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Skill, skill use and wages: a new theoretical perspective

Ineke Bijlsma
Rolf van der Velden

Paper prepared for the Second PIAAC International Conference, Haarlem, 22-24 November 2015

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Ineke Bijlsma and Rolf van der Velden[2]*, Research Centre for Education and the Labour Market*

1. Introduction

Starting with the seminal work of Becker (1964), researchers have looked at the relation between schooling and productivity, typically using Mincerian wage regressions to assess the effect of schooling and experience on wages (Mincer, 1974). In these equations, schooling and experience are taken as proxies for skills and wages as proxy for productivity. These models are primarily supply-driven and assume that individual productivity is a function of individual skills. With the large increase in higher education enrollments and the subsequent decreasing returns to higher education, this human capital interpretation of the relation between individual skills and productivity has been seriously challenged (Thurow, 1975; Freeman, 1976) leading to a stronger emphasis on job characteristics determining productivity and focusing on the possible negative effects of overeducation (Bills, 2003). Several models and methods have been developed and tested (Van der Velden and van Smoorenburg, 1997; Hartog, 2000; Battu, Belfield and Sloane, 2000; Verhaest and Omey, 2006), and the general conclusion from the empirical evidence is that the effects of educational mismatches are best explained by matching models that assume that the combination of supply and demand determine productivity (Groot and Maassen van den Brink, 2000; Hartog, 2000; McGuiness, 2006; Sattinger, 1993; 2012). That is, productivity is highest when workers' skills are a good match to the skills that are required in the job. When workers' skills are higher than the skills that are required in the job, these workers still have a productivity benefit, but not fully as the utilization of their additional skills in their work is restricted by job characteristics. And conversely, workers that lack some of the skills that are required in their job will not reach the same productivity level as their co-workers who have matching skills.

Although the empirical results of educational mismatches are quite consistent over time and across countries, it has proven difficult to simply interpret these as skill mismatches (Halaby, 1994; Allen and Van der Velden, 2001; Green and McIntosh, 2007; Quintini, 2011). This was partly due to a lack of adequate measures of individual skills. The newly developed Program for the International Assessment of Adult Competencies (PIAAC) from the Organization for Economic Cooperation and Development (OECD) provided a first opportunity to look at educational mismatches and skills at the same time (Levels, Van der Velden and Allen, 2014). Nonetheless, having information on possessed skills is not enough. In order to measure the effects of skill mismatches (as opposed to educational mismatches), we need information on the skill requirements as well. The problem is that no large data set exists that contains direct information on these skill requirements. Instead three approaches have been developed to proxy the skill requirements: worker self-assessment (asking the worker about the required level, e.g. by asking "How important are the following skills for doing your current job"), realized matches (taking the average or median skill level in an occupation as the required skill level) and the job requirement approach (taking the use of skills in a job as a proxy for the required skill level). All of these approaches have their own weaknesses, both theoretically and empirically.

In this paper we develop a new perspective by integrating skill proficiency and skill use into a new concept 'skill effort'. Skill effort is defined as a multiplicative function of skill proficiency and skill use. The intuitive understanding of this concept is that there can be no effect of a skill if it is not

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2. Corresponding author: Rolf van der Velden: R.vanderVelden@Maastrichtuniversity.nl.

used and vice versa there can be only little impact of using a certain skill if the proficiency level is low. The new concept is firmly rooted in theories on use-it-or-loose-it, engagement and self-efficacy and has a parallel in previous theories on performance. We use this concept to develop a matching model, based on an integration of the realized matches and the job requirement approach, using PIAAC data. The results show that the newly developed model is superior to alternative specifications of the same variables or alternative models using other approaches to explain wage differences in the different countries. In the paper we discuss some remaining issues on the measurement of this concept and present different ways to address these.

2. Earlier approaches

As indicated above, the main problem of existing data sets is that direct information on the skill requirements in the job is lacking. Three approaches have been developed to gain a proxy of these skill requirements: worker self-assesment (WS), realized matches (RM) and the job requirement approach (JRA).

The WS approach typically asks the worker directly about the required level. The CEDEFOP EU Skills Survey[3] for example uses the following question: "On a scale from 0 to 10, …how important are the following skills for doing your current job", followed by a list of skills. Similar approaches are used in many surveys among graduates (e.g. the REFLEX survey, see Allen and Van der Velden, 2011). One of the major problems in this approach is that the answer scales lack an objective anchor (Allen and Van der Velden, 2005) and are prone to social bias ('talking up your job'). The anchoring problem has been addressed in several surveys by introducing clear anchors in the scale (e.g. the O*NET survey[4]) or by using vignettes (King, Murray, Salomon and Tandon, 2004; King and Wand, 2004). Also the social bias problem has been addressed by focusing on activities and using time intensity or frequency scales instead of importance or skill level (as in the JRA approach: e.g. in the British Skills Survey, see Green, Felstead and Gallie, 2013; or the PIAAC survey, OECD, 2013a, 2013b). Still both problems have not been completely solved (see later on JRA).

A different version of the WS asks workers to indicate a skill mismatch directly. The European Survey on the Working Conditions (ESWC[5]) for example poses the following question to workers: "Which of the following alternatives would best describe your skills in your own work?" with answers 1. "I need further training to cope well with my duties", 2. "My present skills correspond well with my duties" and 3. "I have the skills to cope with more demanding duties". The problem with this approach is again that it is prone to social bias (people may overestimate their own skill level). Apart from that there is no separate estimate of the required skill level. This is all the more serious as we know that part of the educational mismatches are just apparent and do not reflect a skill mismatch at all (Allen and Van der Velden, 2001; Green and McIntiosh, 2007; Quintini, 2011). This is because the lower skilled at a certain educational level get sorted into jobs that are less complex. These people may be formally 'overeducated' for these jobs but in fact these jobs match their skills quite well. Levels et al. (2014) found evidence that this is indeed the case, especially in countries with low labour market regulation.

The second approach to assess skill requirements and skill mismatches is the RM approach. This approach takes the average or median skill level in an occupation as the required skill level and defines a worker as overskilled or underskilled if he or she has a skill proficiency level of – usually – one or one-and-a half standard deviation above or below that occupation-specific level. One example is Perry, Wiederhold and Ackermann-Piek (2014) who used PIAAC data to assess the average skill level of each 2-digit occupation in Austria, Germany and the United States (leaving out those occupations with less than 30 observations). A more complex model was used by

3. http://www.cedefop.europa.eu/en/publications-and-resources/publications/8088
4. https://www.onetcenter.org/questionnaires.html#generic
5. http://www.eurofound.europa.eu/publications/report/2012/working-conditions/fifth-european-working-conditions-survey-overview-report

Pellizari and Fichen (2013), also using the PIAAC data. They use a sort of combination of the WS and the RM approach. First they select all those who identify themselves as being well-matched. For this they use two questions from the PIAAC background questionnaire: “Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job” and “Do you feel that you need further training in order to cope well with your present duties”. Only respondents who answer ‘no’ to both questions are considered well-matched in a subjective way (this applies for only some 20% of the workers). They then assess the range of skill proficiency levels of all workers who identify themselves as well-matched per country per ISCO 1-digit occupation. This range is then trimmed (leaving out the bottom and upper 5%) and regarded as the ‘normal’ skill range in that 1-digit occupation. Any worker – regardless of what he or she answered to the two subjective questions - is considered well-matched if his or her skill proficiency level falls in the country-occupation specific skill range. Anyone with a skill proficiency level above the 95% score is defined as overskilled and anyone below the 5% range is defined as underskilled. Based on this model 86% is defined as well-matched, 10% is defined as overskilled and only 3% as underskilled in both the numeracy and the literacy domain (Pellizari and Fichen, 2013).

One theoretical problem with the RM approach (not only here but also in the case of educational mismatches, see Hartog, 2000; Battu et al., 2000; Verhaest and Omey, 2006) is that the definition of well-matched is in fact a bit arbitrary. Basically it defines workers with an average skill proficiency level in a certain occupation as being well-matched. However, as there is no objective criterion that defines the actual required skill level, all of these workers may in fact be overskilled or underskilled. Assuming that the majority of workers will have a job that in fact matches their skills may not be a wild guess in general, but the RM approach typically ignores differences in skill mismatches across countries or across occupations (due to the standardization per country and per occupation).

Apart from this there is a statistical problem. Occupational categories are heterogeneous and contain occupations that might well differ in required skill level. This is of course more true at the aggregated level of ISCO 1-digit codes than at the more disaggregated ISCO 4-digit level. The basic issue here is that workers in an ISCO 1-digit occupation might be wrongfully classified as matched or mismatched, although the required skill level at a more detailed level would suggest differently. The problem is that in surveys like PIAAC, one usually does not have enough respondents to assess the average skill level at - say – the ISCO 3- or 4-digit level in each country. Even the ISCO 2-digit level is often not possible due to the small number of observations. This was one of the reasons why Pellizari and Fichen (2013) resorted to using skill proficiency levels at the ISCO 1-digit level per country. But these categories are far too heterogeneous to allow a correct determination of a worker being well-matched, overskilled or underskilled.

The third approach, the JRA, was developed by Green and colleagues for the British Skills Survey (Green et al. 2013) and was also applied in the PIAAC survey. Instead of asking about the importance of a certain skill in a job, this approach asks about the time intensity or frequency of use of a certain skill. A typical question would be: “In your job how often do you usually read letters, memos or e-mails?” with answers ranging from “never” to “every day” (PIAAC: OECD, 2013b). A set of items relating to a certain skill domain – say literacy – and reflecting different complexity levels is then used to construct a scale on skill use. The interpretation of this scale is that it reflects the skill requirements in the job (hence the term job requirement approach). The assumption is that a high level of skill use reflects a higher level of required skills. Allen, Levels and Van der Velden (2013) have used this to construct a measure of skill mismatch that they call *relative use of skill.* Using PIAAC data they standardised both measures of skill use and proficiency for a domain and then subtracted them. Workers with a level of using skills that is one and a half standard deviation higher than what would have been predicted on the basis of their skill proficiency are classified as overusing their skills, and workers with a level of using skills that is one and a half standard deviation lower than what would have been predicted on the basis of their skill proficiency level are classified as underusing their skills. In a strict sense this concept is probably closest to the concepts of over- and underutilisation, if the reference is the worker rather than the job. In other words, if we look at a worker, overutilisation really means that a person is using his or her skills more than his/her proficiency level would allow. That is different from a perspective in which the job is the reference: in that case overutilization means that the job requirements are higher than the level a worker possesses.

