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Abstract

Skill mismatches have strong negative effects on productivity, job satisfaction, and other outcomes. To reduce skill mismatches, governments need to rely on accurate data on the prevalence of these mismatches. The Programme of the International Assessment of Adult Competences (PIAAC) is currently the most important data source providing excellent and unparalleled information for many countries on two key information-processing skills (i.e., literacy and numeracy skills). However, although these data contain rich information about *possessed* skills, countries lack directly comparable information on the *required* skills in those domains. Hence, it has been difficult to use the PIAAC data to identify skill mismatches, other than through proxies of required skills (e.g., the average skill level in occupations) or workers' self-assessments of skill mismatch.

In this paper, we use the Job Analysis Method (JAM) to determine the required skill levels of literacy and numeracy for all 4-digit ISCO08 unit groups of occupations in the same metric and scale as was used in PIAAC. JAM involves the use of occupational experts to rate the skill requirements in the different occupations. JAM has never been used before to identify required skill levels for literacy and numeracy as measured in PIAAC, and the paper thus presents the first results on the prevalence of skill shortages and skill surpluses in these key information-processing skills across different OECD countries and across different occupations and sectors that is based on a more direct estimate of the required skills. We provide estimates for the proportions of well-matched, overskilled and underskilled workers per country, and compare these with estimates based on alternative methods for estimating skill mismatch. We also compare JAM with these other methods in explaining wage differentials, as well as job satisfaction. We conclude that there are large differences in the estimates of the prevalence of skill mismatches depending on the method used. We show several advantages using JAM and discuss some of the limitations as well.

JEL classification: I26, J24
Keywords: Skill shortages, underskilling, skill surpluses, overskilling, skill mismatch, wages, Job Analysis Method, Realized Matches Approach

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1 Introduction

Skill mismatch refers to a situation in which the level of skills possessed by the worker does not correspond to the level of skills required by the job (European Centre for the Development of Vocational Training 2014; McGuinness, Pouliakas, and Redmond 2018). Skill surplus or overskilling represents a situation in which the worker's potential is not fully exploited, while skill shortage or underskilling represents a situation in which the job's requirements are not optimally fulfilled. Matching theories have pointed out that workers reach an optimal productivity in their job if the possessed skills are in line with the required skills (Sattinger 1993, 2012; Hartog 2000). This is confirmed in many empirical research findings across western countries. The wage returns for overskilled workers are less than for similar workers who are well-matched, while underskilled workers usually face a wage penalty (Groot and Maassen van den Brink 2000; McGuinness 2006; Nordin, Persson, and Rooth 2010; Quintini 2011). Skill mismatches do not only affect wages, but also job satisfaction and other outcomes (Allen and van der Velden 2001; McGuinness and Wooden 2009). Note that in the case of job satisfaction, minor underskilling may still have a positive effect (van der Velden and Verhaest 2017).

Both skill surpluses and skill shortages may hamper economic growth (Quintini 2011, 23). Therefore, skills policies figure prominently on the policy agenda (Global Agenda Council on Employment 2014; Cedefop 2015; OECD 2016; McGowan and Andrews 2017). There is evidence that the degree of skill mismatch in OECD countries persists over time (OECD 2016), but also varies considerably across countries (Wolbers 2003; Muñoz de Bustillo Llorente et al. 2018). To design an optimal skills policy, governments need to rely on accurate data on the prevalence of skill mismatches. Although attempts have been made to identify skill shortages and skill surpluses in a more systematic way (CEDEFOP 2018; The Skills Panorama project by CEDEFOP, 2020), good indicators for important skill domains like literacy and numeracy are still lacking. Literacy and numeracy are key information-processing skills that are essential for functioning well in the job. This is not only because these skills are required in the job, but also because these skills are prerequisites for acquiring both job-specific technical skills and other general skills that are crucial. This also explains why skill mismatches in these domains explain educational mismatches to a large degree (Levels, van der Velden, and Allen 2014). Additionally, these skills are among the strongest predictors of economic and non-economic outcomes (OECD 2016).

With the arrival of the large-scale Programme of the International Assessment of Adult Competences (PIAAC; OECD 2013a, 2013c, 2013b), countries have excellent and unparalleled information on the *possessed* literacy and numeracy skills of their workers, but they lack equivalent occupational information on the *required* skills in those domains. While there is some information on required literacy and numeracy skill levels available from other sources (e.g., the requirements regarding Reading Comprehension and Mathematics in the US Occupational Information Network O*NET 2019), this information does not match with the definition of literacy and numeracy in PIAAC, nor does it provide those skill levels in the same metric and scale as the PIAAC skill proficiency scales. Hence it is impossible to use the PIAAC data to directly identify potential shortages or surpluses in these areas. Although proxies have been used to measure the required skill levels in these domains (e.g., Allen, Levels and van der Velden, 2013; Perry, Wiederhold, and Ackermann-Piek 2014; Pellizzari and Fichen 2013, 2017), these proxies have important inherent weaknesses (van der Velden and Bijlsma 2019).

In this paper we will use the so-called Job Analysis Method (JAM) to assess the required skill levels of two key information-processing skills (i.e., literacy and numeracy) for all 4-digit International Standard Classification of Occupations 2008 (ISCO08) unit groups of occupations

(International Labour Organization 2012) in the same metric and scale as was used in PIAAC. JAM has never been used before to identify required skill levels for literacy and numeracy as measured in PIAAC, and the paper thus presents the first results on the prevalence of skill shortages and skill surpluses in these key information-processing skills across different OECD countries and across different occupations and sectors that is based on a more direct estimate of the required skills. This is a major contribution to the skill mismatch literature as literacy and numeracy are considered to be the most important skills that affect economic and non-economic outcomes (OECD 2016; Levels et al. 2014). Moreover, we also examine to what extent the skill mismatch estimates derived with JAM can explain wage differentials and job satisfaction, and how the explanatory power of these estimates compares to estimates based on other methods to determine skill mismatch.

The paper proceeds as follows. In Section 2 we briefly review existing methods to measure skill mismatches in the domains of literacy and numeracy. Section 3 describes how we applied JAM. Section 4 outlines the data and analysis plan. In Section 5 we provide estimates for the proportions of well-matched, overskilled and underskilled workers per country, per occupation and per sector using JAM and compare these with alternative estimates. In this section, we also compare JAM with other methods in explaining wage differentials, as well as job satisfaction. Section 6 concludes and discusses limitations, implications for policy makers and future directions for research.

2. Measuring skill mismatch

In the literature, four different methods can be distinguished to measure skill mismatch: JAM (asking job experts to assess the required level of skills in different occupations), worker self-assessment (WSA: asking workers to assess the level required for their job), the realized matches approach (RMA: taking the average or median possessed skill level of workers in an occupation as a proxy for the required level in that occupation), and the job requirement approach (JRA: taking the frequency of use of certain skills by workers in a job as a proxy for the required level of such skills in that job). It is important to note that each of these methods serve different purposes and all have their pros and cons (see also Table 1 for a short summary).

JAM involves the assessment of skill requirements in jobs by occupational experts (Hartog 2000; Verhaest and Omey 2006; McGuinness, Pouliakas, and Redmond 2018). The primary purpose of JAM has been referred to as having an 'objective' indication of the prevalence of skill surpluses and skill shortages (Hartog 2000). However, the core methodology is that occupational experts assess what would be the optimal or critical skill requirements to function well in a job. Therefore, JAM is also sometimes referred to as the 'normative' approach. JAM is only considered a valid approach if the information used by the experts is accurate and up to date (van der Velden and van Smoorenburg 1997; Dahlstedt 2011). Moreover, a problem with using JAM is that experts cannot assess each individual job. Instead, JAM relies on assessing required levels for jobs that are grouped into occupational clusters in an occupational classification, thus disregarding within-occupation heterogeneity. Another obstacle using JAM is that it is a rather time-consuming and thus expensive method to assess skill mismatches.

WSA is the subjective counterpart of JAM. The primary purpose of WSA is to assess to what extent workers themselves *believe* that they are overskilled or underskilled. A typical question might be: "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.” (European Working Conditions Survey: Eurofound 2012). WSA has been criticized, mainly because workers are likely to overestimate their job’s skill requirements (Allen and van der Velden 2005; Perry et al. 2014), thus causing a bias in the estimates. Still, it might give very useful information, specifically when compared with JAM. Apart from identifying skill mismatches, it is important to know whether workers are aware of these mismatches. Skill policies to improve workers’ skills are unlikely to be successful if workers themselves believe there is no mismatch. Although it is likely that WSA is strongly correlated to other subjective outcomes such as job satisfaction, it is difficult to interpret this due to reverse causality (i.e., job satisfaction might affect the answers to the WSA questions).

RMA relies on using the average or median skill level in an occupation and identifies the over- and underskilled workers in that occupation by using a cut-off point of usually one standard deviation. Note that, by definition, RMA defines the average worker in an occupation as being well-matched, without considering the real requirements of the job (Desjardins and Rubenson 2011). Therefore, the primary purpose is not to assess the actual extent of skill surpluses or shortages in a country but to provide a proxy that can be used when assessing the effects of skills mismatches on outcomes. For this purpose, RMA is a relatively valid method, and easy to apply. Like JAM, RMA relies on estimates per occupation and ignores within-occupation heterogeneity.

The fourth approach, the JRA, was initially developed by Green, Felstead, and Gallie (2013) for the British Skills Survey and was also used to measure skill mismatches in PIAAC (Allen et al. 2013). JRA focuses on the time intensity or frequency of using certain skills. 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 2013c). A set of items relating to a certain skill domain is then used to construct a scale on skill use. The interpretation of this scale is that it reflects the skill requirements on 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. JRA is criticized as the use of skills might simply not be a good proxy of skill requirements and is also measured in a different metric than skill proficiency (Perry et al. 2014). Still, in a literal sense, it might reflect tensions at an individual level on the extent to which workers need to use their skills at a higher level than their proficiency level would allow. This tension might certainly be related to outcomes such as job satisfaction.

Table 1. Overview of different skill mismatch methods

Method	**Primary goal**	**Pros**	**Cons**
JAM	Objective or normative assessment of skill mismatches	Experts’ views on critical skill requirements Required skills are assessed directly, rather than approached through proxies	Ignores within-occupation heterogeneity Expensive Risk of inaccurate and out of date information as it is based on existing task descriptions
WSA	Subjective assessment of skill mismatches	Easy to apply Individual job level	Social bias Reverse causality with relevant outcomes
RMA	Assessment of average or median skill level Proxy of skill mismatches to be used in analyses of outcomes	Easy to apply	Average worker by definition well-matched Ignores within-occupation heterogeneity

JRA	Assessment of relative skill use Proxy of skill mismatches to be used in analyses of outcomes	Easy to apply Individual job level	Skill use is not the same as skill requirement Scales not comparable which makes the definition of well-matched difficult

In this paper, we will use JAM to identify required literacy and numeracy skill levels for workers in OECD countries, using PIAAC data. JAM enables us to provide a direct estimate of the *prevalence* of skill mismatches across countries that does not rely on proxies of required skills or on workers' self-assessments of skill mismatch. We compare these estimates of the prevalence of skill surpluses and skill shortages with proxies based on variations of RMA. This comparison will allow countries to assess to what extent they would arrive at different conclusions on the *prevalence* of skill mismatches if they base their skill policies on JAM or on these proxies, and to what extent the estimates from the various methods are in line with the existing literature on skill mismatch. We do not compare our results with WSA, as in PIAAC the WSA questions refer to general skill mismatch, and not to mismatch in the domains of literacy and numeracy. Apart from that, the WSA questions were not well posed, leading to a serious underestimation of the proportion of well-matched workers.[1] We will also not compare our results with JRA as this is a different concept comparing workers' skill use to their own skill proficiencies.

Apart from having good estimates of the *size* of skill mismatches, policy makers and researchers are also interested in the *effects* of skill mismatches on a range of outcomes. This is a different issue, and we can derive different expectations about which method performs best at *predicting outcomes* such as wages or job satisfaction. The extent to which JAM or RMA is better at predicting wage effects of skill mismatches is dependent on the wage setting regime. If wages are solely based on inherent job requirements, one would expect JAM to predict wages better than RMA. However, if employers base their wages on average characteristics of their workers, then RMA is more likely to predict the wages correctly.

