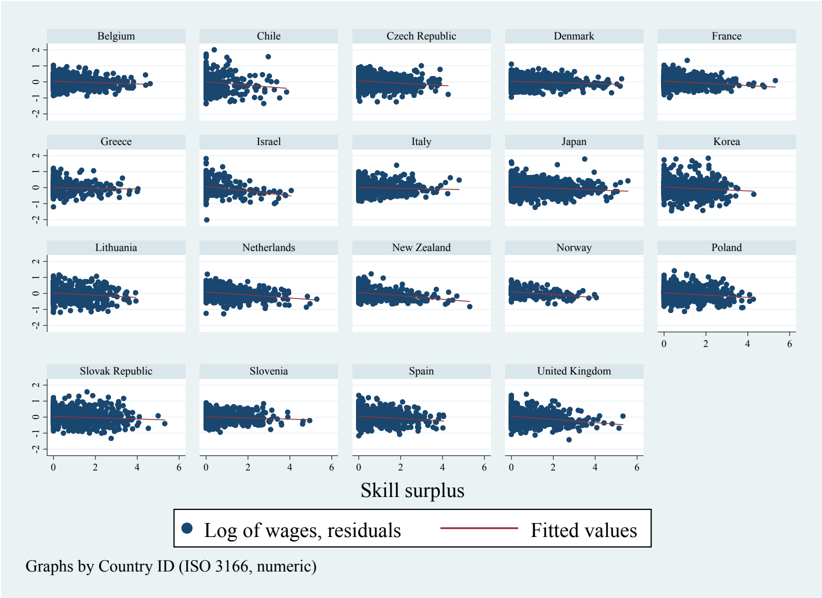
FIGURE 1
Distribution of Skill Surplus and Skill Deficit



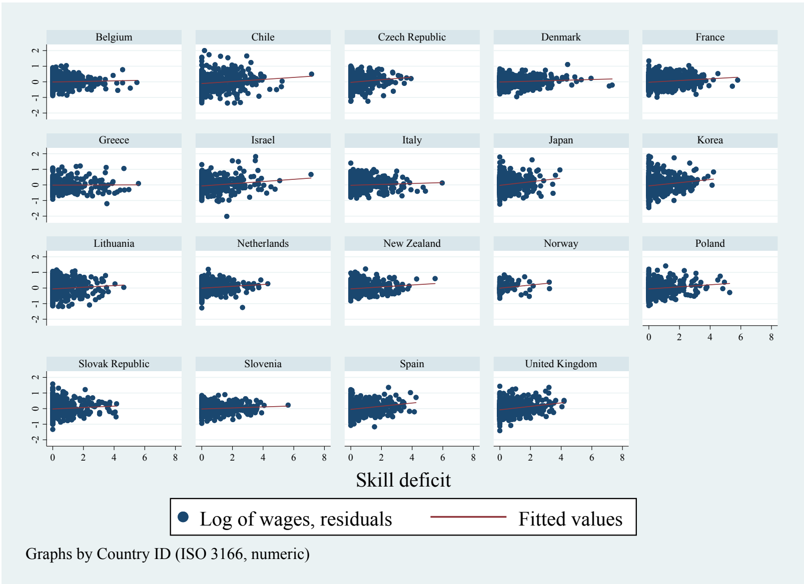
Source: PIAAC and O*net
Notes: Calculated by the author. Skill surplus takes positive values, while skill deficit takes negative values.

FIGURE 2

(a) The relationship between hourly wages and skill surplus



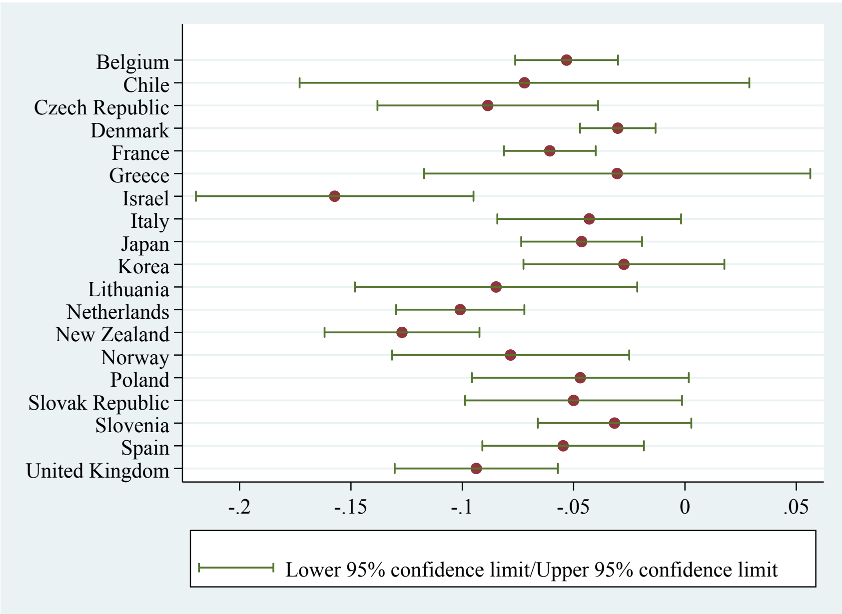
(b) The relationship between hourly wages and skill deficit