A theoretical problem with the JRA approach is that the use of skills is not necessarily a good proxy for skill requirements. Moreover, the two concepts that are being used to construct the mismatch variable, skill use and skill proficiency, are in practice closely linked, both empirically and theoretically. This makes it difficult to regard skill use as an independent measure of skill requirement as it also reflects the skill proficiency. There is also a measurement problem in the JRA approach, as has been highlighted by Pellizari and Fichen (2013). Both constructs are measured on a different scale. Standardising both constructs actually disguises the fact that the two scales are fundamentally different. In that sense, the JRA approach suffers from the same forced equilibrium problem as the RM approach: both consider workers that have average skills compared to either the average use or the average in their occupation as being well-matched. But this is not necessarily true.

3. Towards a new theoretical model

The assumption in the JRA approach that skill use and skill proficiency are different, forces us to rethink both concepts. Can skill use be seen as a proxy for skill requirements or is it so closely related to skill proficiency that it is hard to disentangle the two? There are at least three strands of literature that suggest the latter: the use-it-or-lose-it theory, self-efficacy theory and engagement theories.

The use-it-or-lose-it-theory (Mincer and Ofek, 1982; Krahn and Lowe, 1998; Bynner and Parsons, 1998; Salthouse, 2006; Desjardins and Warnke, 2012) argues that skills that are not being used depreciate over the life cycle. For example Bynner and Parsons (1998) show that time out of paid employment is detrimental for the numeracy skills. This was less evident when looking at literacy skills. This is interpreted by the authors by the fact that reading is more related to everyday life and so does not stop when leaving paid employment, while numeracy skills are much more related to work and are much less used in everyday life. Levels and Van der Velden (2013) use PIAAC data to document the factors that affect the acquisition and the decline of skills over the life cycle. They conclude that the use of skills is strongly related to hampering or accelerating skill proficiency, although the causal direction is not quite clear. People may lose skills because they don’t use it anymore, or they may have stopped using them because they lost it.

Whatever the causal direction, self-efficacy and engagement theories suggest that the two concepts are closely interlinked. Self-efficacy theory, developed by Bandura (1977) states that task-related self-efficacy increases the likelihood of being engaged in a more challenging task, thus increasing the skill level and the self-efficacy. Self-efficacy is one of the motivational variables that has been studied as one of the driving factors of engagement, which is a result of cognitive factors, motivational factors as well as a positive attitude to use certain skills (Guthrie and Wigfield, 2000). In the conceptual foundation of skills surveys like PIAAC, reading engagement and numeracy engagement are considered driving factors in the acquisition of these key skills (OECD, 2012a). Self-efficacy has been shown to be a good predictor of a range of academic outcomes (Multon, Brown and Lent, 1991). Reading engagement and numeracy engagement have been shown to be closely linked to skill proficiency levels (OECD, 2012a).

If the concepts of skill use and skill proficiency are so closely linked, we need to rethink their relation to productivity. Are skill use and skill proficiency two sides of the same coin, or are they different? Can they be seen as supplementary or as complementary? One of the driving questions challenging the human capital interpretation of the relation between skills and wages, is: why would employers pay for skills that are not required? We can pose a similar question for skill use: why would employers pay for skills that are not being used? All of the previous empirical work on the relation between skills and wages, implicitly assumes that the wage premium for skills is related to using those skills in the job. If that would not be the case, we would be back in a pure signaling or credential type of explanation (Spence, 1973; Collins, 1979), where employers are assumed to pay for schooling or skills that are actually not required in the job. Most of the empirical evidence however suggest that this is not the case (Hanushek and Woessmann, 2011; Hanushek, Schwerdt, Wiederhold and Woessmann, 2014)

We believe that we need to develop a concept that firmly integrates skill proficiency and skill use into one new concept: skill effort. For this we need the following assumptions:

1. Productivity is a multiplicative function of two inputs: skills and effort.
2. There are multiple skills dimensions that determine the productivity, but each does so in an additive way, in other words there is no interaction effect of the skill dimensions in determining productivity.
3. The effort to use a particular skill is a function of the use of that particular skill in a job.

The first assumption is the most critical, but its intuitive understanding is straightforward. Skills can affect productivity but only when they are put to use.[6] There is no reward for skills that are not being used at all. This is in line with a basic human capital framework assuming that there can only be a reward for skills that are actually being used. Conversely, the effect of using a particular skill is moderated by the skill proficiency level. If the proficiency level is low, using that skill has less effect on the productivity than when the proficiency level is high. The idea of regarding productivity as a multiplicative function of two inputs is not new. In the early 60s, the psychologist Vroom (1964) developed the Expectancy theory in his study on the motivations for decision-making. According to his theory, performance is a multiplicative function of ability and motivation. This theory has been applied and tested in different settings, mainly in education and in work. A recent review by Van Iddekinge, Aguinis, and Mackey (2014) shows that the empirical research has provided mixed evidence, except in the case of job performance where the results seem to support this theory.

The second assumption is theoretically not crucial, but is an important practical assumption to allow the determination of the effects of a separate skill domain, without having to include other skill domains.[7]

The final assumption is more related to a measurement issue than a theoretical issue. We lack data on effort, but we think that the frequency and time intensity of using a particular skill can be viewed as a good proxy since these are closely related.

We now need to put this into a formal model.

Let
S_i = individual skill proficiency of individual i
U_i = individual skill use of individual i
P_i = individual productivity level of individual i
W_i = individual wage level of individual i
u_i = idiosyncratic error term

Then

6. One can think of certain skills where this relation is less straightforward. For example a pilot needs to be very proficient in dealing with emergency situations, and he/she will also be rewarded for that type of skill, although it is not necessary that this skill will have to be used often. This model therefore pertains to skills which use is assumed to be central for functioning in a job. This is true for all key skills, such as numeracy, literacy, problem solving, social skills etc.
7. Given the nature of the matching models (with up to 9 terms for each skill domain) this would unnecessarily complicate the model.

$P_i = W_i = a1 + a2S_i * U_i + u_i$ (eq. 1)

For assessing the effect of skill mismatches, we need to turn this into a standard matching model. We follow the conventional so-called ORU-model (Overeducation, Required education, Undereducation) developed by Duncan and Hoffman (1981). In this model own schooling level (OS) is broken down into its three components:

- years or required education (RE),
- years of overeducation (OE) defined as OS-RE if OS>RE, else 0
- years of undereducation (UE) defined as RE-OS if OS<RE, else 0

This means that OS = RE + OE – UE and the standard wage regression is $W_i = a1 + a2*RE_i + a3*OE_i + a4*UE_i + u_i$. In other words, the ORU-model assumes a wage premium for required years of schooling (a2), a wage premium for years of overeducation (a3), and a wage penalty for years of undereducation (a4). Empirical findings around the world usually show that a2>a3>Ia4I (Hartog, 2000; Groot and Maassen Van den Brink, 2000; Levels et al., 2014).

We can develop a similar model for skill mismatches. We assume that each occupation has a standard required level of skill and a standard required level of skill use. Workers can perform above or below these standards and will receive a wage premium/penalty accordingly. However, in line with the matching theories and the empirical results from educational mismatch research, there are decreasing returns/penalties to performing above or below the standard.

Let's assume that both S_i and U_i are both standardized variables with mean 10[8] and standard deviation 1. Now let

RS_j = mean S_{ij} = standard required skill proficiency in occupation j
$OS_{ij} = (S_i - RS_j)$ for $(S_i - RS_j) > 0{,}5$, else 0 = extent to which individual i has a higher skill proficiency (at least 0,5 standard deviation higher) than standard required in occupation j
$US_{ij} = (RS_j - S_i)$ for $(RS_j - S_i) > 0{,}5$, else 0 = extent to which individual i has a lower skill proficiency (at least 0,5 standard deviation lower) than standard required in occupation j
RU_j = mean U_{ij} = standard required skill use in occupation j
$OU_{ij} = (U_i - RU_j)$ for $(U_i - RU_j) > 0{,}5$, else 0 = extent to which individual i has a higher skill use (at least 0,5 standard deviation higher) than standard required in occupation j
$UU_{ij} = (RU_j - U_i)$ for $(RU_j - U_i) > 0{,}5$, else 0 = extent to which individual i has a lower skill use (at least 0,5 standard deviation lower) than standard required in occupation j

Now equation 1 can be written as:

$$\begin{aligned} W_i &= a1 + a2\, S_i * U_i + u_i \\ &= a1 + a2\,(RS_j + OS_{ij} - US_{ij}) * (RU_j + OU_{ij} - UU_{ij}) + u_i \end{aligned} \quad \text{(eq. 2)}$$

and this can be rewritten as

$$\begin{aligned} &= a1 + a2\, RS_j\, RU_j + a3\, OS_{ij}\, RU_j - a4\, US_{ij}\, RU_j \\ &+ a5\, RS_j\, OU_{ij} + a6\, OS_{ij}\, OU_{ij} – a7\, US_{ij}\, OU_{ij} \\ &+ a8\, RS_j\, UU_{ij} + a9\, OS_{ij}\, UU_{ij} – a10\, US_{ij}\, UU_{ij} + u_i \end{aligned} \quad \text{(eq. 3)}$$

In which
a2 = return to standard job requirements
a3 = return to overskilling with standard use
a4 = return to underskilling with standard use
a5 = return to overutilisation with standard skills
a6 = return to overutilisation with high skills
a7 = return to overutilisation with low skills
a8 = return to underutilisation with standard skills

8. The mean 10 is taken to avoid negative values and zeros.

a9 = return to underutilisation with high skills
a10 = return to underutilisation with low skills

Like in previous research we expect the returns to standard job requirements to be higher than the returns to overskilling/overutilization and these in turn to be higher than the returns to underskilling/underutlisation

4. Data and method

We make use of the PIAAC data set (OECD, 2013b), which assesses the proficiency of the adult population in key information-processing skills in OECD countries. The survey is designed to be cross-culturally and cross-nationally valid. The original dataset comprises 24 countries and some 166,000 respondents. The national samples are representative samples of non-institutionalized persons aged 16-65. Most countries have around 5.000 respondents in the sample, with the exception of Canada which has more than 27,000 respondents. From this dataset we excluded Australia, because of data protection rules, and the Russian Federation because we are not fully sure about the data quality. From the Canadian sample we took a random sample of some 20% to avoid an overrepresentation of the Canadian sample in the total data set.