In the case of job satisfaction, the mechanism is slightly different. Job satisfaction is mainly driven by whether workers' initial expectations about the job conditions are being met (Warr 2007, 2013). These expectations can be based on the job's inherent characteristics (as being assessed in JAM) or based on what people observe for workers with a similar background (which is typically measured in RMA). If the latter is the dominant mechanism, we would expect that RMA predicts job satisfaction better than JAM. The extent to which this is the case is an empirical question which will be addressed in this paper.

3. Applying JAM to determine required literacy and numeracy

The contribution of this paper to the existing literature is that we use JAM to determine the required skill levels for literacy and numeracy[2] for almost every ISCO 4-digit unit group: a total of 433 occupational unit groups. For the assessment, six international occupational experts who were all very experienced in rating skill requirements in national and international settings and

[1] Based on the sample we use in this paper, the proportion of well-matched is estimated to be only 9% of the workers if we rely on the WSA questions.
[2] PIAAC also assessed a third domain, Problem Solving in Technology-Rich Environments. However, as not all respondents took this test and the measurement will change between the first and the second cycle of PIAAC, we decided to focus only on literacy and numeracy.

two domain experts in the areas of measuring literacy and numeracy were brought together. The domain experts were included to ensure that the occupational experts were trained to be familiar with the concepts and frameworks used to measure literacy and numeracy in PIAAC (for more details on the project, see Pérez Rodríguez et al. 2020).

The concept of numeracy in PIAAC is defined as “the ability to access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life” (OECD 2013b, 20). Literacy is defined as “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. It encompasses a range of skills from the decoding of written words and sentences to the comprehension, interpretation, and evaluation of complex texts” (OECD 2013b, 20). It should be noted here that writing skills are not covered in the literacy framework of PIAAC. The reason for this is partly practical: it is difficult to assess writing skills through test-based assessments, especially if the aim is to achieve comparable skill proficiency scores across countries.

For both literacy and numeracy, the PIAAC framework distinguishes five different levels (for an overview, see Appendix A; for more information, see OECD 2013b). To illustrate, the description for a literacy task at level 1 starts with: “Most of the tasks at this level require the respondent to read relatively short digital or print continuous, non-continuous, or mixed texts to locate a single piece of information that is identical to or synonymous with the information given in the question or directive …..” (OECD 2013b, 69-70). At level 5, the literacy requirements start with: “At this level, tasks may require the respondent to search for and integrate information across multiple, dense texts; construct syntheses of similar and contrasting ideas or points of view; or evaluate evidence-based arguments….” (ibid). These examples show that the PIAAC assessment of literacy and numeracy goes beyond basic reading and numeracy and ranges from very basic to very complex levels. Just to give an indication: some 17% of the population of working adults in OECD countries have a proficiency level for literacy of level 1 or below, while only 1% reaches proficiency level 5. For numeracy, these proportions are respectively 19% and 1%.

For the assessment, we went through the following phases:

- *Phase 0*: Pilot study to develop the proof of concept for a limited number of exemplary occupations. In the pilot study we developed the background material for the experts, consisting of 2-page notes for each 4-digit occupational unit group with a list of tasks and examples of job titles, as well as the required education and experience to do the job (for relevance, Surrette, Aamodt, and Johnson 1990; Dierdorff and Wilson 2003; Jenkins and Curtin 2006).
- *Phase 1*: Plenary session in which the concepts and frameworks of literacy and numeracy were explained by the domain experts (these were the chairs of the PIAAC literacy and numeracy expert groups).
- *Phase 2*: Plenary sessions in which for each of the ISCO 2-digit Sub-Major Groups, one so-called anchor occupation was discussed jointly. These anchor occupations (40 in total) were chosen to be the most representative 4-digit occupational unit group in that Sub-Major Group. The domain experts were present during these sessions to help the occupational experts in applying the PIAAC framework to the literacy and numeracy requirements in the anchor occupation (for relevance of joint training, see Voskuijl and van Sliedregt 2002; Lievens and Sanchez 2007). The six occupational experts needed to reach unanimous decisions on the required literacy and numeracy levels for each of these anchor occupations.

- *Phase 3*: The anchor occupations were used as a starting point to rate all occupational unit groups in relation to the corresponding anchor in that Sub-Major Group. This was done in two subgroups. In each subgroup three occupational experts rated a set of occupations, all belonging to the same 2-digit Sub-Major Groups. Subgroups were formed to be as diverse as possible (Mullins and Kimbrough 1988) and changed in composition after rating half of the unit groups. Experts were asked to rate a set of occupations individually in advance. After receiving the initial ratings, occupations that were (almost) unanimously rated were not further discussed. This applied to some two thirds of the occupations. The remaining one third of the occupations was discussed in a subgroup session. In most cases, one of the three experts disagreed with only one level difference and only in less than 10% of the cases there was more disagreement. If the three experts could not reach full agreement, the occupation in question was referred to Phase 4.
- *Phase 4*: Plenary session in which occupations were discussed for which a subgroup could not find full agreement. This applied only to three occupational unit groups.
- *Phase 5*: Plenary session with all experts, including the domain experts, in which an overview of the ratings for all occupations was discussed. Instead of discussing the occupations per Sub-Major Group, all occupations were now rank ordered by required level. By discussing them in this way we wanted to ensure consistency across the different Sub-Major Groups. This final review did not lead to any changes in the original ratings.

It is important to keep the following characteristics of the rating process in mind:

- The assessment of the required level is based on the international ISCO08 task description (International Labour Organization 2012). This means that the required level for a certain unit group of occupations is the same in all countries regardless of the actual skill proficiency level in those countries. This is possible as ISCO is *task-based*: if an occupation in a country represents other tasks and thus other skill requirements, this should be reflected in coding this to a different occupation in ISCO.
- Experts were asked to rate the *critical* required level, that is the minimum level of skills required *to do* the job, rather than the *optimal* required level.
- Experts were asked to look at the *current* required levels. This means that in some cases they used other information than the ILO task descriptions if they thought that these were outdated. This ensures that the assessment is up to date.
- Experts were asked to assess the level required for *standard* jobs within the unit group, rather than that required for junior or senior positions.
- In some cases, the required level of literacy or numeracy was in-between two adjacent levels. In those cases, the experts assigned an *in-between level* (e.g., level 2.5). This happened in 26% of the cases for numeracy and 27% for literacy.
- In some cases, the 4-digit occupational unit groups were rather heterogeneous, consisting of occupations that vary in required level. In those cases, experts gave *combined ratings* (e.g., level 2+3). This happened in 13% of the cases for numeracy and 8% for literacy.

An overview of the resulting scores per ISCO 4-digit occupation is given in Supplementary Materials, Appendix C.

4. Data and analysis

4.1 Data and sample selection

To date, PIAAC covers a total of 38 different countries. PIAAC collects data from national representative samples of individuals ranging from 16 to 65 years old. It includes direct measures of adults' proficiency in several key skill domains (with scores ranging from 0 to 500), as well as a series of questions regarding the use of these skills at work and at home. Furthermore, PIAAC includes a background questionnaire comprising demographic, educational, and labor status information (OECD 2013c).

For the current analysis, we used data from 31 OECD countries that participated in PIAAC. We focus only on OECD countries given that the ratings were decided with the OECD target population in mind. Therefore, we exclude Cyprus, Ecuador, Kazakhstan, Peru, Russia and Indonesia as they are not OECD members. We also excluded Australia due to issues around data protection legislation. From the Canadian sample, we took a random sample of about 20 percent to avoid overrepresentation of that country in the dataset. We excluded individuals who are unemployed or out of the labour force, people working in occupations related to the armed forces (in compulsory military or community service as well as military workers), unpaid family workers, and respondents who stated that their main status is student or intern, as for these workers the relation between wages and skill requirements is less well defined. We excluded respondents with a missing value on one of the variables in the analysis (this led to only 3.1% loss as item non-response is very low in PIAAC). We also excluded respondents for which we only have occupation codes available at the first digit (ISCO Major Group). The analytical sample consists of 103,115 employees working in 31 industrial countries. In the wage analyses we excluded the self-employed and trimmed the wages per country leaving out the 1st and 99th percentile, thus having an analytical sample of 84,078 respondents.

4.2 Comparison between JAM and other skill mismatch measures

In the analysis, we compare JAM with four other empirical skill mismatch measures: three different specifications of the RMA and the Pellizari-Fichen Model (PFM). For the RMA, we follow Perry et al. (2014). They assess the average skill level per country for each two-digit ISCO Sub-Major Group and use a cut-off point of one standard deviation to identify the over- and underskilled. Note that this specification differs in two respects from JAM: first, it is country-specific and, second, it is based on 2-digit Sub-Major Groups instead of 4-digit unit groups. Therefore, we will also assess a similar version of RMA using 4-digit codes across all countries as well as a version using 2-digit codes across all countries.

PFM is a rather innovative model developed by Pellizzari and Fichen (2013), combining elements of the WSA and RMA. First, they selected all workers who identified themselves as being well-matched, based on two questions in the PIAAC survey: "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?" The authors then assessed the range of skill proficiency levels of all the workers who identified themselves as well-matched per country for each 1-digit ISCO Major Group of occupations, excluding Major Group 6 (1.6% of the observations) and Major Group 0, the latter having been already left out of our analytical sample as it refers to the armed forces. In addition, they treat Major Groups 1 and 2 as a unique category (Pellizzari and Fichen 2013).[3] This skill proficiency range was then trimmed (omitting the lower and upper 5%) and regarded

[3] Pellizzari and Fichen (2017) used two-digit ISCO Major Groups; however, using this approach led to a large drop of observations, as there were many cases in which there were not enough (if any) workers who self-defined as well-matched in each Sub-Major Group per country. We have decided to use the 1-digit instead for the analysis to allow for a fair comparison with JAM and RMA.

as the “normal” skill range in that Sub-Major Group. Any worker - regardless of what he or she answered to the two subjective questions - was considered well-matched if their skill proficiency levels fell in the country-occupation specific skill ranges. Anyone with a skill proficiency level above the 95% score was defined as overskilled and anyone below the 5% range was defined as underskilled.

Note that both country-specific estimates (Perry et al. 2014 and Pellizari and Fichen 2013) are based on 2-digit Sub-Major Groups respectively 1-digit Major Groups. Given the small number of observations per country, it is not possible to derive these estimates at the more detailed 4-digit unit group level. We decided not to compare our JAM measure to the recently developed effective skill measure (van der Velden and Bijlsma 2019). The rationale of the effective skill measure is that skills only affect wages through the use of relevant skills. In their specification, van der Velden and Bijlsma (2019) also use an RMA approach but based on the product of skills proficiency and skill use. Comparing this to JAM would not be fair, as in developing the JAM measure, we only gathered information on the required skill *proficiency* according to occupational experts and not on the required skill *use* according to occupational experts.

4.3 Analytic strategy and models

In all analyses, we will follow the conventional so-called overeducation–required education–undereducation model (ORU) developed by Duncan and Hoffman (1981). In this model, a worker’s skill proficiency level (WSP) is broken down into its three components:
• Required Skill Proficiency (RSP)
• OverSkilling Proficiency (OSP), defined as WSP – RSP if WSP > RSP and zero otherwise
• UnderSkilling Proficiency (USP) defined as RSP – WSP if WSP < RSP and zero otherwise.
In formula:

$$WSP = RSP + OSP - USP \qquad [1]$$

Although JAM intends to provide us with a good measure of RSP, we still need to define in which cases there is a match (when is WSP equal, lower or higher than RSP?). In RMA this is defined as having a skill difference of one standard deviation. For JAM we will use the same range of one standard deviation.

For RSP we will use the midpoint of the required level as indicated by the experts. In consultation with the experts, and in line with the common practice in PIAAC, we decided not to make a distinction between levels 4 and 5. The number of respondents reaching a level 5 proficiency is very low (only 1% for both literacy and numeracy (OECD 2019)) and it was felt that it is difficult to define mismatches at this very high end of the scale. An overview of these midpoints is given in Table 2, column 2. Given the fact that each level in PIAAC comprises a range of 50 points, the range of well-matched is set at 100 points (which is roughly equivalent to two standard deviations (OECD 2013b: p. 61). This means that someone with a proficiency level of at least 50 points (or 1 standard deviation) higher than the RSP is defined as overskilled and someone with a proficiency level of at least 50 points lower is defined as underskilled. For the so-called combined ratings, we used the full range of both levels. The resulting ranges are shown in column 3 of Table 2.