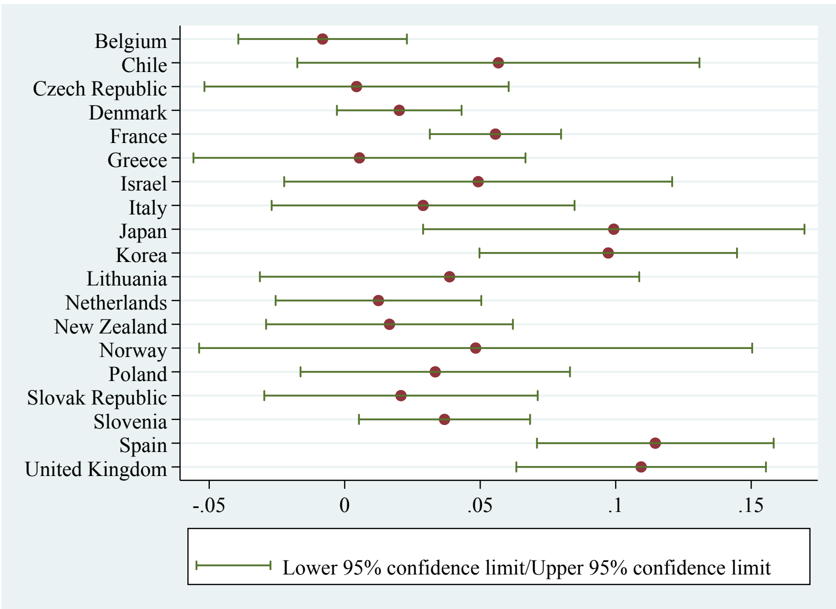
Source: PIAAC and O*net
Notes: Hourly wages denominated in U.S. Dollars. Male regular workers only.
Residuals of log wages obtained by regressing log wages on PIAAC score, experience, experience squared, tenure, tenure squared, and dummy variables for industry, occupation, education, and immigrant.
The top and bottom 1% of the hourly wages are dropped.

FIGURE 3

(a) The coefficients of skill surplus by country



(b) The coefficients of skill deficit by country



Source: PIAAC and O*net
Notes: All estimates are weighted by sampling weights.
The dependent variable is the log of hourly wages including bonuses.
All regressions include average numeracy and literacy scores, tenure, tenure squared, and dummy variables for immigrants and native language.

APPENDIX

TABLE A1

	Mean	Std. Dev.	Min	Max
Log of hourly wages	2.7179	0.5761	0.9435	4.0450
Skill surplus	0.8461	0.9581	0	5.5647
Skill deficit	0.5212	0.8509	0	7.3271
Skill surplus×EPL	1.8518	2.1415	0	15.0151
Skill deficit×EPL	1.1557	1.9312	0	18.1250
Skill surplus×ALMP	27.1905	52.9160	0	592.3609
Skill deficit×ALMP	17.7393	45.3373	0	824.6635
Skill surplus×Unemployment benefit	28.2614	55.9577	0	558.6213
Skill deficit×Unemployment benefit	17.7521	43.9975	0	663.6231
Skill surplus×PES and administration	5.2264	9.1712	0	88.2620
Skill deficit×PES and administration	3.2491	7.5976	0	122.8752
Skill surplus×Training	5.1947	12.0393	0	144.5245
Skill deficit×Training	3.5460	10.2214	0	201.2018
Skill surplus×Employment incentives	3.6036	6.4818	0	69.7360
Skill deficit×Employment incentives	2.0703	5.2461	0	97.0839
Skill surplus×Sheltered and supported employment and rehabilitation	4.4177	12.4688	0	145.3139
Skill deficit×Sheltered and supported employment and rehabilitation	2.6115	9.7878	0	202.3008
Skill surplus×Startup incentives	0.6261	1.5071	0	14.9483
Skill deficit×Startup incentives	0.4697	1.3715	0	15.7038
Skill surplus×Direct job creation	1.7941	3.5833	0	40.1414
Skill deficit×Direct job creation	1.1411	3.1387	0	43.7470

Source: PIAAC and O*net

Notes: The number of observations for wages, Skill surplus, Skill deficit, skill surplus × EPL, Skill deficit × EPL, Skill surplus × PES and administration, Skill deficit × PES and administration, Skill surplus × Sheltered and supported employment and rehabilitation, Skill deficit × Sheltered and supported employment and rehabilitation, Skill surplus × Startup incentives, and Skill deficit × Startup incentives is 12,798. That of Skill surplus × ALMP and Skill deficit × ALMP is 10,404. That of Skill surplus × UB and Skill deficit × UB is 12,316. That of Skill surplus × Training and Skill deficit × Training is 11,523. That of Skill surplus × Employment incentives and Skill deficit × Employment incentives is 11,981. That of Skill surplus × Direct job creation and Skill deficit × Direct job creation is 11,221.