PIAAC comprises a combination of computer based assessment and – for those who were not able or willing to take the computer based test – paper-and-pencil data collection strategies to assess the proficiency of respondents on three key information-processing skills: numeracy, literacy and problem solving in technology-rich environments. In this paper we only focus on numeracy and check comparability of the results for literacy. The reason to leave out problem solving is that around one third of the respondents did not take the test, because they lacked computer skills or because they choose to only use paper-and-pencil tests (which was not available for the problem solving domain). Moreover, some countries (France, Cyprus, Spain and Italy) decided not to have this test. Adaptive testing and item response techniques were used to calculate 10 plausible values for each of these two domains. Together, these plausible values on numeracy and literacy provide an unbiased estimate of the 'real' score if the respondent would have taken all the numeracy and literacy related items (OECD, 2013b). The numeracy scale has a range from 0 to 500 with an OECD international average of 273 and the literacy scale has a similar range with an OECD average of 270.

Respondents were further interviewed on non-cognitive skills, key demographic and socio-economic characteristics, as well as the extent to which they use key information processing skills in the workplace or at home. For this paper the key variables of interest are the numeracy and literacy proficiencies as well as their correlates in using these skills at work. We constructed two scales based on the items that are closest to the proficiency domains that were measured: 6 items on the use of numeracy skills at work (e.g. "In your job, how often do you usually a) calculate prices, costs or budgets, b) use or calculate fractions, decimals or percentages" etc.) and 8 items on the use of reading[9] skills at work (e.g. "In your job, how often do you usually a) read directions or instructions, b) read letters, memos or e-mails" etc.). We computed simple average scores for these sets of items. The Cronbach's alphas for these two scales are 0.803 and 0.806 respectively.

To estimate the average skill proficiency and skill use levels for each ISCO 2-digit occupation in the different countries, we made use of the calculations performed by Allen and Bijlsma (2015), who developed occupational profiles for each country. A problem with the PIAAC data set is that it has only a limited number of observations available for each ISCO 2-digit occupation in a country. To avoid inaccuracies in the assessment of the average skill proficiency and skill use

9. The PIAAC questionnaire also has 4 items related to writing skills, such as "In your job, how often do you usually a) write letters, memos or e-mails, b) write articles for newspapers, magazines or newsletters" etc.). Conceptually the reading items are closer to the domain of literacy which is about understanding written information, which is why we decided not to use the writing items.

levels for these occupations, Allen and Bijlsma developed a cross-classified multilevel model in which individuals are nested in both international ISCO 2-digit occupations as well as in national ISCO 1-digit occupations. In this way, the national averages for each ISCO 2-digit occupations are a function of both the national data for the ISCO 1-digit occupation to which the individual belongs as well as the international data of the ISCO 2-digit occupation to which an individual belongs. To illustrate the idea, the average numeracy level of Dutch building trade workers (ISCO 71) is estimated as a weighted average of the numeracy level of all Dutch craft workers (ISCO 7), the numeracy levels of building trade workers in other countries, as well as the directly observed numeracy level of Dutch building trade workers in the data. To avoid the problem that certain countries may actually have very different skill profiles and thus would yield a systematic bias, the contribution of other countries is weighted such that countries that are more similar to the reference country (in this case the Netherlands) also have a higher weight. These weights are based on the between-country correlation between the preliminary 2-digit occupational skill estimates of the reference country and all other countries in the data. This correlation is squared, and can thus be conceived of as the amount of variance in the reference country's occupational skill structure that can be explained by the occupational skill structures of the other countries. By definition the respondents in the reference country get weight 1 and those in the other countries get a weight between 0 and 1 (usually around 0.7). The estimates were done for all 2-digit occupations with the exception of army occupations (ISCO 0).

This means that we have a country-specific estimate for the average skill proficiency level and average level of skill use for all ISCO 2-digit occupation in each of the two domains for all countries. At the individual level, we also have the scores on each of these 4 variables. For the proficiency scores we used the average of the plausible values for each domain. We now standardize these variables for each country separately with a mean 10 and standard deviation 1. The mean of 10 was chosen to avoid negative values and zeros.

Next we selected male, fulltime working employees. This selection is done to avoid different wage setting regimes for part-timers and women. Also the relation between skills and earnings for self-employed is quite different from that for employees. Fulltime is defined as working 32 hours or more per week. We only selected respondents for whom we have valid information on skills proficiency, skill use and hourly wages. Wages were trimmed per country leaving out the 1st and 99th percentile of the respondents in each country.

The resulting dataset includes 22 countries and 32,420 individuals. To avoid outliers in the distribution of skill proficiency per country-specific ISCO 2-digit, we left out the 1st and 99th percentile of the respondents in each occupation per country. This leaves us with a working sample of 29,550 individuals. We use a multilevel model to account for the nested structure, allowing for clustering of errors at the country level. We estimate the following model:

$$W_{ic} = a_c1 + a2S_{ic} * U_{ic} + a3C_{ic} + u_{ic} + v_c \qquad \text{(eq. 4)}$$

In which W_{ic} is the natural logarithm of the hourly wages[10] of individual i in country c, a_c1 is a country-specific constant, S_{ic} is the skill proficiency level of individual i in country c, U_{ic} is the corresponding skill use of that individual, $S_{ic} * U_{ic}$ is the skill effort measure of eq. 1, C_{ic} is a vector of control variables (with only two variables age and age squared), and u_{ic} and v_c are idiosyncratic error terms at the individual and country level respectively. We will start the analyses with numeracy proficiency level and the level of use of numeracy skills and later check whether similar results are obtained for literacy.

First we will check the skill effort model with alternative specifications, to check the validity of the first assumption, namely that productivity is a multiplicative function of skill and effort (proxied by skill use). We compare eq. 4 with a model in which we take up the skill proficiency level and skill

10. The hourly wages are all adjusted for cross-national differences by a Purchasing Power Parity (PPP) conversion.

use level as separate effects, as well as a model in which we include both main effects and the interaction effect:

$$W_{ic} = a_c1 + a2S_{ic} + a3U_{ic} + a4C_{ic} + u_{ic} + v_c \qquad \text{(eq. 5)}$$

$$W_{ic} = a_c1 + a2S_{ic} + a3U_{ic} + a4S_{ic} * U_{ic} + a5C_{ic} + u_{ic} + v_c \qquad \text{(eq. 6)}$$

If only the main effects in eq. 6 are significant, then the assumption that productivity is a multiplicative function of skill and effort has to be rejected. If only the interaction term is significant, then assumption 1 is fully supported. When both main effects and the interaction effect are significant, we can conclude that the assumption is partly supported. One reason for this might be that the variable S_{ic} (for example numeracy) is also correlated with other cognitive skills (e.g. general cognitive ability), so that any remaining effect of S_{ic} might reflect these other skills. This may also hold for U_{ic}.

From eq. 5 we also derive information whether or not both components S_{ic} and U_{ic} should have equal weights when calculating the skill effort measure. Remember that we started with standardizing both variables with a mean 10 and standard deviation 1, thus giving both components the same weight in the product term. However if eq. 5 shows that the parameters a2 and a3 are different, we can adjust these weights to properly reflect the contribution of each component in the skill effort measure.

We next estimate the full model of skill effort matches variables, using the set of variables in eq. 3.

$$W_{ic} = a_c1 + a2SE_{ic} + a3C_{ic} + u_{ic} + v_c \qquad \text{(eq. 7)}$$

In which SE_{ic} is a vector of skill effort match variables, containing the 9 variables described earlier in eq. 3. As a robustness check we also estimate eq. 7 using the percentile rank in the country-specific wage distribution as dependent variable. This is done to check whether in certain countries with a compressed wage distribution, the explained variance is better if we use the rank score, rather than the log wage.

We will do some further robustness checks by splitting up the analysis for young, prime age and older workers.

In the next model we test the validity of the second assumption (about the additive effects of skill effort in different domains). First we test eq. 7 separately for the literacy domain and then add both domains in the model.

$$W_{ic} = a_c1 + a2S_LE_{Lic} + a3S_NE_{Nic} + a4C_{ic} + u_{ic} + v_c \qquad \text{(eq. 8)}$$

In which SE_{ic} is the vector of skill effort match variables again and the subscript $_N$ and $_L$ denote the numeracy and literacy domains respectively. By comparing the results for literacy and numeracy from eq. 7 with those from eq. 8 we can see whether the parameter estimates are affected by including other skill domains. If the parameters of both models are substantially different, assumption 2 does not hold.

We further test assumption 2 by extending eq. 4 with similar estimates for literacy and then include an interaction term.

$$W_{ic} = a_c1 + a2S_{Nic} * U_{Nic} + a3S_{Lic} * U_{Lic} + a4S_N * U_{Nic} * S_{Lic} * U_{Lic} + a5C_{ic} + u_{ic} + v_c \qquad \text{(eq. 9)}$$

If the interaction term a4 is significant, this is also a violation of assumption 2.