Table 2: Required proficiency levels and range in proficiency levels of well-matched workers using JAM

Level	RSP	Range well-matched
0	150	1-200
0.5	175	126-225
0+1	175	1-250
1	200	151-250
1.5	225	176-275
1+2	225	151-300
2	250	201-300
2.5	275	226-325
2+3	275	201-350
3	300	251-350
3.5	325	276-375
3+4	325	251-400
4	350	301-500
4.5	375	301-500
4+5	375	301-500
5	400	301-500

For some workers in the PIAAC sample, we do not have information at the 4-digit level available, but only at a more aggregate level (3-digit, 2-digit, or 1-digit). As indicated above, we dropped the respondents for which we had only 1-digit information available and for the remaining cases, we assigned the weighted average required level of the relevant underlying 4-digit occupations and applied a range of 150 points (75 points above or below that weighted average) to define the well-matched for JAM (equivalent to the range for combined ratings). We followed the same procedure in the case of the 4-digit version of RMA (for the other versions of RMA and for PFM, this is not relevant as these are already defined at the 2-digit and 1-digit level respectively).

For the wage analysis we ran the following equation:

$$LnW_{ijc} = \alpha_c + \beta_1 RSP_j + \beta_2 OS_{ij} + \beta_3 US_{ij} + \beta_4 C1_{ijc} + \upsilon_{ic} + \omega_c \qquad [2]$$

where LnW_{ijc} is the natural log of the hourly wage of individual i in unit group j in country c; α_c is the country-specific constant; RSP_j the required skill level in unit group j, OS_{ij} and US_{ij} are dummies for being overskilled and underskilled, $C1_{ijc}$ is a vector of control variables[4], including age, age squared, gender, working fulltime (i.e., working 32 hours or more per week), dummy for working in an occupation that has a combined rating and the share of self-employment in unit group j to account for the fact that the wage analyses excludes self-employed, while the ratings included them. The idiosyncratic error term at the individual level is represented by υ_{ic}. We include country fixed effects. The standard errors are clustered by country.

For the job satisfaction analysis, we ran the following equation:

$$JS_{ijc} = \alpha_c + \beta_1 RSP_{jc} + \beta_2 OS_{ijc} + \beta_3 US_{ijc} + \beta_4 C2_{ijc} + \upsilon_{ic} + \omega_c \qquad [3]$$

[4] These control variables account for cross-occupational differences in the composition of the workforce.

where JS_{ijc} is the Job Satisfaction of the worker, and $C2_{ijc}$ is a vector of control variables, including age, age squared, gender, working fulltime (i.e., working 32 hours or more per week), dummy for working in an occupation that has a combined rating and a dummy for being self-employed. We look at the parameter estimates to evaluate the four measures.

5. Results

First, we look at the proportions of underskilled, well-matched, or overskilled workers according to the different methods. As indicated above, the RMA measure developed by Perry et al. (2014) differs in two aspects from the JAM measure we developed. First, it focuses on 2-digit instead of 4-digit occupations and second, the average realized match is calculated per country. To compare whether the difference between the two measures is related to any of these two differences, we also calculated the RMA using 2-digit occupations for all countries and using 4-digit codes for all countries.

Table 3: Proportions underskilled, well-matched, and overskilled according to different methods

Domain	Match	JAM	PFM	RMA 2-digit per country	RMA 2-digit all countries	RMA 4-digit all countries
Numeracy	Underskilled	22%	6%	12%	14%	14%
	Well-matched	61%	84%	76%	72%	73%
	Overskilled	17%	10%	12%	14%	13%
Literacy	Underskilled	19%	6%	11%	12%	12%
	Well-matched	58%	85%	80%	76%	77%
	Overskilled	23%	9%	10%	11%	11%

We can draw several conclusions from this comparison. First, we note that the proportion of well-matched workers differs considerably depending on the measure used. According to the JAM measure, some 60% of workers have the required literacy or numeracy skills for their job. But according to the different RMA-based measures, this is true for some 75% of the workers, while according to the PFM measure this holds for some 85% of the workers.

Second, we observe that for all three RMA-based measures the proportion of overskilled workers is roughly the same as the proportion of underskilled workers. However, in the case of JAM and PFM these proportions are different. This is directly related to how RMA-based measures are constructed. They define the average skilled worker in an occupation as being well-matched and define the overskilled or underskilled workers as those with a skill proficiency of one standard deviation above or below that average skill level. If the distribution of workers' skills proficiency levels within an occupation is symmetric (skewness is zero), we would expect the same proportions of overskilled and underskilled workers by definition. And this is what we observe. In the case of PFM, we observe a higher proportion of overskilled workers than underskilled workers for both numeracy and literacy, namely some 10% versus 6%. In the case of JAM, we observe a clear difference. For numeracy the proportion of overskilled and underskilled workers are 17% and 22% respectively, while for literacy the order is reversed with 23% and 19% respectively.

Third, the difference between JAM and the RMA measure developed by Perry et al. (2014) is not caused by the fact that the latter is defined at the 2-digit level per country as all RMA-based measures provide roughly the same estimates.

How does this compare to what we know from estimates of incidence of educational mismatches in the literature? In a meta-analysis, Groot and Maassen van den Brink (2000) present an overall estimate of 23% overeducated workers and 14% undereducated workers. Quintini (2011) using an RMA-based measure on years of schooling and different data sources covering most OECD countries, estimates that one in four workers are overeducated and just over one in five are undereducated. Both estimates are closest to the estimate of JAM and very remote from the PFM measure.

In Table 4 we present the proportions of underskilled, well-matched, and overskilled workers per country. We restrict the overview for RMA-based measures to the 2-digit per country measure as developed by Perry et al. (2014). Countries are rank ordered by proportion of underskilled workers according to JAM. For each of the estimates we indicate the highest and the lowest percentage for the different measures across countries in bold and underlined italics respectively.

Table 4a: Proportions underskilled (US), well-matched (WM), and overskilled (OS) workers per country: Numeracy

	JAM			**PFM**			**RMA 2-digit per country**		
	US	WM	OS	US	WM	OS	US	WM	OS
Chile	**43**	**50**	<u>*7*</u>	**10**	**73**	**17**	**15**	**71**	**14**
Mexico	42	<u>*47*</u>	12	12	<u>*68*</u>	**20**	14	74	12
Israel	34	55	11	5	85	10	**17**	<u>*66*</u>	**17**
Turkey	34	52	14	3	89	8	14	72	14
Singapore	32	59	9	<u>*2*</u>	88	10	16	68	16
Greece	31	54	15	**13**	71	16	12	76	12
Slovenia	28	60	12	4	86	10	13	76	11
United States	28	60	13	3	89	8	14	72	14
Canada	26	59	16	5	86	9	15	71	14
Ireland	25	60	15	7	83	10	12	75	12
Italy	25	60	15	5	83	12	13	76	12
New Zealand	24	61	15	5	88	7	14	73	13
Spain	24	59	17	6	79	15	12	77	11
France	23	63	15	6	87	7	13	74	13
Poland	22	61	18	7	79	14	13	75	12
Lithuania	21	58	20	7	80	13	11	79	10
United Kingdom	20	62	18	5	87	8	12	76	12
Denmark	19	62	19	8	85	7	12	77	11
Estonia	19	63	18	6	86	8	11	80	9

Korea	17	59	24	6	86	9	10	80	10
Netherlands	17	65	18	5	**91**	***4***	11	78	10
Norway	16	65	19	7	87	6	11	77	12
Czech Republic	16	64	20	4	88	8	9	82	9
Germany	16	66	18	4	82	14	11	78	11
Austria	16	66	18	5	76	19	11	79	10
Slovakia	15	61	24	4	87	9	*9*	**82**	*9*
Sweden	15	**67**	18	8	85	7	12	77	12
Hungary	15	64	21	9	83	8	12	77	11
Belgium	14	65	20	5	87	7	12	77	11
Finland	13	63	24	7	87	7	11	78	10
Japan	*10*	64	**26**	6	88	6	11	80	9,22

Countries rank ordered by proportion underskilled workers according to JAM; percentages in **bold** denote the country with the highest proportion in that column, percentages in *underlined italics* denote the country with the lowest percentage.

Table 4b: Proportions underskilled (US), well-matched (WM), and overskilled (OS) workers per country: Literacy

	JAM			**PFM**			**RMA 2-digit per country**		
	US	WM	OS	US	WM	OS	US	WM	OS
Israel	**34**	**53**	**12**	**5**	**90**	***6***	**14**	***72***	**14**
Singapore	34	57	*10*	*2*	88	10	**14**	73	13
Chile	32	56	12	13	76	11	12	76	12
Turkey	32	52	16	4	86	11	11	81	9
Mexico	31	*51*	18	12	77	11	13	76	11
Slovenia	27	57	16	3	90	7	11	79	9
Greece	27	53	21	**15**	*70*	15	12	77	11
Denmark	24	58	18	7	85	8	11	80	9
Italy	23	56	21	6	84	10	11	80	10
Lithuania	23	51	26	7	79	14	9	83	8
Canada	21	58	22	4	86	10	13	75	12
Spain	20	56	24	6	81	13	12	78	10
France	20	60	21	7	86	7	11	78	11
Estonia	19	54	27	6	85	9	10	81	9
New Zealand	18	59	23	6	88	7	11	79	10
Ireland	18	60	22	9	83	8	11	80	10
United States	18	61	21	5	87	8	12	78	10
Netherlands	17	60	23	7	88	6	11	80	10
Sweden	16	62	22	7	86	7	11	80	9
United Kingdom	16	59	25	5	89	6	10	80	10
Slovakia	16	55	30	4	86	10	*8*	**86**	*6*
Belgium	15	60	24	5	89	6	10	80	10
Hungary	15	61	24	8	85	7	9	84	7

Norway	14	**68**	18	6	84	10	9	82	8
Austria	14	66	20	6	83	10	9	83	7
Germany	14	66	20	4	78	**19**	10	81	9
Czech Republic	14	58	28	3	88	9	10	83	8
Poland	13	56	31	8	84	7	12	78	10
Korea	11	55	34	6	84	10	9	84	7
Finland	11	58	32	7	86	7	11	79	10
Japan	*7*	52	**41**	5	88	6	9	84	7

Countries rank ordered by proportion underskilled workers according to JAM; percentages in **bold** denote the country with the highest proportion in that column, percentages in *underlined italics* denote the country with the lowest percentage.

We can observe several remarkable differences in the rank order of countries, depending on the skills mismatch measure. The proportion of underskilled workers for numeracy and literacy according to JAM ranges from a low 10% and 7% in Japan to a high 43% in Chile and 34% in Israel. In the case of PFM, the highest-ranking country is Greece with 13% and the lowest-ranking country is Singapore with 2%. Note that these two countries both rank number 6 and 5 in the rank order according to JAM. Similar discrepancies can be noted when comparing the RMA 2-digit per country measure with JAM or with PFM.

The above results indicate that the ranking of countries in terms of proportions underskilled, well-matched, or overskilled changes considerably if we use one or the other measure. This is best observed by looking at the correlations at the country level in Table 5.

Table 5: Correlation at the country level between different measures of mismatch

	Numeracy			Literacy		
	JAM	PFM	RMA 2-digit per country	JAM	PFM	RMA 2-digit per country
Proportion underskilled						
JAM	1			1		
PFM	-0.04	1		0.16	1	
RMA 2-digit per country	-0.81	-0.01	1	0.67	0.11	1
Proportion well-matched						
JAM	1			1		
PFM	0.55	1		0.16	1	
RMA 2-digit per country	0.53	0.06	1	0.20	0.07	1
Proportion overskilled						
JAM	1			1		
PFM	-0.37	1		-0.15	1	
RMA 2-digit per country	-0.80	0.07	1	-0.60	-0.04	1

From Table 5 we can draw several conclusions. First, the correlations between the PFM measure and the RMA 2-digit per country are the lowest ranging from a low -0.04 (proportion overskilled workers in literacy) to 0.11 (proportion underskilled workers in literacy). This means that countries that rank high e.g., in the proportion well-matched according to PFM may rank low according to RMA and vice versa. Second, if we look at the proportion well-matched workers per country, we observe the highest correlations between JAM and the other two measures (both around 0.55), but this still means a correlation that is moderate at best, explaining only 25-30% of the between-country variation. Third, we observe strong negative correlations between the proportions of overskilled or underskilled workers in the domain of numeracy across countries when comparing JAM with both other measures. For literacy, we also observe negative correlations but only for the proportions of overskilled workers, while it is positive for the proportions of underskilled workers.