TABLE A2

Sample selection

	Belgium	Chile	Czech Republic	Denmark
All male respondents	2,700	2,198	2,769	3,430
Test score is available	2,467	2,189	2,756	3,382
Regular workers	1,359	823	1,114	1,679
Skill mismatch infromation is available	1,315	809	1,108	1,652
Wage is available	1,263	769	990	1,601
All information is available	939	415	669	1,082
	France	Greece	Israel	Italy
All male respondents	3,615	2,220	2,790	2,235
Test score is available	3,590	2,214	2,686	2,220
Regular workers	1,969	527	802	929
Skill mismatch infromation is available	1,847	485	750	850
Wage is available	1,792	395	646	724
All information is available	1,158	284	307	580
	Japan	Korea	Lithuania	Netherlands
All male respondents	2,517	3,102	2,033	2,545
Test score is available	2,468	3,092	2,004	2,501
Regular workers	1,518	976	1,016	1,296
Skill mismatch infromation is available	1,501	963	958	1,286
Wage is available	1,433	954	923	1,232
All information is available	997	815	471	819
	New Zealand	Norway	Poland	Slovak Republic
All male respondents	2,667	2,655	4,733	2,706
Test score is available	2,613	2,557	4,733	2,697
Regular workers	1,215	1,633	1,171	1,079
Skill mismatch infromation is available	1,063	201	1,149	1,046
Wage is available	1,047	201	1,038	963
All information is available	477	141	634	684
	Slovenia	Spain	United Kingdom	
All male respondents	2,616	2,964	3,737	
Test score is available	2,592	2,929	3,693	
Regular workers	1,125	1,037	1,698	
Skill mismatch infromation is available	1,108	1,020	1,288	
Wage is available	934	940	1,238	
All information is available	681	754	858	

Source: PIAAC and O*net

TABLE A3

Wage regression with skill mismatch by country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Belgium	Chile	Czech Republic	Denmark	France	Greece	Israel	Italy	Japan	Korea
Skill surplus	-0.0531***	-0.0721	-0.0886***	-0.0302***	-0.0607***	-0.0304	-0.1573***	-0.0430**	-0.0464***	-0.0274
	(0.0118)	(0.0514)	(0.0252)	(0.0086)	(0.0105)	(0.0441)	(0.0317)	(0.0210)	(0.0138)	(0.0230)
Skill deficit	-0.0082	0.0567	0.0044	0.0201*	0.0556***	0.0054	0.0493	0.0289	0.0993***	0.0973***
	(0.0158)	(0.0377)	(0.0286)	(0.0117)	(0.0123)	(0.0311)	(0.0364)	(0.0285)	(0.0359)	(0.0242)
No. of observations	939	415	669	1,082	1,158	284	307	580	997	815
R-squared	0.3130	0.3751	0.2903	0.2874	0.3762	0.3060	0.3672	0.2509	0.3829	0.3192
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	
	Lithuania	Netherlands	New Zealand	Norway	Poland	Slovak Republic	Slovenia	Spain	United Kingdom	
Skill surplus	-0.0848***	-0.1009***	-0.1271***	-0.0783***	-0.0470*	-0.0500**	-0.0316*	-0.0547***	-0.0937***	
	(0.0323)	(0.0147)	(0.0177)	(0.0269)	(0.0248)	(0.0248)	(0.0176)	(0.0185)	(0.0187)	
Skill deficit	0.0387	0.0125	0.0165	0.0483	0.0334	0.0208	0.0368**	0.1146***	0.1094***	
	(0.0356)	(0.0193)	(0.0232)	(0.0516)	(0.0253)	(0.0257)	(0.0161)	(0.0222)	(0.0235)	
No. of observations	471	819	477	141	634	684	681	754	858	
R-squared	0.2412	0.3667	0.3906	0.4258	0.2922	0.2286	0.3769	0.3876	0.4153	

Source: PIAAC and O*net
Notes: All estimates are weighted by sampling weights.
The dependent variable is the log of hourly wages including bonuses.
All regressions include average numeracy and literacy scores, tenure, tenure squared, and dummy variables for immigrants and native language.