Next we include the coverage rate as explanatory variable at the country level, to see whether this explains cross-country variation in the effect of the skill effort match variables. Coverage rate is defined[11] as the number of employees covered by a collective agreement, divided by the total number of wage and salary-earners in a country and is based on OECD (2012b). The variable has a range of 13.6 to 99.[12] We calculate cross-level interactions with the vector SE_{ic} as in indicated in the following model.

$$W_{ic} = a_c1 + a2SE_{ic} + a3CR_c + a4\ CR_c * SE_{ic} + a5C_{ic} + u_{ic} + v_c \qquad \text{(eq. 10)}$$

In which CR_c is the country-specific coverage rate. We expect a general positive effect of CR_c at the country level: a high degree of workers falling under a collective wage agreement will increase the general wage level. On the other hand we expect the interaction effects of CR_c to have a depressing effect on the skill effort match variables SE_{ic}. In other words, in countries where many workers fall under a collective wage agreement, wages are less affected by individual's matching variables with respect to skill effort.

We also test a model in which we look at the effect of working in a public sector and the interaction effects on the skill effort match variables.

$$W_{ic} = a_c1 + a2SE_{ic} + a3PS_{ic} + a4\ PS_{ic} * SE_{ic} + a5C_{ic} + u_{ic} + v_c \qquad \text{(eq. 11)}$$

In which PS_{ic} is a dummy indicating whether an individual is working in the public sector (PS) or not.

Finally, we will compare the new model with alternative models as suggested by Allen et al. (2013), Pellizari and Fichen (2013) and a standard ORU model. The following alternative models are estimated:

$$W_{ic} = a_c1 + a2S_{ic} + a3U_{ic} + a4OU_{ic} + a5UU_{ic} + a6C_{ic} + u_{ic} + v_c \qquad \text{(eq. 12)}$$

In which OU_{ic} and UU_{ic} are dummies denoting being overusing (OU) or underusing (UU) the skills according to Allen et al. (2013). Similarly we estimate:

$$W_{ic} = a_c1 + a2S_{ic} + a3U_{ic} + a4OS_{ic} + a5US_{ic} + a6C_{ic} + u_{ic} + v_c \qquad \text{(eq. 13)}$$

In which OS_{ic} and US_{ic} are dummies denoting being overskilled (OS) or underskilled (US) according to Pellizari and Fichen (2013).

The alternative ORU model is the standard Duncan and Hoffman (1981) model in which we look at educational mismatches instead of skill mismatches.

$$W_{ic} = a_c1 + a2RE_{jc} + a3OE_{ic} + a4UE_{ic} + a5C_{ic} + u_{ic} + v_c \qquad \text{(eq. 14)}$$

In which RE_{jc} denotes the years of required education in occupation j in country c[13], OE_{ic} denotes the years of overeducation (defined as own schooling OS_i minus RE_{ic} if $OS_i > RE_{ic}$, else 0) and UE_{ic} as the years of undereducation (defined as RE_{jc}-OS_i if $OS_i < RE_{jc}$, else 0). As education produces more skills than just numeracy (or literacy), we expect this ORU model to be better than the model in which we only include the skill effort match variables with respect to numeracy.

11. See https://stats.oecd.org/glossary/detail.asp?ID=3554
12. We also check an alternative measure using the Employment Protection Legislation (EPL) from the OECD (2012c, see http://www.oecd.org/employment/emp/EPL-timeseries.xlsx). These results are presented in the appendix. However we prefer the coverage rate as the most theoretical relevant one.

[13] We use the Allen and Bijlsma method to calculate the country-specific estimates of the required years of schooling per ISCO 2-digit.

5. Results

First we compare the skill effort model with alternative specifications, to check the validity of the first assumption, namely that productivity is a multiplicative function of skill and effort (proxied by skill use). We compare eq. 4 with a model in which we take up the skill proficiency level and skill use level as separate effects, as well as a model in which we include both main effects (eq. 5) and the interaction effect (eq. 6). Results are displayed in Table 1.

<Table 1 about here>

When only the main effects are entered in the model (eq. 5), both numeracy proficiency and the use of numeracy skills show a positive significant effect on the wages. A one standard deviation increase in the numeracy skill raises the wages with 13.2% and a similar increase in the use of numeracy skills raises the wages with 9.3%. This model 1 explains 12.6% of the between-country (=(0.119-0.104)/0.119*100), and 28.9% of the within-country variation. But with the inclusion of the interaction effect in eq. 6 (model 2) these main effects are not significant anymore and only the interaction effect is significant, while the residual variation stays the same. Only including the interaction term as in eq. 4 (model 3), hardly changes these parameters. This is a very strong support of the first assumption that states that productivity is a multiplicative function of skill and effort. There is no effect of numeracy skills on wages other than through using these skills and vice versa the use of numeracy skills only affects wages in combination with some proficiency.

As indicated, the parameters in eq. 5 show that numeracy proficiency affects wages stronger than does using these skills. The difference in effect size is about 1.5 to 1. This suggests that we need to readjust the weights of these components in the skill effort measure such that they correspondent to this difference. This is done by setting the standard deviation of the skill proficiency variable to 1.5 instead of 1.0. The last column of Table 1 presents the results of eq. 4 using these adjusted weights. The results show that an increase of a one standard deviation in the proficiency of numeracy skill with average use of these skills yields a wage premium of 13.8 (=0.918*1.5*10)% and an increase of one standard deviation in the use of numeracy skills with average proficiency yields a premium that is 9.2%.

<Table 2 about here>

In Table 2 we present the results for the full model as outlined in eq. 7, using the adjusted weights. The first column shows the result for the full model with all 9 parameters. We find significant effects for 6 of the 9 parameters. For three parameters we find no significant effects. All significant parameters (with the exception of the last one) relate to situations in which at least one of the components is typically required. In other words, skills pay off, but only when their use is typically required and vice versa using skills pay off but only if the worker has the skills that are typically required. As indicated the only exception is the last parameter which is only significant at the 5% level and which shows an unexpected very strong positive return to having lower skills than is typically required in the job and using these skill less frequent than is typically required. Theoretically this does not make any sense. We expect that this result is driven by certain occupations that require a low level of numeracy skills, but are paid well, e.g. because they require hard or dangerous work. We checked this by excluding unskilled occupations, but this does not basically change the results. We also checked other specifications and then the parameter sometimes turns insignificant and is therefore quite unstable. We therefore decided to ignore this parameter in the reduced model.

The reduced model[14], displayed in column 3, only takes up variables in which at least one of the components (either skill proficiency or skill use) is typically required. As expected we find positive

14. The appendix shows a number of robustness checks. Table A1 shows the results if we use 1 standard deviation difference instead of 0.5 standard deviation to distinguish over/underskilled resp. overused/underused from the well-matched workers. This does not substantially change the results although the effects for the non-matched are generally larger, which is not surprising as these are now more extreme groups. The residual variance in the case of

effects for the returns to average expected skill proficiencies and skill use. A one standard deviation increase in the numeracy proficiency with average use is associated with an increase of 15.9% (= 1.058*1.5*10) in wages while a one standard deviation increase in the use of these skill (with average proficiency) yields a wage premium of 10.6%. Bringing one standard deviation more skills to the job than is typically required, but with an average skill use also yields a premium of 10.5% which is positive but less than the premium on required skills. The return on using the skills more than is typically required (but with a required skill proficiency level) also yields a positive return of 7.0%. Bringing less skills to the job than is typically required is associated with a wage penalty of 11.3%. This is not statistically different in absolute terms than the positive effect of bringing more skills to the job than is typically required (10.5%). And underusing the skills is associated with a wage penalty of 5.7% which is slightly (but significantly) lower in absolute terms than the positive effect of overusing the skills.

If we compare these results with what is usually found in the educational mismatch literature we see a strong similarity in results. The returns to required skill proficiency levels are larger than the returns to being overskilled and underskilled. And similarly, the returns to the required levels of skill are larger than the returns to overusing or underusing the skills. Also we find that the wage penalty to underusing your skills is less in absolute terms than the wage premium to overusing your skills, which is consistent with the lower penalties for undereducation compared to the premiums for overeducation. Only in the case of over- and underskilling do we see no significant difference between the two parameters in absolute sense. This suggests a more linear relation between skills proficiency and productivity, with an additional premium for workers who have a matching skill level.

<Figure 1 about here>

Figure 1 shows the explained variance of this reduced model for the different countries plotted against the coverage rate in a country. We note that the explained variance at the individual level differs quite markedly between countries, ranging from some 20% in the Slovak Republic and Estonia to some 50% in the Netherlands and Austria, but there is no systematic relation with the coverage rate. We note that some countries that are typically regarded as Occupational Labour Markets (Gangl, 2001), such as Austria, Germany and the Netherlands, rank quite high, but so do some typical flexible and Internal Labour Markets like the United States and the United Kingdom. The countries that show the lowest relation between the different skill effort match variables and wages are the typical Eastern-European transition economies and some Southern-European countries like Italy and Spain. In Canada wages are also much less related to the skill effort match variables.

<Figure 2 about here>

This changes hardly when we look at the percentile rank in the country's wage distribution, which might work better for countries with a compressed wage distribution. Figure 2 shows the results comparing the explained variances for each model (full results are displayed in Table A2 of the appendix). It shows that using the percentile rank in the country's wage distribution does not improve the model at all. All countries are well above the diagonal, although for some countries the difference is not big. The only country where we see no difference is the Slovak Republic.

<Figure 3 about here>

In Figure 3 we compare the cross-national variation in the explained variance for the reduced model with the explained variance that we get from a simple ORU-model. This shows more or

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using a cut-off point of 1 standard deviation is also larger. Given this fact and the fact that 0.5 standard deviation difference within an occupation is in fact quite large, we stick to the cut-off point of 0.5 standard deviation difference. Table A2 compares the reduced model using log wages with a model that uses the percentile rank in the country's wage distribution. The latter model does considerably worse, if we compare the residual variance of the intercept model with the actual models.

less the same pattern as we saw in Figure 1, meaning that most countries are close to the diagonal. This means that the low explained variance in the Eastern-European countries is not driven by a weak relation between skills and wages, but by a weak relation between schooling and wages as well. We interpret this finding that in well-functioning labour markets, whether these are typical OLM types like the ‘Rheinland’ countries, or whether they are very open and flexible, like the Anglo-Saxon countries, wages are primarily driven by skills and the use of these skills.