This means that for international comparisons, it really matters which measure is being used. Here it is good to consider that both PFM and the RMA 2-digit per country measures are calculated per country. Specifically, the RMA 2-digit per country measure assumes the average worker in a specific occupation and a specific country to be well-matched. But to able to compare the proportions underskilled or overskilled workers across countries, a common yardstick should be used. This could either be JAM or an RMA-based measure that is not calculated per country. Conceptually, the RMA 2-digit per country measure is therefore least likely to compare countries in a systematic way.

Which occupational unit groups have relative high levels of skill shortages or skill surpluses? Table 6 provides an overview of the top 3 occupational unit groups with the highest proportions of skill surpluses or skill shortages using the three different measures.

Table 6: Top 3 of skill surpluses or skill shortages per occupational unit group using different skill mismatch measures

Domain	**Measure**	**Overskilled**	**%**	**Underskilled**	**%**
Numeracy		Unit group		Unit group	
	JAM	9622 Odd-job Persons	84	2230 Traditional and Complementary Medicine Professionals	80
		9334 Shelf Fillers	83	1343 Aged Care Services Managers	76
		9621 Messengers, Package Deliverers and Luggage Porters	82	3142 Agricultural Technicians	75
	PFM	9623 Meter Readers and Vending-machine Collectors	31	2355 Other Arts Teachers	15
		5113 Travel Guides	26	2114 Geologists and Geophysicists	15
		4227 Survey and Market Research Interviewers	25	3255 Physiotherapy Technicians and Assistants	14
	RMA 2-digit per country	5111 Travel Attendants and Travel Stewards	30	5212 Street Food Salespersons	29
		5113 Travel Guides	29	9611 Garbage and Recycling Collectors	28

		3153 Aircraft Pilots and Related Associate Professionals	28	3132 Incinerator and Water Treatment Plant Operators	28
Literacy					
	JAM	9334 Shelf fillers	89	1343 Aged Care Services Managers	76
		9622 Odd-job Persons	87	2114 Geologists and Geophysicists	76
		5111 Travel Attendants and Travel Stewards	85	2352 Special Needs Teachers	69
	PFM	5111 Travel Attendants and Travel Stewards	25	3132 Incinerator and Water Treatment Plant Operators	17
		4227 Survey and Market Research Interviewers	25	3434 Chefs	14
		5113 Travel Guides	24	2114 Geologists and Geophysicists	12
	RMA 2-digit per country	5111 Travel Attendants and Travel Stewards	37	5212 Street Food Salespersons	29
		6122 Poultry Producers	34	3132 Incinerator and Water Treatment Plant Operators	28
		5113 Travel Guides	32	9612 Refuse Sorters	28

A first thing to be noted is that the proportions overskilled and underskilled workers vary much more according to JAM than according to PFM and RMA 2-digit per country. This makes sense as the latter two are based on within-occupation variation, thus dampening extreme variation across occupations. Nevertheless, the JAM measure seems to produce very extreme results when we look at individual occupations. We will return to this issue later.

According to JAM, we find the occupational unit groups with the highest proportions of overskilled workers in the Major Group ‘Elementary Occupations’: ‘Odd-job Persons’, ‘Shelf Fillers’, and ‘Messengers, Package Deliverers and Luggage Porters’. This makes sense as the skill requirements in these jobs are very low, leading any worker with a literacy or numeracy level of 2 or above to be overskilled. But if we look at PFM or RMA 2-digit per country, we find most overskilled workers in the Major Group ‘Services and Sales Workers’. The only occupational unit group where all three measures coincide, at least for literacy, is the unit group ‘Travel Attendants and Travel Stewards’. Remarkably, we find unlikely high proportions of overskilled workers according to PFM in the occupational unit group ‘Survey and Market Research Interviewers’ (both numeracy and literacy) and according to RMA 2-digit per country in occupational unit group ‘Aircraft Pilots and Related Associate Professionals’ (only numeracy).

If we look at occupational unit groups with a high proportion of underskilled workers according to JAM, we find them in the Major Group ‘Managers’ (‘Aged Care Services Managers’), Major Group ‘Professionals’ (e.g., ‘Traditional and Complementary Medicine Professionals’, ‘Geologists and Geophysicists’) and Major Group ‘Technicians and Associate Professionals’ (‘Agricultural Technicians’). The only two occupational unit groups where we find some agreement between the different measures are ‘Geologists and Geophysicists’ (correspondence between JAM and PFM) and ‘Incinerator and Water Treatment Plant Operators’ (correspondence between PFM and RMA 2-digit per country). Remarkably, we find unlikely high proportions of underskilled workers according to RMA 2-digit per country in the occupational unit groups ‘Street Food Salespersons’, ‘Garbage and Recycling Collectors’ and ‘Refuse Sorters’.

Finally, Table 7 provides an overview of the 3 industrial sectors with the highest proportions of skill surpluses or skill shortages using JAM.

Table 7: Top 3 of skill surpluses or skill shortages per sector using different skill mismatch measures

Domain	**Measure**	**Overskilled**	**%**	**Underskilled**	**%**
Numeracy		Sector		Sector	
	JAM	N Administrative and support service activities	35	A Agriculture; forestry and fishing	37
		H Transportation and storage	30	Q Human health and social work activities	30
		T Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	29	M Professional, scientific and technical activities	29
	PFM	B Mining and quarrying	16	U Activities of extraterritorial organizations and bodies	7
		H Transportation and storage	14	Q Human health and social work activities	6
		J Information and communication	14	A Agriculture; forestry and fishing	5
	RMA 2-digit per country	B Mining and quarrying	15	T Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	20
		M Professional, scientific and technical activities	14	E Water supply; sewerage, waste management and remediation activities	17
		H Transportation and storage	14	A Agriculture; forestry and fishing	16
Literacy					
	JAM	I Accommodation and food service activities	44	P Education	35
		H Transportation and storage	40	M Professional, scientific and technical activities	30
		N Administrative and support service activities	37	J Information and communication	26
	PFM	U Activities of extraterritorial organizations and bodies	13	U Activities of extraterritorial organizations and bodies	7
		K Financial and insurance activities	12	F Construction	6
		J Information and communication	12	A Agriculture; forestry and fishing	6
	RMA 2-digit per country	B Mining and quarrying	11	T Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	18
		R Arts, entertainment and recreation	11	E Water supply; sewerage, waste management and remediation activities	16

		I Accommodation and food service activities	11	A Agriculture; forestry and fishing	14

When we look at the top 3 of sectors with overskilled workers, there is only one sector where all three measures overlap, namely ‘Transportation and storage’ (only for numeracy). The same holds for the proportion of underskilled workers, with ‘Agriculture, forestry and fishing’ being the only sector where all three measures overlap (again only for numeracy). In all other cases, the overlap is not systematic. This is not surprising as the differences by sector for a large extent capture aggregated differences by occupation and these rankings do not overlap either.

The next step in the analyses is to examine how the different skill measures predict relevant outcomes such as wages and job satisfaction. Table 8 provides the results for the wages.

Table 8: Wage effects of required skills, overskilling and underskilling using different skill mismatch measures

Numeracy

VARIABLES	(1) JAM	(2) PFM	(3) RMA 2-digit per country	(4) RMA 2-digit	(5) RMA 4-digit
Required skill (std)	0.283*** (0.015)	0.314*** (0.015)	0.304*** (0.013)	0.242*** (0.012)	0.258*** (0.012)
Overskilled dummy	0.162*** (0.013)	0.111*** (0.008)	0.107*** (0.007)	0.109*** (0.008)	0.098*** (0.007)
Underskilled dummy	-0.148*** (0.012)	-0.159*** (0.008)	-0.124*** (0.008)	-0.149*** (0.016)	-0.136*** (0.015)
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	84,078	83,208	84,078	84,078	84,078
R-squared	0.627	0.631	0.636	0.636	0.641

Literacy

VARIABLES	(1) JAM	(2) PFM	(3) RMA 2-digit per country	(4) RMA 2-digit	(5) RMA 4-digit
Required skill (std)	0.291*** (0.016)	0.314*** (0.014)	0.302*** (0.013)	0.238*** (0.012)	0.253*** (0.012)
Overskilled dummy	0.128*** (0.013)	0.106*** (0.006)	0.098*** (0.007)	0.094*** (0.009)	0.084*** (0.007)
Underskilled dummy	-0.104*** (0.009)	-0.143*** (0.012)	-0.119*** (0.009)	-0.140*** (0.016)	-0.129*** (0.016)

Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	84,078	83,208	84,078	84,078	84,078
R-squared	0.637	0.626	0.629	0.629	0.634

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age squared, gender, fulltime worker, share of self-employment per occupation, and a dummy indicating whether the occupation was heterogeneous according to JAM (combined rating).

In general, the explained variance is very high for all models with an R-square of around 64%. If we first look at the estimates for required skill level, we note that the differences between the skill measures are small. Both JAM, PFM and the RMA 2-digit per country predict some 28% (range 25-31%) increase in wages for every standard deviation increase in required skills. This holds for both numeracy and literacy. We also observe that the RMA-based measures that are not specified per country (columns 4 and 5) provide significantly lower estimates. This indicates that RMA-based measures that are not specified per country contain more noise. Note that the JAM measure does not suffer from the fact that it is based on across-country estimates of the required skill levels.

The main differences between the skills measures lie in the estimation of the effects for overskilling and underskilling. The PFM and RMA-based measures provide significantly lower estimates for the returns to being overskilled and – only for literacy - significantly higher penalties for being underskilled compared to the JAM measure. We also note that the penalties for being underskilled for these two measures are higher in absolute value than the returns to being overskilled. The JAM measure on the other hand provides results that are more in line with usual findings in the literature, namely that the returns to be being overskilled are larger in absolute value than the penalties of being underskilled (Hartog 2000; Groot and Maassen van den Brink 2000; Quintini 2011).

We conclude that the overall results do not differ that much between the different measures (looking at the proportion explained variance or the effect of required skills), but the wage effects of being overskilled or underskilled are probably more accurate for the JAM measure than for the alternative measures. This finding suggests that the wages are primarily based on inherent job requirements, instead of the average characteristics of their workers. If the latter would have been the case, the RMA-based measures would have been more likely to predict the wages correctly.

Table 9 provides the results for the analyses on job satisfaction. Job satisfaction is measured on a scale from 1 (Extremely dissatisfied) to 5 (Extremely satisfied).

Table 9: Job satisfaction and effects of required skills, overskilling and underskilling using different skill mismatch measures

	Numeracy				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	JAM	PFM	RM 2-digit per country	RM 2-digit	RMA 4-digit

Required skill (std)	0.078*** (0.008)	0.105*** (0.018)	0.095*** (0.014)	0.083*** (0.007)	0.088*** (0.008)
Overskilled dummy	-0.014 (0.013)	-0.051*** (0.011)	-0.025* (0.009)	-0.018** (0.009)	-0.033*** (0.009)
Underskilled dummy	-0.018** (0.009)	-0.008 (0.017)	0.013 (0.011)	0.012 (0.011)	0.016 (0.011)
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	103,113	100,387	103,114	103,114	103,113
R-squared	0.074	0.075	0.074	0.076	0.076

	Literacy				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	JAM	PFM	RM 2-digit per country	RMA 2-digit	RMA 4-digit
Required skill (std)	0.082*** (0.009)	0.108*** (0.017)	0.099*** (0.014)	0.085*** (0.007)	0.090*** (0.008)
Overskilled dummy	-0.029** (0.014)	-0.047*** (0.014)	-0.021* (0.012)	-0.018 (0.011)	-0.032** (0.012)
Underskilled dummy	-0.001 (0.008)	-0.005 (0.016)	0.012 (0.011)	0.013 (0.011)	0.014 (0.013)
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	103,113	100,387	103,114	103,114	103,113
R-squared	0.077	0.075	0.075	0.076	0.077

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Controls include age, age squared, gender, fulltime worker, self-employed, and a dummy indicating whether the occupation was heterogeneous according to JAM (combined rating).