<Table 3 about here>

In Table 3 we run the model for different age groups (16-34; 35-49; 50-65). The results indicate that the parameters are strongest for the prime age (35-49) and older age (50-65) workers. For the younger workers (16-34) the effects of required skill and required skill use, overskilling, underskilling, overusing and underusing are considerably smaller.[15] This is consistent with previous work by Altonji and Pierret (2001) who showed that wages of young workers are more affected by schooling variables, while wages of prime age and older workers are more affected by actual skills. In general we see fewer differences between prime age and older workers, but they are still interesting to point out. Older workers get a significantly higher wage premium for required skills and skill use compared to prime age workers (1.277 compared to 1.165). More striking is the difference in the wage premiums and wage penalties for overusing or underusing the skills. Older workers get a much higher premium for overusing their skills (1.027 compared to 0.623) and get far less penalized for underusing their skills (-0.437 compared to -0.768). These differences are all statistically significant.

<Table 4 about here>

Table 4 compares the reduced numeracy model with a reduced model for literacy both separately and taken up together. For comparison, Column 1 shows the estimates for the reduced numeracy domain again, as presented earlier in Table 2. Column 2 shows the estimates for the literacy domain separately. They follow the same pattern as for the numeracy items, but are also always a bit higher. The returns to required literacy skills and literacy use are 1.291 compared to 1.058 for numeracy. Also the difference in the returns to being overskilled is remarkable (0.970 vs 0.697). This is some 25% difference. However, in a joint model (eq. 8, column 3), the numeracy items clearly outweigh the literacy related items, thus confirming previous results showing stronger effect of numeracy on wages compared to literacy (Levels et al., 2014). The effect sizes are reduced with some 65-70% for the literacy items and ‘only’ some 25-30% for the numeracy items. The only exceptions are the items related to over- or underusing the skills. Here the reduction for the literacy items is only some 10-15% compared to 35-55% in the case of numeracy items. In the joint model, overusing literacy skills with one standard deviation yields a wage premium of 6.5% compared to 3.7% in the case of numeracy skills. And conversely, underusing the literacy skills with one standard deviation yields a wage penalty of 6.2% compared to 3.6% in the case of numeracy skills.

<Table 5 about here>

Table 5 presents the results of eq. 9, which furthers tests assumption 2. Is there an interaction effect between skill effort measures of two different domains, in this case numeracy and literacy? We see that the interaction combining the skills effort measures of both domains is indeed significant, but very low. Reflecting on both results, we conclude that assumption 2 is indeed seriously violated. The effects of literacy are seriously overestimated if they are assessed without including the effects of the other skill domains. The changes in the parameters are also significant for the numeracy domain, although the difference is not that large. The significant interaction effect in eq. 9 also points in the same direction although the effect size is not substantial. Nevertheless we conclude that the effects of skill effort in different domains is not simply additive:

15. The explained variance for the three age groups is not so different if we compare the residual variance of the models with the intercept models, but the variance among prime age and older workers is larger to start with.

the skill effort in both numeracy and literacy overlap substantially, which leads to an overestimation of the effects of one skill domain if the other is not included as well. We will have to take this into account when looking at the results of the following analyses, which focus on numeracy again.

In the next model we continue with the reduced numeracy model and include the country's coverage rate as well as interaction terms with the skill effort match parameters.[16] As indicated before, the coverage rate is only available for 19 of the 22 countries. The results are presented in Table 6.

<Table 6 about here>

The analysis shows some interesting results. First, we see that including the coverage rate decreases the variance component at the country level with 29.4% compared to the intercept model and 4.2% compared to the simple reduced model in column 2. The residual variance at the individual level decreases with 36.8% compared to the intercept model and 0.5% compared to the simple reduced model. There is a strong general positive effect of coverage rate, once you include the cross-level interaction effects with the skill effort match variables.[17] That is, a strong coverage rate increases the overall wages, regardless of the skills proficiency or skill use levels. An increase of the coverage rate with 10% increases the wages in a country with some 8.3% But this effect is offset by the negative interaction of coverage rate with the skill proficiency and skill use parameters. The skill effort match variables show the effect of required skill proficiency and skill use, overskilling, underskiling, overuse and underuse in a situation where the coverage rate is zero. If we compare these results with the parameters of the reduced model without the coverage rate for the same 19 countries (column 2), we see that all the parameters for the skill effort match variables are much stronger for countries where the coverage rate is zero. The difference with the effect of the same variables in countries with an average coverage rate is some 25-30%. For example the effect of a one standard deviation increase in skill proficiency level with average skill use in a country with no coverage rate is 20.2% (=1.347*1.5*10), but this effect is decreased with 0.75% (=-0.005*1.5) for every percentage increase in the coverage rate. We see similar depressing effects of coverage rate on the returns to being overskilled (b=-0.005), and overuse (b=-0.008) and a decreasing penalty for being underskilled (b=0.005).

<Figure 4 about here>

This is illustrated in Figure 4 that shows the different returns to required skill effort by coverage rate. We see a clear negative relation between the strength of the effect of required skill effort, and the coverage rate, ranging from some 1.5 in the United States to some 0.8 in Sweden and Belgium.

<Table 7 about here>

In Table 7, we look at the effect of working in the public sector. Column 1 presents the results of the main effects model, including a dummy for working in the public sector in the reduced model. The general wage premium of working in the public sector is 7.1%. However it is clear that this not evenly distributed across the whole range of skill proficiency and skill use. Column 2 provides the results of (eq. 11) where interaction effects are added to the model. The general wage premium of working in the public sector is now 26.8% which is the wage premium for workers with zero skills and zero skill use. The interaction effect with required skills effect is negative (b = -0.174). This means that for workers in an occupation where the required skill proficiency and skill use is average (both 10), the wage premium is reduced with 17.4% turning into a negative effect

16. An alternative model using the EPL is presented in the appendix. The results are quite similar to the ones that are shown here, although the explained variance is a bit lower.
17. A model with coverage rate at the country level alone does not a significant effect, because it also depresses the effects of individual skill proficiencies and skill use.

for occupations with a required skill proficiency and skill use level of 2 standard deviations above average. Unexpectedly, workers in the public sector are more heavily penalised for having lower skill than are typically required (b = -0.16). But at the same time they get much less penalised for underusing their skills compared to what is required in the job. Put simply, there is a wage premium for working in the public sector which is highest for low skilled jobs, and for workers who shirk. But workers who lack the skills that are required are more heavily penalised.

<Table 8 about here>

Finally in Table 8 we show the results of our reduced model and compare it with some other models. Column 1 shows the same parameters as in Table 2, column 3. Column 2 presents the results of the Allen et al. (2013) method, with the numeracy proficiency level, the skill use level and dummies for relative overutilization or underutilization of skills compared to the skill proficiency level. To compare the results, the skill proficiency and skill use have the same scale as in the previous models (mean 10 and standard deviation of 1.5 and 1.0 respectively). The results show the expected positive effects for skill proficiency and skill use. One standard deviation extra skills yields a wage premium of 12.9% and one standard deviation more use yield a wage premium of 9.8%. The effect of relative overuse of skills compared to the skills level is not significant. But being overskilled relative to the use of skills (which is the same as underusing the skills), has a significant positive effect. Note that the reference here is skill use in the job, which turns the parameter into a positive effect (just like the effect of overeducation in the ORU-model). Being overskilled compared to the use of the skills pays off with some 3.2%. Nevertheless, the Allen et al. (2013) performs less well than the previously introduced reduced skill effort match model. The percentage explained variance of the model compared to the intercept model is much lower than for the reduced model (22.6% versus 29.1%). Column 3 shows similar results for the Pellizari and Fichen (2013) measure. The returns to one standard deviation increase in skill proficiency is 15.7%, and a similar increase in the use of numeracy skills has a wage return of 8.7%. The penalty for being overskilled is 8.6%[18] and the wage premium for being underskilled is 10.7%. Although these effects are all significant, the explained variance of the model is again lower than the explained variance in the reduced skill effort match model (22.9% versus 29.1%). Finally in column 4, we compare the reduced skill effort match model with a standard ORU model. To make the results more comparable to the reduced model, we used the average years of schooling in an occupation as the proxy for required education (using the same algorithm as Allen and Bijlsma, 2015). The results show the familiar outcomes of some 9.8% increase in wages for each additional year of schooling, 3.1% return to years of overschooling and a similar wage penalty for years of underschooling. As education imparts more skills than just numeracy, we expected this model to do better than the skill effort match model. This is indeed the case but the difference is quite small: 31.0% versus 29.1%. This is again a strong support for the skill effort match model showing that wages are driven by a multiplicative function of skill proficiency and skill use.

6. Conclusions

There is convincing evidence that wage effects of education are largely driven by skills (Hanushek and Woessmann, 2011; Hanushek et al., 2015), although this is weaker in less institutionalised settings (Levels et al. 2014). There is also strong evidence of different returns in the case of educational mismatches (Hartog, 2000; Groot and Maassen van den Brink, 2000). In general workers get more rewarded for years of required education than for years of overeducation, while the penalties for years of undereducation are least severe.

As opposed to educational mismatches, the research on skill mismatches has produced more mixed results. This is partly due to the fact that educational mismatches and skill mismatches are

18. Remember that the reference here is the well matched worker and not the required skill level, hence the reverse of signs.

not simply the same, due to heterogeneity in skills within educational levels and the sorting of the least skilled graduates from each level to less complex jobs (Allen and Van der Velden, 2001; Green and McIntosh, 2007). But part of the problem is also the lack of good measures for skill requirements. Three approaches have been developed to proxy these skill requirements: worker self-assessment (asking the worker about the required level), realized matches (taking the average or median skill level in an occupation as the required skill level) and the job requirement approach (taking the use of skills in a job as a proxy for the required skill level).

In this paper we discussed the pros and cons of each of these approaches and concluded that each of these approaches have their own weaknesses, both theoretically and empirically. Elaborating on this, we discussed the different views one can have on skill use. On the one hand one can view the use of skills as a proxy for skill requirement as is done in the job requirement approach or one can see the use of skill as complementary to skill proficiency. This latter approach is more close to how the use of skills is viewed in the engagement literature, where using skills is an essential component of the literacy and numeracy constructs (OECD, 2012a). The link between skill proficiency and skill use is also firmly rooted in use-it-or-lose-it theories (Salthouse, 2006) and self-efficacy theory (Bandura, 1977).

In this paper we develop this idea further by explicitly linking skill use and skill proficiency into a new concept, skill effort. Skills effort is defined as a multiplicative function of skill proficiency and skill use and has an intuitively appealing notion. There can be no productivity effect of the skill proficiency of a worker if his/her skills are not being used and vice versa the productive use of skills is moderated by the proficiency level of the worker. The idea of using a multiplicative function to combine skill proficiency and skill use, has a parallel in the performance literature on ability and motivation (Vroom, 1964), where performance is viewed as the result of a multiplicative function of ability and motivation.

Results show that the new developed model is indeed much better than the original concepts of using skill proficiency and skill use as separate predictors of wages. In a joint model, the multiplicative term takes over all the effect of the separate terms, which is a strong indication of the basic notion of our skill effort model, namely that there can be no productivity effect of skill proficiency when skills are not being used and vice versa.

We next developed a skill effort matching model, similar to the ORU model (Duncan and Hoffman, 1981) for educational mismatches. The model distinguishes nine components, one for the returns to required skill proficiency and skill use, and eight others for different situations of mismatches. It turns out that a reduced model of five components best fits the model, which apart from the returns to required proficiency and use, relates to the returns to overskilling and underskilling in combination with required use, and the returns to overusing and underusing in combination with required proficiency.

The results show that one standard deviation increase in required skill level (with average use) is associated with a wage premium of 15.9%. Bringing more skills to the job than required also yields a premium but not as much, namely 10.5% and bringing less skills to the job than is typically required yields a wage penalty of 11.3%. The return to a one standard deviation increase in the required use of skill (with average proficiency) yields a wage premium of 10.6%, while the return on using the skills more than is typically required (but with a required skill proficiency level) yields a positive return of 7.0%. Underusing the skills is associated with a wage penalty of 5.7%.

As indicated earlier, we have to be a bit cautious when interpreting these results. These effects are all estimated without including the skill effort match variables of other domains. In an additional analyses we showed that the above mentioned effects all decrease with some 25-30% if we include the skill effort match variables of literacy. This means that the above effect sizes should be regarded as an upper bound of the effect of numeracy skill effort.

The results can best be explained with matching theory. The premium for required skills is larger than the premium for being overskilled and the premium for the required use of these skills is larger than the premium for overusing the skill. In the case of skill proficiencies, the wage penalty for being underskilled is just as large in absolute terms as the wage premium for being overskilled. But in the case of use of skills, the wage penalty for underutilisation of the skills is lower – in absolute terms - than the premium for overusing these skills. We found no effects of the other parameters. In other words, skill proficiency and skill use only pay off if at least one of the components is required. Put differently, being overskilled pay off but only if their use is required and working hard also pays off, but only with the required skill proficiency level.

We explored some additional analyses, looking at differences between age groups. The results indicate that, consistent with Altonji and Pierret (2001), the model works best for the prime age and older age workers. For the younger workers the effects of the skill effort match variables are considerably smaller. Interestingly, we see older workers get a much higher premium for overusing their skills and get far less penalized for underusing their skills.

We also included the coverage rate of a country in the model and interacted these with the skill effort match variables. We found the strongest effects of the skill effort match variables in countries with a low percentage of workers falling under a collective wage agreement, which is consistent with theories about labour market institutions (Marsden, 1999). This is broadly in line with the results of an alternative model in which we looked at the effect of working in the public sector and the interaction with the skill effort match variables. We showed that there a wage premium for working in the public sector, and this wage premium is highest for workers in occupations with low requirements on skill proficiency and skill use. Interestingly, workers in the public sector who are underusing their skills compared to what is required in their occupation get less penalised compared to similar workers in the private sector, while workers who lack the skills that are required are more heavily penalised.

Finally, we compared the skill effort matching model, to other models looking at skill mismatches in the labour market, namely Allen et al. (2013), Pellizari and Fichen (2013) and a simple educational mismatch (ORU) model. The results show that the skill effort matching model is superior to the alternative models that assess the effects of skill matches (Allen et al., 2013; Pellizari and Fichen (2013) in terms of explained variances and almost as good as a standard ORU model. This is again a strong support for the developed skill effort matching model. The predictive validity when we look at wage differences is far better than existing alternative skill match variables. As schooling variables reflect more skills than just numeracy or literacy, we had expected that the ORU-model is better. The fact that the explained variance of our skill effort matching model is very close to this ORU-model is therefore very encouraging.

This does not mean that this approach needs no further development. Although the basic idea of skill effort is empirically and theoretically sound, there is an inherent weak point when we turn this into a matching model. Our skill effort matching model is based on a realised matches (RM) approach, with the two problems associated with that approach. The first problem is that of heterogeneity within occupational groups. Our RM approach uses the mean skill proficiency or skill use level in an occupation as an indicator of the required level of the skill proficiency or skill use in that occupation. If occupational groups are very heterogeneous, this might lead to a wrong assignment of workers as being matched or non-matched. In this paper we have used country-specific estimates of the average skill proficiency and skill use levels in each ISCO 2-digit occupation. If we could use a more refined classification, e.g. the ISCO 3-digit level or even 4-digit level, this might reduce the problem of the within-occupation heterogeneity. The Allen and Bijlsma (2015) method of obtaining robust estimates using a multilevel model already stretches the possibilities of the current PIAAC data set to the limit and cannot be used to get estimates at 3- or 4-digit level. A very promising possibility is using so-called Small Area Estimation (SAE) models to arrive at these more detailed estimates. The basic idea is to use other datasets in combination with the PIAAC data to get a more precise and reliable indicator of the average skill proficiency level in detailed occupations. Van den Brakel, Bijlsma and Van der Velden (forthcoming) have used the Dutch Labour Force Survey (LFS) data and PIAAC data to arrive at estimates at the 3-digit level. The basic idea of SAE is to develop a prediction model on a smaller dataset (in this case PIAAC) and use a larger dataset (in this case the LFS) with the same predictors to make a synthetic estimate of the dependent variable in each ISCO 3-digit occupation. The outcome is a weighted sum of direct estimates (from PIAAC) and synthetic estimates where the weight is based on the precision of each of the two estimates. The results show that in general the coefficients of overskilling and underskilling decrease somewhat and the coefficients for required education increase due to better measurement properties.

The second problem in using the RM approach is the problem of a forced equilibrium. Basically RM models take the average levels as indicating a match, but of course this need not be the case. To give an example, the fact that 80% of the workers in an occupation has a skill proficiency level that is not higher or lower than a half standard deviation difference from the mean, does not automatically imply that all these workers are well-matched. In fact most workers in that occupation might have a skill proficiency level that is too high or too low for that occupation. There is no direct way to deal with this problem, as we lack direct information on skill requirements from employers. One way to solve this would be to have expert opinions on the required skill level in each ISCO 2-digit occupation. Basically this is identical to what has been called the Job Analyst (JA) method in identifying educational mismatches (Hartog, 2000). This JA method is generally regarded as potentially the most reliable source to identify educational mismatches (Verhaest and Omey, 2006). These experts would need to express these required skill levels in the same scale metric as in which the possessed skills are measured, in order to be able to directly compare the two. We advise the OECD to take an initiative to consult national job experts and international domain-specific experts (e.g. in numeracy, literacy, problem solving), to provide estimates of the required skill levels for each ISCO 2-digit occupation for the countries currently participating in PIAAC and its follow-ups.

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Figure 1 Explained variance reduced models per country plotted against the coverage rate

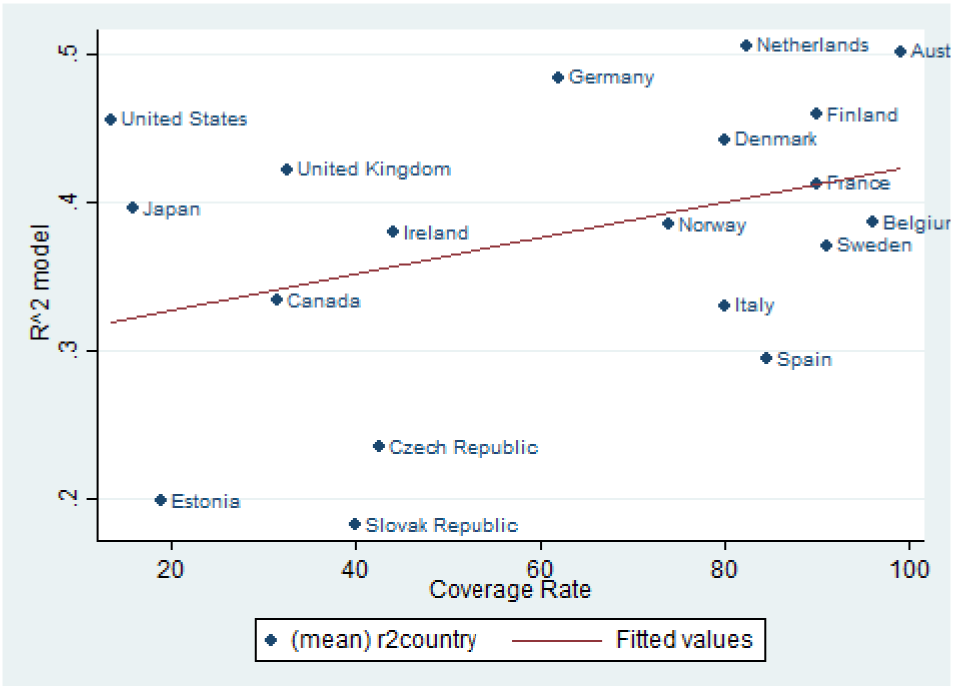

Figure 2 Explained variance log wage and percentile rank wage distribution per country