In general, the results are not very different if we compare the different measures. Overall, we observe that the explained variance is quite low (R-square is around 8%) and the effects are quite small (and sometimes only significant at the 5 or 10% level). A one standard deviation increase in the required skill level is associated with less than one-tenth of a level increase on the scale for job satisfaction (with a range from 1-5). This implies that the level of required skills in an occupation only has a very small effect on the job satisfaction of workers. We also observe that the dummies for overskilling and underskilling are non-significant in 11 out of 20 cases and significant at the 1% level in only three cases. In two cases this relates to the PFM measure. Remember that this measure is partly based on the worker's self-assessment whether the skills possessed match with the skills required. This is in line with previous findings from Fregin (2019) that objective skill mismatches have no effect on job satisfaction, while subjective skill measures such as WSA are related to job satisfaction. In other words, whether a worker is satisfied with his or her job is related to whether he or she *feels* that the job does not match their own skill proficiency, and not whether there is 'real' mismatch in an objective sense. The PFM measure probably picks up this subjective element more than the JAM or RMA-based measures do.

6. Conclusions, policy implications and limitations

The PIAAC data are the leading source for information on skill proficiency levels for individuals in modern economies. The PIAAC data are unique in combining a validated assessment-based measurement of two key information-processing skills (i.e., literacy and numeracy) that are essential for developing a wide range of more specific skills with coverage of many OECD countries. However, to assess the degree of skill mismatch, one also needs to have information on the required skill level in the occupations in which these individuals work. That type of information is currently lacking in the PIAAC data. Although proxies of required skill levels have been used to estimate skill mismatch with the PIAAC data (e.g., Allen et al. 2013; Perry et al. 2014; Pellizzari and Fichen 2013, 2017), these proxies come with significant limitations (van der Velden and Bijlsma 2019).

In this paper, we applied the Job Analysis Method (JAM) to assess skill mismatches in the domains of literacy and numeracy. These key information-processing skills can be considered the most important skills that affect general functioning at work. In JAM, occupational experts identify the critical required skill level needed to execute the relevant tasks in the occupation. We compare JAM with two alternative measures: the Pellizari-Fichen (2013) model (PFM) and the Perry et al. (2014) model. Both alternative models use some form of Realised Matches Approach (RMA). In RMA, the average worker in an occupation is considered to be well-matched and workers with a proficiency level of 1 sd above or below that level as overskilled or underskilled. Perry et al. (2020) apply this on ISCO two-digit occupations per country (hence we refer to this as RMA 2-digit per country). The PFM model uses a restriction to this RMA by looking at workers who consider themselves well-matched and take their skill range to define the well-matched workers per one-digit occupation per country (regardless, whether these workers define themselves as well-matched or not).

The findings show that estimates of skill mismatch depend substantially on the method used. The proportion of well-matched workers is some 60% if we use JAM, some 75% if we use RMA-based measures and some 85% if we use PFM. At the same time, the JAM estimates of the proportions of overskilled workers and underskilled workers are higher than for the alternative measures. If we compare this to estimates of the prevalence of educational mismatches from the literature, with some 20-25% overeducated workers and 15-20% undereducated workers, we conclude that these are closest to the estimate of JAM and most remote from the PFM measure.

Additionally, we find that the different methods lead to different conclusions when comparing countries. The correlations in the ranking of well-matched workers are only some .55, while the correlations in the ranking of overskilled (both literacy and numeracy) or underskilled (only numeracy) workers are negative when comparing JAM with the two other measures. Additionally, the correlation between PFM and RMA 2-digit is lower than 0.11, indicating that ranking according to PFM is basically uncorrelated with a ranking according to RMA 2-digit.

This means that for international comparisons, it really matters which measure is being used. Given the fact that both PFM and the RMA 2-digit per country measures are calculated per country, there is good reason to believe that the JAM measure or RMA-based measures that are not calculated per country, provide more credible results as they use a common yardstick to compare countries.

Also, if we look at proportions overskilled or underskilled workers per occupation or per sector, we note that the JAM, PFM and RMA 2-digit per country come up with different sets of top 3s. Moreover, we note that in the overview of occupations with the highest percentages of overskilled or underskilled workers JAM shows occupations that appear to have more face validity than the two alternative measures. The main problem here is not so much the rank order of occupations that JAM provides, but rather the huge variation in these proportions leading to (unrealistic) high estimates for certain occupations. We will return to this later.

For the moment, we conclude that different methods yield quite different results if one is interested in the prevalence of skill mismatches and that there is good reason to believe that JAM provides the most accurate estimate of the *absolute* level of skill mismatches in the OECD as a whole, and also a better estimate in the *relative* ranking of countries or occupations when considering the proportion of workers that is seriously underskilled or overskilled.

This does not automatically imply that JAM is also better in predicting relevant outcomes related to skill mismatch. The relation with outcomes such as wages or job satisfaction is not only related to how well skill mismatch is measured, but also to how close the different measures capture the underlying mechanism driving these effects. If wages are solely driven by the inherent skill requirements of the job and the actual skills of the worker, we would expect JAM to be a superior predictor of wages. However, if wages are predominantly driven by the average characteristics of the workers, we would predict that RMA-based measures are a better predictor. In this paper we compared the different skill mismatch measures on their effect on wages and job satisfaction.

For wages, we find that the main differences between the mismatch measures are related to the effects of overskilling and underskilling on wages. We observe that the PFM- and RMA-based measures yield lower estimates for the wage returns to being overskilled, and (for literacy) higher wage penalties for being underskilled in comparison to the JAM-based measure. Additionally, whereas the PFM- and RMA-based measures suggest that the penalties for being underskilled are higher in absolute value than the returns to being overskilled, the JAM-based measure suggests the opposite, which is more in line with usual findings in the mismatch literature (Hartog 2000; Groot and Maassen van den Brink 2000; Quintini 2011). We therefore conclude that the JAM-based measure probably gives a more accurate estimation of the wage effects of skill mismatches than the alternative measures. Also, this implies that wages are mostly determined by inherent job requirements, rather than by the average characteristics of the workers in these jobs.

For job satisfaction, our results do not suggest any major differences between the mismatch measures. The explained variance is generally quite low, which may partly be due to the limited variation in the job satisfaction measurement. All in all, we find that the level of required skills in an occupation is only modestly related to the job satisfaction of workers, and that there is generally no significant impact of overskilling and underskilling on job satisfaction. This suggests that workers' job satisfaction is not dependent on any measure of 'objectively' assessed skill mismatch (whether based on JAM, RMA or PFM). Instead, and in line with previous research, we argue that job satisfaction is related with subjective perceptions of the match between a worker's job and a worker's skills (see e.g., Fregin 2019). And in this association, reversed causality might very well drive the results in the sense that a low job satisfaction might make a worker feel mismatched.

Policy implications

The findings may have some important policy implications. Determining the objective requirements for occupations at an international level through this approach helps to paint a clearer picture of the actual prevalence of skill mismatch in Western economies. The results have pointed out that using different methods leads to widely varying estimates of the proportions of workers that are overskilled or underskilled. Moreover, using alternative methods such as PFM or RMA to determine skill mismatch may lead policy makers to underestimate the prevalence of underskilling and therefore inhibit policies to increase the skill levels of the working population. Moreover, JAM also seems to yield better estimates on the effects of skill mismatches on wages. As wages are regarded as a good proxy for productivity, this has also major implications for economic policy, for example in identifying which sectors and occupations suffer most from skill shortages or underskilling. Taken together, this implies that policy makers who aim to use the PIAAC data to examine skill mismatch should consider looking at the JAM method rather than any of the alternative methods.

However, this should also be done with caution. Overskilling or underskilling in the domain of literacy or numeracy skills, is different from identifying overall skill mismatches. Workers in an occupation who are uderskilled in numeracy might still be very productive in the job if they can compensate this with other skills, or when this is compensated in the team in which they are working. In that sense, all measures that were discussed here have a rather one-dimensional focus that does not do justice to the complexity of how workers with different skills can meet the different skill requirements at work. Looking at skill mismatch in just one domain, may therefore give a distorted view on the overall skill mismatch situation in a country, even if these domains are two of the critical key information-processing skills that are crucial for functioning well in the job. As said, this caution holds for JAM as well as for the other measures that identify skill mismatches in numeracy or literacy. For the future application of JAM, it is also good to consider its current limitations.

Current limitations and directions for future research

According to Hartog (2000), the purpose of JAM is objectivity, as trained occupational experts evaluate the job focusing on its technology and the type of activities to be done. Nonetheless, it can be questioned to what extent JAM is objective as it will always reflect the aggregated opinion of experts. Some of the results reflect that. We find much more variation across occupations using JAM than in using the other measures in terms of proportions overskilled or underskilled workers, with sometimes very extreme proportions (80% or above). Partly the stronger variation across occupations is realistic as the variation according to the alternative measures is downward-biased. Nevertheless, we feel that the variation is more extreme than would be expected on face validity and this is certainly true for the occupations at the upper end of the required skills levels. These are the occupations that were classified as requiring level 4 or 5 in numeracy or literacy proficiency. As indicated earlier, we already decided not to differentiate between levels 4 and 5 when determining the cut-off points for well-matched workers. This is also related to the extreme low percentages of PIAAC respondents reaching the highest level 5. As a follow-up, we suggest it would be good to crosscheck our estimates with the estimates of a broader panel of occupational experts and domain experts, specifically looking at the upper end of the job distribution.

Moreover, JAM as we applied it, assumes that occupations do not vary in required skill levels across countries. Notwithstanding the fact that ISCO is task-based, it is quite likely that the same coded occupation (e.g., carpenter) may still have different skill requirements in different countries. In the future it would be good to further develop our JAM estimates and check to what extent the different levels apply equally for the different countries. This would require the involvement of national occupational experts who could use the current estimates as a starting point and indicate to which extent these should be adjusted up or down.

Finally, the success of JAM critically relies on the existence of detailed and updated data, as highly aggregated classifications are prone to bias and can quickly become outdated (Dahlstedt 2011). This was the reason why during the project the occupational experts did not solely rely on the task descriptions in ISCO08. Some of these task descriptions were considered slightly out-of-date due to technological developments in the job, which may have affected working conditions and skill requirements in several jobs, and which will probably be updated in the upcoming revision of ISCO. The experts therefore also used their own insights and knowledge of occupations and national classifications. In this sense, it is fair to describe JAM as a normative approach, rather than an objective approach. However, it is this deep expert knowledge that is crucial for a successful application of JAM, and that contributes significantly to some of the strengths of this approach compared to other methods.

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Supplementary materials

Appendix A: PIAAC Proficiency levels: literacy and numeracy

The following table shows the different proficiency levels for literacy and numeracy from PIAAC (OECD 2013b). They range from 1 to 5, including an extra category accounting for individuals whose proficiency level is below level 1. Participants are classified into each level based on their score on the tests, as shown in the table. An explanation of the tasks related to each level is also provided.