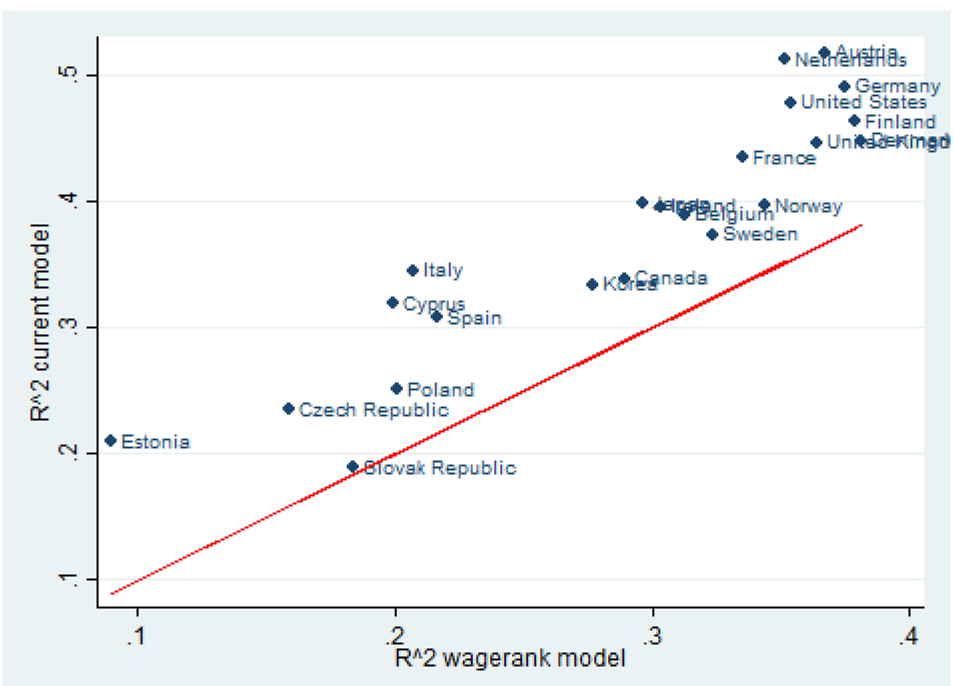

Figure 3 Explained variance skill effort matching model and ORU model per country

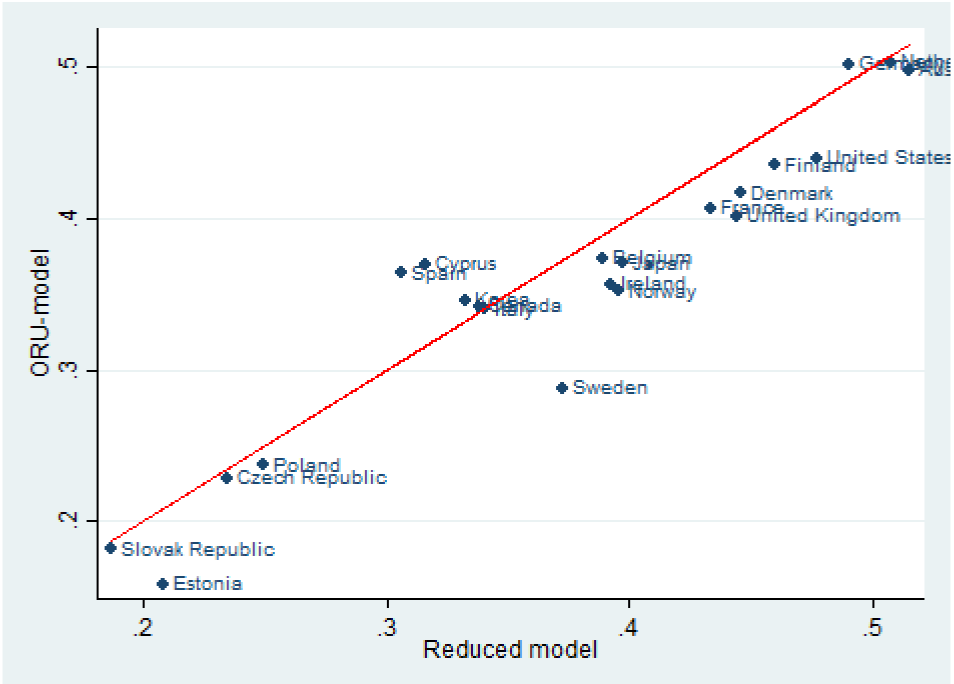

Figure 4 Relation between coverage rate and wage effect of required skill effort

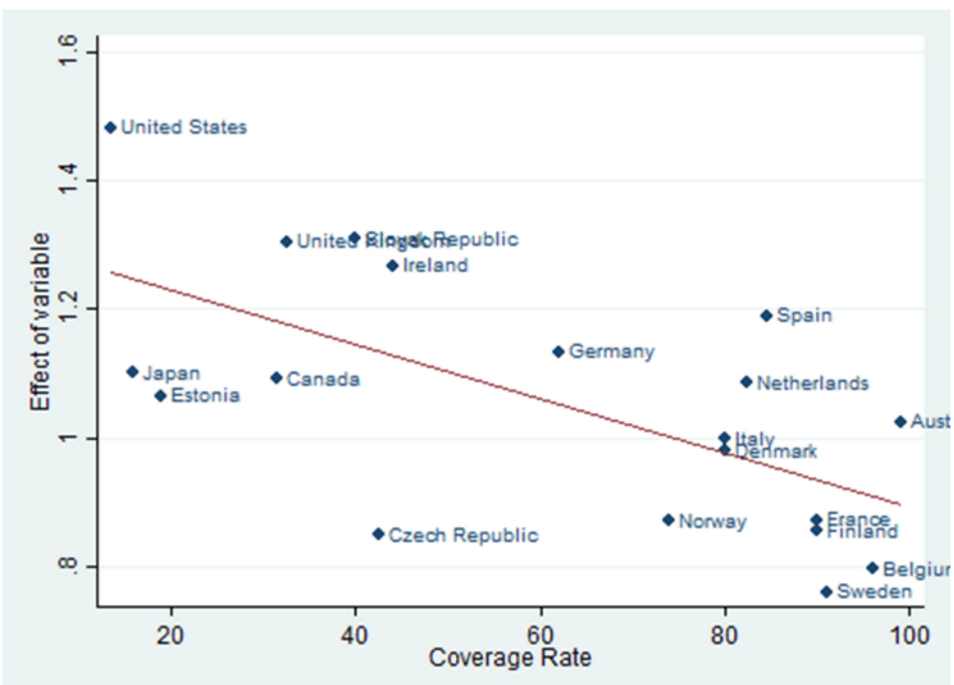

Table 1 Comparing other specifications of the skill effort model

VARIABLES	Model 1 (Eq. 5)	Model 2 (Eq. 6)	Model 3 (Eq. 4)	Model 4 (Eq. 4 with adj. weights)
Skill Proficiency	13.168*** (0.267)	1.622 (2.412)		
Skill Use	9.285*** (0.248)	-2.557 (2.471)		
Proficiency * Use		1.173*** (0.244)	1.114*** (0.014)	0.918*** (0.011)
$N_{individuals}$	29047	29047	29047	29551
$N_{countries}$	22	22	22	22
BIC	26575	26562	26635	27890

Variance components	Intercept model	Model 1	Model 2	Model 3	Model 4
Between Variance	0.119	0.104	0.104	0.104	0.103
Within Variance	0.204	0.145	0.145	0.145	0.147
Total Variance	0.323	0.139	0.139	0.139	0.140

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Table 2 Skill effort matching model (eq. 7)

VARIABLES	Model 1 Full model	Model 2 Without ISCO 9	Model 3 Reduced model
Returns to average utilisation with average skills	1.062***	1.057***	1.058***
	(0.011)	(0.012)	(0.011)
Returns to average utilisation with high skills	0.690***	0.725***	0.697***
	(0.045)	(0.048)	(0.038)
Returns to average utilisation with low skills	-0.792***	-0.787***	-0.754***
	(0.042)	(0.043)	(0.034)
Returns to overutilisation with average skills	0.733***	0.720***	0.703***
	(0.079)	(0.082)	(0.058)
Returns to overutilisation with high skills	-0.050	-0.264	
	(0.652)	(0.732)	
Returns to overutilisation with low skills	-2.185	-2.146	
	(1.399)	(1.499)	
Returns to underutilisation with average skills	-0.679***	-0.680***	-0.567***
	(0.076)	(0.076)	(0.054)
Returns to underutilisation with high skills	-0.737	-1.423	
	(1.665)	(1.678)	
Returns to underutilisation with low skills	1.701**	1.717**	
	(0.747)	(0.753)	
$N_{individuals}$	29551	27764	29551
$N_{countries}$	22	22	22
BIC	25258	23781	25227

Variance components	Intercept model	Model 1	Model 2	Model 3
Between Variance	0.119	0.093	0.092	0.093
Within Variance	0.204	0.136	0.136	0.136
Total Variance	0.323	0.229	0.228	0,229

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Table 3 Skill effort matching model for different age groups

VARIABLES	Young age	Prime age	Old age
Returns to average utilisation with average skills	0.739***	1.165***	1.277***
	(0.018)	(0.017)	(0.023)
Returns to average utilisation with high skills	0.442***	0.851***	0.772***
	(0.056)	(0.061)	(0.092)
Returns to average utilisation with low skills	-0.600***	-0.832***	-0.883***
	(0.059)	(0.052)	(0.061)
Returns to overutilisation with average skills	0.485***	0.623***	1.027***
	(0.088)	(0.092)	(0.127)
Returns to underutilisation with average skills	-0.549***	-0.768***	-0.437***
	(0.092)	(0.084)	(0.099)
$N_{individuals}$	11053	11403	7095
$N_{countries}$	22	22	22
BIC	8891	9206	6182

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Young Age

Variance components	Intercept model	Model
Between Variance	0.086	0.074
Within Variance	0.180	0.128
Total Variance	0.266	0.202

Prime Age

Variance components	Intercept model	Model
Between Variance	0.121	0.103
Within Variance	0.184	0.129
Total Variance	0.305	0.232

Old Age

Variance components	Intercept model	Model
Between Variance	0.152	0.132
Within Variance	0.202	0.136
Total Variance	0.354	0.268

Table 4 Skill effort matching model for literacy and numeracy

VARIABLES	Model 1 Numeracy only	Model 2 Literacy only	Model 3 Numeracy + Literacy
Returns to average utilisation with average skills (literacy)		1.291***	0.447***
		(0.015)	(0.035)
Returns to average utilisation with high skills (literacy)		0.970***	0.314***
		(0.055)	(0.065)
Returns to overutilisation with low skills (literacy)		-0.827***	-0.243***
		(0.037)	(0.051)
Returns to overutilisation with average skills (literacy)		0.724***	0.654***
		(0.051)	(0.054)
Returns to underutilisation with average skills (literacy)		-0.707***	-0.618***
		(0.055)	(0.058)
Returns to average utilisation with average skills (numeracy)	1.058***		0.771***
	(0.011)		(0.027)
Returns to average utilisation with high skills (numeracy)	0.697***		0.499***
	(0.038)		(0.047)
Returns to average utilisation with low skills (numeracy)	-0.754***		-0.568***
	(0.034)		(0.045)
Returns to overutilisation with average skills (numeracy)	0.703***		0.369***
	(0.058)		(0.062)
Returns to underutilisation with average skills (numeracy)	-0.567***		-0.359***
	(0.054)		(0.056)
$N_{individuals}$	29551	29532	29131
$N_{countries}$	22	22	22
BIC	25227	25564	24512

Variance components	Intercept model	Model 1	Model 2	Model 3
Between Variance	0.119	0.093	0.083	0.092
Within Variance	0.204	0.136	0.138	0.134
Total Variance	0.323	0.229	0.221	0.226

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Table 5 Skill effort model and the Interaction between literacy and numeracy

VARIABLES	Parameters
Proficiency * Use (numeracy)	0.165***
	(0.053)
Proficiency * Use (literacy)	0.110**
	(0.048)
Proficiency * Use (numeracy) * Proficiency * Use (literacy)	0.004***
	(0.000)
$N_{individuals}$	29551
$N_{countries}$	22
BIC	27312

Variance components	Intercept model	Model
Between Variance	0.119	0.103
Within Variance	0.204	0.144
Total Variance	0.323	0.247

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Table 6 Skill effort matching model with coverage rate

VARIABLES	Coverage rate model	Reduced model
Returns to average utilisation with average skills (a2)	1.347***	1.052***
	(0.027)	(0.012)
Returns to average utilisation with high skills (a3)	1.004***	0.719***
	(0.093)	(0.043)
Returns to average utilisation with low skills (a4)	-1.085***	-0.755***
	(0.081)	(0.034)
Returns to overutilisation with average skills (a5)	1.215***	0.691***
	(0.154)	(0.063)
Returns to underutilisation with average skills (a8)	-0.648***	-0.538***
	(0.123)	(0.055)
Coverage Rate	0.826***	
	(0.234)	
Coveragerate * a2	-0.005***	
	(0.000)	
Coveragerate * a3	-0.005***	
	(0.001)	
Coveragerate * a4	0.005***	
	(0.001)	
Coveragerate * a5	-0.008***	
	(0.002)	
Coveragerate * a8	0.001	
	(0.002)	
$N_{individuals}$	25392	25392
$N_{countries}$	19	19
BIC	20429	20537

Variance components	Intercept model	Coverage rate model	% explained	Reduced model	% explained
Between Variance	0.119	0.084	29,4	0.089	25,2
Within Variance	0.204	0.129	36,8	0.130	36,3
Total Variance	0.323	0.213	34,1	0.219	32,2

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Table 7 Skill effort matching model with public sector

VARIABLES	Only main effect	Plus interaction effects
Returns to average utilisation with average skills (a2)	1.053***	1.084***
	(0.011)	(0.012)
Returns to average utilisation with high skills (a3)	0.704***	0.691***
	(0.038)	(0.042)
Returns to average utilisation with low skills (a4)	-0.742***	-0.711***
	(0.033)	(0.038)
Returns to overutilisation with average skills (a5)	0.660***	0.723***
	(0.058)	(0.068)
Returns to underutilisation with average skills (a8)	-0.610***	-0.688***
	(0.054)	(0.063)
Public sector	7.142***	26.773***
	(0.539)	(3.246)
Public sector * a2		-0.174***
		(0.028)
Public sector * a3		0.059
		(0.095)
Public sector * a4		-0.160**
		(0.079)
Public sector * a5		-0.207
		(0.130)
Public sector * a8		0.388***
		(0.118)
$N_{individuals}$	29551	29551
$N_{countries}$	22	22
BIC	25048	25062

Variance components	Intercept model	Main effect model	% explained	Interaction effect model	% explained
Between Variance	0.119	0.092	29,4	0.092	25,2
Within Variance	0.204	0.136	36,8	0.135	36,3
Total Variance	0.323	0.228	34,1	0.227	32,2

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Table 8 Skill effort matching model compared with alternative models

VARIABLES	Model 1 Reduced model	Model 2 Allen et al. (2013)	Model 3 Pellizari and Fichen (2013)	Model 4 ORU model
Returns to average utilisation with average skills (a2)	1.058***			
	(0.011)			
Returns to average utilisation with high skills (a3)	0.697***			
	(0.038)			
Returns to average utilisation with low skills (a4)	-0.754***			
	(0.034)			
Returns to overutilisation with average skills (a5)	0.703***			
	(0.058)			
Returns to underutilisation with average skills (a8)	-0.567***			
	(0.054)			
Overskilled compared to Use		3.151***		
		(0.890)		
Overuse compared to Skill		-0.116		
		(0.969)		
Overskilled			-8.599***	
			(0.745)	
Underskilled			10.683***	
			(0.993)	
Skill Proficiency		8.580***	10.451***	
		(0.299)	(0.198)	
Skill Use		9.833***	8.733***	
		(0.342)	(0.246)	
Overeducation				3.139***
				(0.155)
Required Education				9.762***
				(0.108)
Undereducation				-3.010***
				(0.181)
$N_{individuals}$	29551	30144	29770	29842
$N_{countries}$	22	22	22	22
BIC	25227	27931	27188	26335

Variance components	Intercept model	Model 1	Model 2	Model 3	Model 4
Between Variance	0.119	0.093	0.103	0.104	0.084
Within Variance	0.204	0.136	0.147	0.145	0.139
Total Variance	0.323	0.229	0.250	0.249	0.223

% explained variance	Model 1	Model 2	Model 3	Model 4
Between Variance	21,8	13,4	12,6	29,4
Within Variance	33,3	27,9	28,9	31,9
Total Variance	29,1	22,6	22,9	31,0

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Appendix

Table A1 Robustness check comparing the reduced model using different cut-off points

VARIABLES	Model 1 St.dev.= 0.5	Model 2 St.dev.=1.0
Returns to average utilisation with average skills	1.058***	1.292***
	(0.011)	(0.016)
Returns to average utilisation with high skills	0.697***	2.034***
	(0.038)	(0.103)
Returns to average utilisation with low skills	-0.754***	-1.309***
	(0.034)	(0.056)
Returns to overutilisation with average skills	0.703***	1.163***
	(0.058)	(0.076)
Returns to underutilisation with average skills	-0.568***	-0.898***
	(0.054)	(0.084)
$N_{individuals}$	29551	29551
$N_{countries}$	22	22
BIC	25227	26714

Variance components	Intercept model	Model 1	Model 2
Between Variance	0.152	0.093	0.096
Within Variance	0.202	0.136	0.143
Total Variance	0.354	0.229	0.239

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Table A2 Robustness check comparing the skill effort matching model using log wages or percentile rank in the wage distribution

VARIABLES	Model 1 Log wage	Model 2 Percentile rank
Returns to average utilisation with average skills	1.058***	0.624***
	(0.011)	(0.007)
Returns to average utilisation with high skills	0.697***	0.328***
	(0.038)	(0.025)
Returns to average utilisation with low skills	-0.754***	-0.307***
	(0.034)	(0.021)
Returns to overutilisation with average skills	0.703***	0.456***
	(0.058)	(0.037)
Returns to underutilisation with average skills	-0.568***	-0.414***
	(0.054)	(0.034)
$N_{individuals}$	29551	29551
$N_{countries}$	22	22
BIC	25227	1225

Variance components	Intercept model	Model 1	Intercept	Model 2
Between Variance	0.119	0.093	0.000	0.002
Within Variance	0.204	0.136	0.083	0.061
Total Variance	0.323	0.229	0.083	0.063

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.

Table A3 Skill effort matching model with EPL

VARIABLES	EPL
Returns to average utilisation with average skills (a2)	1.363***
	(0.034)
Returns to average utilisation with high skills (a3)	0.931***
	(0.108)
Returns to average utilisation with low skills (a4)	-1.155***
	(0.118)
Returns to overutilisation with average skills (a5)	1.599***
	(0.224)
Returns to underutilisation with average skills (a8)	-0.583***
	(0.152)
EPL	6.469
	(10.027)
EPL * a2	-0.152***
	(0.016)
EPL * a3	-0.103*
	(0.054)
EPL * a4	0.201***
	(0.055)
EPL * a5	-0.435***
	(0.105)
EPL * a8	0.003
	(0.073)
$N_{individuals}$	28758
$N_{countries}$	21
BIC	24543

Variance components	Intercept	EPL model	% explained
Between Variance	0.127	0.097	23,6
Within Variance	0.201	0.135	32,8
Total Variance	0.328	0.232	29,3

Parameters multiplied by 100; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Controls include age, age2.