Level	Score range	Literacy	Numeracy
Below 1	**Below 176**	The tasks at this level require the respondent to read brief texts on familiar topics to locate a single piece of specific information. There is seldom any competing information in the text and the requested information is identical in form to information in the question or directive. The respondent may be required to locate information in short continuous texts. However, in this case, the information can be located as if the text was non-continuous in format. Only basic vocabulary knowledge is required, and the reader is not required to understand the structure of sentences or paragraphs or make use of other text features. Tasks below Level 1 do not make use of any features specific to digital texts.	Tasks at this level require the respondents to carry out simple processes such as counting, sorting, performing basic arithmetic operations with whole numbers or money, or recognising common spatial representations in concrete, familiar contexts where the mathematical content is explicit with little or no text or distractors.
1	**176 to less than 226 points**	Most of the tasks at this level require the respondent to read relatively short digital or print continuous, non continuous, or mixed texts to locate a single piece of information that is identical to or synonymous with the information given in the question or directive. Some tasks, such as those involving non-continuous texts, may require the respondent to enter personal information onto a document. Little, if any, competing information is present. Some tasks may require	Tasks at this level require the respondent to carry out basic mathematical processes in common, concrete contexts where the mathematical content is explicit with little text and minimal distractors. Tasks usually require one-step or simple processes involving counting; sorting; performing basic arithmetic operations; understanding simple percentages such as 50%; and locating and identifying elements of simple or common graphical or spatial representations.

		simple cycling through more than one piece of information. Knowledge and skill in recognising basic vocabulary determining the meaning of sentences, and reading paragraphs of text is expected.	
2	**226 to less than 276 points**	At this level, the medium of texts may be digital or printed, and texts may comprise continuous, non-continuous, or mixed types. Tasks at this level require respondents to make matches between the text and information, and may require paraphrasing or low-level inferences. Some competing pieces of information may be present. Some tasks require the respondent to • cycle through or integrate two or more pieces of information based on criteria; • compare and contrast or reason about information requested in the question; or • navigate within digital texts to access-and-identify information from various parts of a document.	Tasks at this level require the respondent to identify and act on mathematical information and ideas embedded in a range of common contexts where the mathematical content is fairly explicit or visual with relatively few distractors. Tasks tend to require the application of two or more steps or processes involving calculation with whole numbers and common decimals, percentages and fractions; simple measurement and spatial representation; estimation; and interpretation of relatively simple data and statistics in texts, tables and graphs.
3	**276 to less than 326 points**	Texts at this level are often dense or lengthy, and include continuous, non-continuous, mixed, or multiple pages of text. Understanding text and rhetorical structures become more central to successfully completing tasks, especially navigating complex digital texts. Tasks require the respondent to identify, interpret, or evaluate one or more pieces of information, and often require varying levels of inference. Many tasks require the respondent to construct meaning across larger chunks of text or perform multi-step operations in order to identify and formulate responses. Often tasks also demand that the respondent disregard irrelevant or inappropriate content to answer accurately. Competing information is often present, but it is not more prominent than the correct information.	Tasks at this level require the respondent to understand mathematical information that may be less explicit, embedded in contexts that are not always familiar and represented in more complex ways. Tasks require several steps and may involve the choice of problem-solving strategies and relevant processes. Tasks tend to require the application of number sense and spatial sense; recognising and working with mathematical relationships, patterns, and proportions expressed in verbal or numerical form; and interpretation and basic analysis of data and statistics in texts, tables and graphs.

4	**326 to less than 376 points**	Tasks at this level often require respondents to perform multiple-step operations to integrate, interpret, or synthesise information from complex or lengthy continuous, non-continuous, mixed, or multiple type texts. Complex inferences and application of background knowledge may be needed to perform the task successfully. Many tasks require identifying and understanding one or more specific, non-central idea(s) in the text in order to interpret or evaluate subtle evidenceclaim or persuasive discourse relationships. Conditional information is frequently present in tasks at this level and must be taken into consideration by the respondent. Competing information is present and sometimes seemingly as prominent as correct information.	Tasks at this level require the respondent to understand a broad range of mathematical information that may be complex, abstract or embedded in unfamiliar contexts. These tasks involve undertaking multiple steps and choosing relevant problem-solving strategies and processes. Tasks tend to require analysis and more complex reasoning about quantities and data; statistics and chance; spatial relationships; and change, proportions and formulas. Tasks at this level may also require understanding arguments or communicating well-reasoned explanations for answers or choices.
5	**Equal to or higher than 376 points**	At this level, tasks may require the respondent to search for and integrate information across multiple, dense texts; construct syntheses of similar and contrasting ideas or points of view; or evaluate evidence based arguments. Application and evaluation of logical and conceptual models of ideas may be required to accomplish tasks. Evaluating reliability of evidentiary sources and selecting key information is frequently a requirement. Tasks often require respondents to be aware of subtle, rhetorical cues and to make high-level inferences or use specialised background knowledge.	Tasks at this level require the respondent to understand complex representations and abstract and formal mathematical and statistical ideas, possibly embedded in complex texts. Respondents may have to integrate multiple types of mathematical information where considerable translation or interpretation is required; draw inferences; develop or work with mathematical arguments or models; and justify, evaluate and critically reflect upon solutions or choices.

Note. Adapted from OECD (2013b, 69-70)

Appendix B: Example of the information material provided to occupational experts

2111 Physicists and Astronomers

Definition and Tasks:

Physicists and astronomers conduct research and improve or develop concepts, theories and operational methods concerning matter, space, time, energy, forces and fields and the interrelationship between these physical phenomena. They apply scientific knowledge relating to physics and astronomy in industrial, medical, military or other fields.

Tasks include:

a) conducting research and improving or developing concepts, theories, instrumentation, software and operational methods related to physics and astronomy;
b) conducting experiments, tests and analyses on the structure and properties of matter in fields such as mechanics, thermodynamics, electronics, communications, power generation and distribution, aerodynamics, optics and lasers, remote sensing, medicine, sonics, magnetism and nuclear physics;
c) evaluating results of investigations and experiments and expressing conclusions, mainly using mathematical techniques and models;
d) applying principles, techniques and processes to develop or improve industrial, medical, military and other practical applications of the principles and techniques of physics or astronomy;
e) ensuring the safe and effective delivery of radiation (ionizing and non-ionizin) to patients to achieve a diagnostic or therapeutic result as prescribed by a medical practitioner;
f) ensuring the accurate measurement and characterization of physical quantities used in medical applications;
g) testing, commissioning and evaluating equipment used in applications such as imaging, medical treatment and dosimetry;
h) advising and consulting with medical practitioners and other health care professionals in optimizing the balance between the beneficial and deleterious effects of radiation;
i) observing, analysing and interpreting celestial phenomena and developing methods, numerical models and techniques to extend knowledge of fields such as navigation, satellite communication, space exploration, celestial bodies and cosmic radiation;
j) developing, implementing and maintaining standards and protocols for the measurement of physical phenomena and for the use of nuclear technology in industrial and medical applications;
k) preparing scientific papers and reports.

Examples of the occupations classified here: Astronomer, Medical physicist, Nuclear physicist, Physicist.

Some related occupations classified elsewhere: Radiation oncologist - 2212, Radiologist – 2212, Specialist physician (nuclear medicine) – 2212, Radiographer – 3211.

It should be noted that, while they are appropriately classified in this unit group with other physicists, medical physicists are considered to be an integral part of the health workforce alongside those occupations classified in Sub-major Group 22: Health Professionals and others classified in a number of other unit groups in Major Group 2: Professionals

Required Education and Experience:

Education:	Most of these occupations require graduate school. For example, they may require a master's degree, and some require a Ph.D.
Experience:	Extensive skill, knowledge, and experience are needed for these occupations. Many require more than five years of experience.
Job Training:	Employees may need some on-the-job training, but most of these occupations assume that the person will already have the required skills, knowledge, work-related experience, and/or training.

Appendix C: Required proficiency levels per 4-digit ISCO unit group

The following table shows the required proficiency levels for literacy and numeracy according to JAM. The unit groups in bold represent the anchor occupations in each 2-digit Sub-Major Group.

ISCO-08	Occupation	Literacy	Numeracy
1111	Legislators	Level 5	Level 4
1112	**Senior Government Officials**	**Level 5**	**Level 4**
1113	Traditional Chiefs and Heads of Villages	Level 3	Level 3
1114	Senior Officials of Special-interest Organizations	Level 4.5	Level 4
1120	Managing Directors and Chief Executives	Level 5	Level 4
1211	Finance Managers	Level 5	Level 4
1212	Human Resource Managers	Level 4.5	Level 4
1213	**Policy and Planning Managers**	**Level 5**	**Level 4**
1219	Business Services and Administration Managers Not Elsewhere Classified	Level 4	Level 4
1221	Sales and Marketing Managers	Level 4.5	Level 4
1222	Advertising and Public Relations Managers	Level 4.5	Level 4
1223	Research and Development Managers	Level 4 + 5	Level 4 + 5
1311	Agricultural and Forestry Production Managers	Level 4.5	Level 4.5
1312	Aquaculture and Fisheries Production Managers	Level 4.5	Level 4.5
1321	Manufacturing Managers	Level 4.5	Level 4
1322	Mining Managers	Level 4.5	Level 4
1323	Construction Managers	Level 4.5	Level 4
1324	Supply, Distribution and Related Managers	Level 4.5	Level 4
1330	Information and Communications Technology Services Managers	Level 4 + 5	Level 3 + 4
1341	Child Care Services Managers	Level 4	Level 4

1342	**Health Services Managers**	**Level 5**	**Level 4**
1343	Aged Care Services Managers	Level 4	Level 4
1344	Social Welfare Managers	Level 4	Level 4
1345	Education Managers	Level 4 + 5	Level 3 + 4
1346	Financial and Insurance Services Branch Managers	Level 4	Level 4
1349	Professional Services Managers Not Elsewhere Classified	Level 4 + 5	Level 4
1411	Hotel Managers	Level 3 + 4	Level 3 + 4
1412	Restaurant Managers	Level 3	Level 3
1420	**Retail and Wholesale Trade Managers**	**Level 3.5**	**Level 4**
1431	Sports, Recreation and Cultural Centre Managers	Level 3 + 4	Level 3 + 4
1439	Services Managers Not Elsewhere Classified	Level 3 + 4	Level 3 + 4
2111	Physicists and Astronomers	Level 4.5	Level 5
2112	Meteorologists	Level 4.5	Level 5
2113	Chemists	Level 4.5	Level 5
2114	Geologists and Geophysicists	Level 4.5	Level 5
2120	**Mathematicians, Actuaries and Statisticians**	**Level 4.5**	**Level 5**
2131	Biologists, Botanists, Zoologists and Related Professionals	Level 4.5	Level 4.5
2132	Farming, Forestry and Fisheries Advisers	Level 4.5	Level 4
2133	Environmental and Protection Professionals	Level 4.5	Level 4.5
2141	Industrial and Production Engineers	Level 4.5	Level 4.5
2142	Civil Engineers	Level 4.5	Level 5
2143	Environmental Engineers	Level 4.5	Level 5
2144	Mechanical Engineers	Level 4.5	Level 5
2145	**Chemical Engineers**	**Level 4.5**	**Level 5**

2146	Mining Engineers, Metallurgists and Related Professionals	Level 4.5	Level 5
2149	Engineering Professionals Not Elsewhere Classified	Level 4.5	Level 5
2151	Electrical Engineers	Level 4.5	Level 5
2152	Electronics Engineers	Level 4.5	Level 5
2153	Telecommunications Engineers	Level 4.5	Level 5
2161	Building Architects	Level 4.5	Level 5
2162	Landscape Architects	Level 4.5	Level 4
2163	Product and Garment Designers	Level 4	Level 3 + 4
2164	Town and Traffic Planners	Level 4.5	Level 4.5
2165	Cartographers and Surveyors	Level 4.5	Level 4.5
2166	Graphic and Multimedia Designers	Level 4	Level 3.5
2211	Generalist Medical Practitioners	Level 5	Level 4.5
2212	**Specialist Medical Practitioners**	**Level 5**	**Level 5**
2221	**Nursing Professionals**	**Level 3 + 4**	**Level 4**
2222	Midwifery Professionals	Level 4	Level 4
2230	Traditional and Complementary Medicine Professionals	Level 4	Level 4
2240	Paramedical Practitioners	Level 4	Level 4
2250	Veterinarians	Level 5	Level 5
2261	Dentists	Level 5	Level 4.5
2262	Pharmacists	Level 5	Level 5
2263	Environmental and Occupational Health and Hygiene Professionals	Level 4	Level 4.5
2264	Physiotherapists	Level 4	Level 3.5
2265	Dieticians and Nutritionists	Level 4	Level 4
2266	Audiologists and Speech Therapists	Level 4	Level 4
2267	Optometrists and Ophthalmic Opticians	Level 4	Level 4
2269	Health Professionals Not Elsewhere Classified	Level 4	Level 4
2310	University and Higher Education Teachers	Level 5	Level 4 + 5
2320	Vocational Education Teachers	Level 4	Level 3 + 4
2330	Secondary Education Teachers	Level 4	Level 3 + 4

2341	**Primary School Teachers**	**Level 3.5**	**Level 3**
2342	Early Childhood Educators	Level 3.5	Level 2.5
2351	Education Methods Specialists	Level 5	Level 4
2352	Special Needs Teachers	Level 4	Level 3
2353	Other Language Teachers	Level 3.5	Level 2.5
2354	Other Music Teachers	Level 3 + 4	Level 3
2355	Other Arts Teachers	Level 3 + 4	Level 2.5
2356	Information Technology Trainers	Level 4	Level 4
2359	Teaching Professionals Not Elsewhere Classified	Level 3 + 4	Level 3 + 4
2411	Accountants	Level 4 + 5	Level 4 + 5
2412	Financial and Investment Advisers	Level 4 + 5	Level 4 + 5
2413	Financial Analysts	Level 5	Level 4.5
2421	Management and Organization Analysts	Level 5	Level 4
2422	Policy Administration Professionals	Level 5	Level 4
2423	Personnel and Careers Professionals	Level 4	Level 3
2424	Training and Staff Development Professionals	Level 4	Level 3
2431	Advertising and Marketing Professionals	Level 4	Level 3.5
2432	Public Relations Professionals	Level 4	Level 3.5
2433	**Technical and Medical Sales Professionals (excluding ICT)**	**Level 4**	**Level 4**
2434	Information and Communications Technology Sales Professionals	Level 4	Level 4
2511	Systems Analysts	Level 4.5	Level 4.5
2512	**Software Developers**	**Level 4.5**	**Level 4**
2513	Web and Multimedia Developers	Level 4.5	Level 4
2514	Applications Programmers	Level 4.5	Level 4
2519	Software and Applications Developers and Analysts Not Elsewhere Classified	Level 4.5	Level 4
2521	Database Designers and Administrators	Level 4	Level 4

2522	Systems Administrators	Level 3.5	Level 3.5
2523	Computer Network Professionals	Level 4	Level 4
2529	Database and Network Professionals Not Elsewhere Classified	Level 4	Level 4
2611	Lawyers	Level 5	Level 4
2612	Judges	Level 5	Level 4
2619	Legal Professionals Not Elsewhere Classified	Level 5	Level 4
2621	Archivists and Curators	Level 5	Level 3.5
2622	Librarians and Related Information Professionals	Level 5	Level 3.5
2631	**Economists**	**Level 5**	**Level 5**
2632	Sociologists, Anthropologists and Related Professionals	Level 5	Level 4
2633	Philosophers, Historians and Political Scientists	Level 5	Level 4
2634	Psychologists	Level 5	Level 4.5
2635	Social Work and Counselling Professionals	Level 4 + 5	Level 3 + 4
2636	Religious Professionals	Level 5	Level 3
2641	Authors and Related Writers	Level 4 + 5	Level 3
2642	Journalists	Level 5	Level 3
2643	Translators, Interpreters and Other Linguists	Level 5	Level 2.5
2651	Visual Artists	Level 3 + 4	Level 2
2652	Musicians, Singers and Composers	Level 3 + 4	Level 2 + 3
2653	Dancers and Choreographers	Level 3 + 4	Level 2
2654	Film, Stage and Related Directors and Producers	Level 4.5	Level 3 + 4
2655	Actors	Level 3 + 4	Level 1
2656	Announcers on Radio, Television and Other Media	Level 3 + 4	Level 2 + 3

2659	Creative and Performing Artists Not Elsewhere Classified	Level 2 + 3	Level 1 + 2
3111	Chemical and Physical Science Technicians	Level 3	Level 4
3112	Civil Engineering Technicians	Level 3	Level 4
3113	Electrical Engineering Technicians	Level 3	Level 4
3114	Electronics Engineering Technicians	Level 3	Level 4
3115	Mechanical Engineering Technicians	Level 3	Level 4
3116	Chemical Engineering Technicians	Level 3	Level 4
3117	Mining and Metallurgical Technicians	Level 3	Level 4
3118	Draughtspersons	Level 3	Level 4
3119	Physical and Engineering Science Technicians Not Elsewhere Classified	Level 3	Level 4
3121	Mining Supervisors	Level 3	Level 3
3122	Manufacturing Supervisors	Level 3	Level 3
3123	**Construction Supervisors**	**Level 3**	**Level 3**
3131	Power Production Plant Operators	Level 3	Level 3.5
3132	Incinerator and Water Treatment Plant Operators	Level 3	Level 3.5
3133	Chemical Processing Plant Controllers	Level 3	Level 3.5
3134	Petroleum and Natural Gas Refining Plant Operators	Level 3	Level 3.5
3135	Metal Production Process Controllers	Level 2.5	Level 3
3139	Process Control Technicians Not Elsewhere Classified	Level 3	Level 3.5
3141	Life Science Technicians (excluding Medical)	Level 3	Level 4
3142	Agricultural Technicians	Level 3	Level 4
3143	Forestry Technicians	Level 3	Level 4
3151	Ships' Engineers	Level 3	Level 4
3152	Ships' Deck Officers and Pilots	Level 3	Level 4
3153	Aircraft Pilots and Related Associate Professionals	Level 3	Level 4
3154	Air Traffic Controllers	Level 3	Level 4

3155	Air Traffic Safety Electronics Technicians	Level 3	Level 4
3211	Medical Imaging and Therapeutic Equipment Technicians	Level 3	Level 3 + 4
3212	Medical and Pathology Laboratory Technicians	Level 3	Level 4
3213	Pharmaceutical Technicians and Assistants	Level 3	Level 3.5
3214	**Medical and Dental Prosthetic Technicians**	**Level 2.5**	**Level 3**
3221	Nursing Associate professionals	Level 3	Level 3
3222	Midwifery Associate professionals	Level 3	Level 3
3230	Traditional and Complementary Medicine Associate Professionals	Level 3	Level 2.5
3240	Veterinary Technicians and Assistants	Level 3	Level 3
3251	Dental Assistants and Therapists	Level 2 + 3	Level 3
3252	Medical Records and Health Information Technicians	Level 3.5	Level 3
3253	Community Health Workers	Level 3	Level 3
3254	Dispensing Opticians	Level 2.5	Level 3
3255	Physiotherapy Technicians and Assistants	Level 2.5	Level 3
3256	Medical Assistants	Level 3	Level 3
3257	Environmental and Occupational Health Inspectors and Associates	Level 3	Level 3.5
3258	Ambulance Workers	Level 2 + 3	Level 2 + 3
3259	Health Associate Professionals Not Elsewhere Classified	Level 3	Level 3
3311	Securities and Finance Dealers and Brokers	Level 5	Level 4
3312	Credit and Loans Officers	Level 3	Level 3
3313	Accounting Associate Professionals	Level 3	Level 3
3314	Statistical, Mathematical and Related Associate Professionals	Level 3	Level 4
3315	Valuers and Loss Assessors	Level 3	Level 3
3321	Insurance Representatives	Level 3	Level 3

3322	**Commercial Sales Representatives**	**Level 3**	**Level 3**
3323	Buyers	Level 4	Level 4
3324	Trade Brokers	Level 3	Level 3.5
3331	Clearing and Forwarding Agents	Level 2	Level 2
3332	Conference and Event Planners	Level 2.5	Level 2.5
3333	Employment Agents and Contractors	Level 2	Level 1.5
3334	Real Estate Agents and Property Managers	Level 3	Level 3
3339	Business Services Agents Not Elsewhere Classified	Level 2 + 3	Level 2 + 3
3341	Office Supervisors	Level 2.5	Level 2
3342	Legal Secretaries	Level 3	Level 2.5
3343	Administrative and Executive Secretaries	Level 2.5	Level 2
3344	Medical Secretaries	Level 3	Level 2.5
3351	Customs and Border Inspectors	Level 3	Level 3
3352	Government Tax and Excise Officials	Level 3	Level 3
3353	Government Social Benefits Officials	Level 3	Level 3
3354	Government Licensing Officials	Level 3	Level 3
3355	Police Inspectors and Detectives	Level 4	Level 3
3359	Government Regulatory Associate Professionals Not Elsewhere Classified	Level 3	Level 3
3411	Legal and Related Associate Professionals	Level 3	Level 3
3412	**Social Work Associate Professionals**	**Level 3**	**Level 2 + 3**
3413	Religious Associate Professionals	Level 2	Level 1
3421	Athletes and Sports Players	Level 1 + 2	Level 1 + 2
3422	Sports Coaches, Instructors and Officials	Level 2 + 3	Level 2 + 3
3423	Fitness and Recreation Instructors and Programme Leaders	Level 2	Level 2 + 3
3431	Photographers	Level 2 + 3	Level 3
3432	Interior Designers and Decorators	Level 2 + 3	Level 3.5

3433	Gallery, Museum and Library Technicians	Level 2.5	Level 2.5
3434	Chefs	Level 2.5	Level 3
3435	Other Artistic and Cultural Associate Professionals	Level 2 + 3	Level 2 + 3
3511	Information and Communications Technology Operations Technicians	Level 3	Level 3
3512	Information and Communications Technology User Support Technicians	Level 3	Level 3
3513	**Computer Network and Systems Technicians**	**Level 3**	**Level 3**
3514	Web Technicians	Level 3	Level 3
3521	Broadcasting and Audiovisual Technicians	Level 3	Level 3
3522	Telecommunications Engineering Technicians	Level 3	Level 4
4110	**General Office Clerks**	**Level 2**	**Level 2.5**
4120	Secretaries (general)	Level 2	Level 2
4131	Typists and Word Processing Operators	Level 2	Level 1.5
4132	Data Entry Clerks	Level 1.5	Level 2.5
4211	Bank Tellers and Related Clerks	Level 2	Level 3
4212	Bookmakers, Croupiers and Related Gaming Workers	Level 1 + 2	Level 3 + 4
4213	Pawnbrokers and Money-lenders	Level 1.5	Level 3
4214	Debt Collectors and Related Workers	Level 2	Level 2.5
4221	Travel Consultants and Clerks	Level 2.5	Level 2
4222	Contact Centre Information Clerks	Level 2	Level 2
4223	Telephone Switchboard Operators	Level 1	Level 1
4224	Hotel Receptionists	Level 1.5	Level 1
4225	Inquiry Clerks	Level 1	Level 1
4226	**Receptionists (general)**	**Level 1**	**Level 1**
4227	Survey and Market Research Interviewers	Level 2	Level 1
4229	Client Information Workers Not Elsewhere Classified	Level 1 + 2	Level 1 + 2
4311	Accounting and Bookkeeping Clerks	Level 2	Level 2.5

4312	Statistical, Finance and Insurance Clerks	Level 2	Level 2.5
4313	Payroll Clerks	Level 2	Level 2.5
4321	**Stock Clerks**	**Level 1**	**Level 2**
4322	Production Clerks	Level 2	Level 2
4323	Transport Clerks	Level 2	Level 2
4411	**Library Clerks**	**Level 2**	**Level 1.5**
4412	Mail Carriers and Sorting Clerks	Level 2	Level 1.5
4413	Coding, proofreading and related clerks	Level 2.5	Level 1.5
4414	Scribes and Related Workers	Level 2	Level 1
4415	Filing and Copying Clerks	Level 2	Level 1.5
4416	Personnel Clerks	Level 2	Level 1.5
4419	Clerical Support Workers Not Elsewhere Classified	Level 2	Level 1.5
5111	Travel Attendants and Travel Stewards	Level 1	Level 1.5
5112	Transport Conductors	Level 1	Level 1
5113	Travel Guides	Level 2 + 3	Level 2
5120	**Cooks**	**Level 1**	**Level 2**
5131	Waiters	Level 1	Level 1.5
5132	Bartenders	Level 1	Level 2
5141	Hairdressers	Level 0 + 1	Level 1 + 2
5142	Beauticians and Related Workers	Level 0 + 1	Level 1 + 2
5151	Cleaning and Housekeeping Supervisors in Offices, Hotels and Other Establishments	Level 1	Level 1
5152	Domestic Housekeepers	Level 0	Level 0
5153	Building Caretakers	Level 0	Level 0
5161	Astrologers, Fortune-tellers and Related Workers	Level 1.5	Level 1
5162	Companions and Valets	Level 1.5	Level 1
5163	Undertakers and Embalmers	Level 1 + 2	Level 2
5164	Pet Groomers and Animal Care Workers	Level 1.5	Level 1
5165	Driving Instructors	Level 2	Level 2
5169	Personal Services Workers Not Elsewhere Classified	Level 0 + 1	Level 0 + 1

5211	Stall and Market salespersons	Level 1	Level 1.5
5212	Street Food Salespersons	Level 0.5	Level 1
5221	Shopkeepers	Level 2.5	Level 3
5222	Shop Supervisors	Level 2	Level 2
5223	**Shop Sales Assistants**	**Level 1**	**Level 1 + 2**
5230	Cashiers and Ticket Clerks	Level 1	Level 2
5241	Fashion and Other Models	Level 0	Level 0
5242	Sales Demonstrators	Level 1	Level 0.5
5243	Door-to-door salespersons	Level 1	Level 1
5244	Contact Centre Salespersons	Level 1.5	Level 1
5245	Service Station Attendants	Level 1	Level 1.5
5246	Food Service Counter Attendants	Level 1	Level 1
5249	Sales Workers Not Elsewhere Classified	Level 1	Level 1 + 2
5311	Child Care Workers	Level 2.5	Level 1.5
5312	**Teachers' aides**	**Level 2.5**	**Level 1.5**
5321	Health Care Assistants	Level 2	Level 1.5
5322	Home-based Personal Care Workers	Level 2.5	Level 2
5329	Personal Care Workers in Health Services Not Elsewhere Classified	Level 1 + 2	Level 1 + 2
5411	Firefighters	Level 2.5	Level 2
5412	**Police Officers**	**Level 3**	**Level 2.5**
5413	Prison Guards	Level 2	Level 1
5414	Security Guards	Level 1.5	Level 1
5419	Protective Services Workers Not Elsewhere Classified	Level 1	Level 1
6111	Field Crop and Vegetable Growers	Level 2	Level 3
6112	Tree and Shrub Crop Growers	Level 2	Level 3
6113	Gardeners; Horticultural and Nursery Growers	Level 2	Level 3
6114	Mixed Crop Growers	Level 2	Level 3
6121	**Livestock and Dairy Producers**	**Level 3**	**Level 3**
6122	Poultry Producers	Level 2.5	Level 3

6123	Apiarists and Sericulturists	Level 2	Level 2
6129	Animal Producers Not Elsewhere Classified	Level 2	Level 2.5
6130	Mixed Crop and Animal Producers	Level 2 + 3	Level 3
6210	Forestry and Related Workers	Level 2	Level 2
6221	**Aquaculture Workers**	**Level 2**	**Level 3**
6222	Inland and Coastal Waters Fishery Workers	Level 2	Level 2.5
6223	Deep-sea Fishery Workers	Level 2	Level 2.5
6224	Hunters and Trappers	Level 1	Level 2
6310	**Subsistence Crop Farmers**	**Level 0**	**Level 1**
6320	Subsistence Livestock Farmers	Level 0	Level 1
6330	Subsistence Mixed Crop and Livestock Farmers	Level 0	Level 1
6340	Subsistence Fishers, Hunters, Trappers and Gatherers	Level 0	Level 1
7111	House Builders	Level 1.5	Level 2
7112	**Bricklayers and Related Workers**	**Level 1.5**	**Level 2**
7113	Stonemasons, Stone cutters, Splitters and Carvers	Level 1.5	Level 2
7114	Concrete Placers, Concrete Finishers and Related Workers	Level 1.5	Level 2
7115	Carpenters and Joiners	Level 1.5	Level 2
7119	Building Frame and Related Trades Workers Not Elsewhere Classified	Level 1.5	Level 1.5
7121	Roofers	Level 1.5	Level 2
7122	Floor Layers and Tile Setters	Level 1.5	Level 2
7123	Plasterers	Level 1.5	Level 2
7124	Insulation Workers	Level 1.5	Level 2
7125	Glaziers	Level 1.5	Level 2
7126	Plumbers and Pipe Fitters	Level 2	Level 3
7127	Air Conditioning and Refrigeration Mechanics	Level 2	Level 3
7131	Painters and Related Workers	Level 1.5	Level 2

7132	Spray Painters and Varnishers	Level 1.5	Level 2
7133	Building Structure Cleaners	Level 1	Level 1
7211	Metal Moulders and Coremakers	Level 1.5	Level 2.5
7212	Welders and Flame Cutters	Level 1.5	Level 2
7213	Sheet Metal Workers	Level 1.5	Level 2.5
7214	Structural Metal Preparers and Erectors	Level 1.5	Level 2.5
7215	Riggers and Cable Splicers	Level 1.5	Level 3
7221	Blacksmiths, Hammersmiths and Forging Press Workers	Level 1.5	Level 2
7222	Toolmakers and Related Workers	Level 2	Level 3
7223	Metal Working Machine Tool Setters and Operators	Level 2	Level 3
7224	Metal Polishers, Wheel Grinders and Tool Sharpeners	Level 2	Level 2
7231	**Motor Vehicle Mechanics and Repairers**	**Level 2**	**Level 3**
7232	Aircraft Engine Mechanics and Repairers	Level 2.5	Level 3
7233	Agricultural and Industrial Machinery Mechanics and Repairers	Level 2	Level 3
7234	Bicycle and Related Repairers	Level 2	Level 2
7311	Precision-instrument Makers and Repairers	Level 2	Level 3
7312	Musical Instrument Makers and Tuners	Level 2	Level 2.5
7313	Jewellery and Precious metal Workers	Level 2	Level 2.5
7314	Potters and Related Workers	Level 2	Level 2
7315	Glass Makers, Cutters, Grinders and Finishers	Level 2	Level 2
7316	Signwriters, Decorative Painters, Engravers and Etchers	Level 2	Level 2
7317	Handicraft Workers in Wood, Basketry and Related Materials	Level 1.5	Level 2
7318	Handicraft Workers in Textile, Leather and Related Materials	Level 1.5	Level 2
7319	Handicraft Workers Not Elsewhere Classified	Level 2	Level 2.5
7321	Pre-press Technicians	Level 2	Level 2.5
7322	**Printers**	**Level 2**	**Level 2.5**
7323	Print Finishing and Binding Workers	Level 1.5	Level 2

7411	**Building and Related Electricians**	**Level 3**	**Level 3.5**
7412	Electrical Mechanics and Fitters	Level 2.5	Level 3.5
7413	Electrical Line Installers and Repairers	Level 2	Level 3.5
7421	Electronics Mechanics and Servicers	Level 2.5	Level 3.5
7422	Information and Communications Technology Installers and Servicers	Level 3	Level 3.5
7511	Butchers, Fishmongers and Related Food Preparers	Level 1	Level 2
7512	Bakers, Pastry-cooks and Confectionery Makers	Level 1.5	Level 2.5
7513	Dairy Products Makers	Level 1.5	Level 2.5
7514	Fruit, Vegetable and Related Preservers	Level 1	Level 2
7515	Food and Beverage Tasters and Graders	Level 2	Level 2.5
7516	Tobacco Preparers and Tobacco Products Makers	Level 1	Level 2
7521	Wood Treaters	Level 2	Level 2
7522	Cabinet-makers and Related Workers	Level 2	Level 3
7523	Woodworking Machine Tool Setters and Operators	Level 2	Level 2
7531	Tailors, Dressmakers, Furriers and Hatters	Level 2	Level 2.5
7532	Garment and Related Patternmakers and Cutters	Level 2	Level 2.5
7533	Sewing, Embroidery and Related Workers	Level 1	Level 1.5
7534	Upholsterers and Related Workers	Level 1.5	Level 2
7535	Pelt Dressers, Tanners and Fellmongers	Level 1	Level 2
7536	Shoemakers and Related Workers	Level 2	Level 2.5
7541	Underwater Divers	Level 1 + 2	Level 2 + 3
7542	Shotfirers and Blasters	Level 2.5	Level 3
7543	**Product Graders and Testers (excluding Foods and Beverages)**	**Level 2.5**	**Level 3**
7544	Fumigators and Other Pest and Weed Controllers	Level 1	Level 2
7549	Craft and Related Workers Not Elsewhere Classified	Level 2	Level 2

8111	Miners and Quarriers	Level 1.5	Level 2
8112	Mineral and Stone Processing Plant Operators	Level 2	Level 2
8113	Well Drillers and Borers and Related Workers	Level 2	Level 2
8114	Cement, Stone and Other Mineral Products Machine Operators	Level 2	Level 2
8121	Metal Processing Plant Operators	Level 2	Level 2
8122	Metal Finishing, Plating and Coating Machine Operators	Level 2	Level 2
8131	Chemical Products Plant and Machine Operators	Level 2	Level 2
8132	Photographic Products Machine Operators	Level 2	Level 2
8141	**Rubber Products Machine Operators**	**Level 2**	**Level 2**
8142	Plastic Products Machine Operators	Level 2	Level 2
8143	Paper Products Machine Operators	Level 2	Level 2
8151	Fibre Preparing, Spinning and Winding Machine Operators	Level 2	Level 2
8152	Weaving and Knitting Machine Operators	Level 2	Level 2
8153	Sewing Machine Operators	Level 2	Level 2
8154	Bleaching, Dyeing and Fabric Cleaning Machine Operators	Level 2	Level 2
8155	Fur and Leather Preparing Machine Operators	Level 2	Level 2
8156	Shoemaking and Related Machine Operators	Level 2	Level 2
8157	Laundry Machine Operators	Level 1.5	Level 2
8159	Textile, Fur and Leather Products Machine Operators Not Elsewhere Classified	Level 2	Level 2
8160	Food and Related Products Machine Operators	Level 2	Level 2

8171	Pulp and Papermaking Plant Operators	Level 2	Level 2
8172	Wood Processing Plant Operators	Level 2	Level 2
8181	Glass and Ceramics Plant Operators	Level 2	Level 2
8182	Steam Engine and Boiler Operators	Level 2	Level 2
8183	Packing, Bottling and Labelling Machine Operators	Level 1.5	Level 2
8189	Stationary Plant and Machine Operators Not Elsewhere Classified	Level 2	Level 2
8211	**Mechanical Machinery Assemblers**	**Level 2**	**Level 2**
8212	Electrical and Electronic Equipment Assemblers	Level 2	Level 2
8219	Assemblers Not Elsewhere Classified	Level 2	Level 2
8311	Locomotive Engine Drivers	Level 1.5	Level 2
8312	Railway Brake, Signal and Switch Operators	Level 2	Level 2
8321	Motorcycle Drivers	Level 1	Level 1
8322	**Car, Taxi and Van Drivers**	**Level 1**	**Level 1**
8331	Bus and Tram Drivers	Level 1	Level 1
8332	Heavy Truck and Lorry Drivers	Level 1	Level 2
8341	Mobile Farm and Forestry Plant Operators	Level 1	Level 1.5
8342	Earthmoving and Related Plant Operators	Level 1	Level 1.5
8343	Crane, Hoist and Related Plant Operators	Level 1	Level 2
8344	Lifting Truck Operators	Level 1	Level 1.5
8350	Ships' Deck Crews and Related Workers	Level 1	Level 1
9111	**Domestic Cleaners and Helpers**	**Level 0**	**Level 0**
9112	Cleaners and Helpers in Offices, Hotels and other Establishments	Level 0	Level 0
9121	Hand Launderers and Pressers	Level 0	Level 0
9122	Vehicle Cleaners	Level 0	Level 0
9123	Window Cleaners	Level 0	Level 0
9129	Other Cleaning Workers	Level 0	Level 0

9211	Crop Farm Labourers	Level 0	Level 0
9212	Livestock Farm Labourers	Level 0	Level 0
9213	Mixed Crop and Livestock Farm Labourers	Level 0	Level 0
9214	Garden and Horticultural Labourers	Level 0	Level 0
9215	Forestry Labourers	Level 0	Level 0
9216	**Fishery and Aquaculture Labourers**	**Level 0**	**Level 0**
9311	Mining and Quarrying Labourers	Level 0	Level 0
9312	Civil Engineering Labourers	Level 0	Level 0
9313	Building Construction Labourers	Level 0	Level 0
9321	**Hand Packers**	**Level 0**	**Level 0**
9329	Manufacturing Labourers Not Elsewhere Classified	Level 0	Level 0
9331	Hand and Pedal Vehicle Drivers	Level 0	Level 0
9332	Drivers of Animal-drawn Vehicles and Machinery	Level 0	Level 0
9333	Freight Handlers	Level 0	Level 0
9334	Shelf fillers	Level 0	Level 0
9411	Fast Food Preparers	Level 0	Level 0
9412	**Kitchen Helpers**	**Level 0**	**Level 0**
9510	**Street and Related Services Workers**	**Level 0**	**Level 0**
9520	Street Vendors (excluding Food)	Level 0	Level 1
9611	**Garbage and Recycling Collectors**	**Level 0**	**Level 0**
9612	Refuse Sorters	Level 0	Level 0
9613	Sweepers and Related Labourers	Level 0	Level 0
9621	Messengers, Package Deliverers and Luggage Porters	Level 0	Level 0
9622	Odd-job Persons	Level 0	Level 0
9623	Meter Readers and Vending-machine Collectors	Level 1	Level 1
9624	Water and Firewood Collectors	Level 0	Level 0
9629	Elementary Workers Not Elsewhere Classified	Level 0	Level 0