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How Can Skill Mismatch be Measured? New Approaches with PIAAC

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Abstract

Measuring skill mismatch is problematic, because objective data on an individual skill level are often not available. Recently published data from the *Program for the International Assessment of Adult Competencies* (PIAAC) provide a unique opportunity for gauging the importance of skill mismatch in modern labor markets. This paper systematically compares existing measures of skill mismatch in terms of their implications for labor market outcomes. We also provide a new measure that addresses an important limitation of existing measures, namely, assigning a single competency score to individuals. We find that the importance of skill mismatch for individual earnings differs greatly, depending on the measure of mismatch used.

Keywords: skill mismatch, skill use, labor market, PIAAC, Job Requirement Approach

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Skills are the new "global currency of 21st-century economies" (OECD, 2012, p. 10). However, skills must be put to effective use in order to facilitate economic growth and personal labor market success. When skills are not used effectively, we think of them as being mismatched. Skill mismatch occurs when skills possessed by the workers exceed or do not meet the skills required at their workplace. It can lead to skill depreciation and slower adaptation to technological progress, from a macroeconomic perspective (OECD, 2012), and impacts workers' earnings and job satisfaction, from a microeconomic perspective (e.g., Allen & van der Velden, 2001). Recently, the issue of skill mismatch has gained importance in the policy sphere. For instance, the European Union's *Agenda for New Skills and Jobs* (European Commission, 2010) identifies skill mismatch as one of the core challenges faced by today's labor markets. Similarly, the OECD stresses the importance of understanding the causes and consequences of skill mismatch (OECD, 2012).

However, measuring skill mismatch is problematic, because objective data on skills at the individual level are often not available (Leuven & Oosterbeek, 2011, Allen & van der Velden, 2001). The *Programme of the International Assessment of Adult Competencies* (PIAAC), which is an internationally harmonized test of cognitive skills, offers new opportunities to measure skill mismatch. However, there is no widely accepted skill mismatch measure to date. Instead, a number of different approaches to measure skill mismatch have been suggested. Because the variety of existing skills measures imply different shares of mismatched workers in the population and lead to different conclusions regarding the relationship between skill mismatch and labor market outcomes, they also entail different political implications.

This paper is the first one that systematically compares skill mismatch measures, based on the PIAAC data, and assesses their validity by comparing the various measures in a Mincer regression (Mincer, 1974), thus demonstrating the importance of skills for individual earnings. We also introduce a new direct measure of skill mismatch that improves existing measures (discussed in this paper) across

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several dimensions. Finally, we perform an analysis for three countries (Austria, Germany, and the United States) to investigate whether both the occurrence and consequences of skill mismatch are affected by differences in labor and product market regulations.

The paper proceeds as follows. In the next section, we highlight the importance of analyzing skill mismatch. We then briefly discuss general approaches to measure skill mismatch in Section 3. In Section 4, we present several skill mismatch measures, using the PIAAC data. In Section 5 we explain the method used to compare and validate those measures; in Section 6, we compare the measures regarding their explanatory power in a Mincerian earnings regression. Finally, we critically discuss the results of our analyses and conclude.

Theoretical Background

Skills form the human capital of an economy. They can be cognitive (such as literacy or numeracy skills) and non-cognitive (such as physical or soft skills). Cognitive skills have been found to correlate positively with individuals' success in the labor market, participation in society, and economic growth (Hanushek, Schwerdt, Wiederhold, & Woessmann, 2014; Hanushek & Woessmann, 2008; OECD, 2013a; Rammstedt, 2013). Indeed, several studies indicate that the above correlations reflect a causal effect of skills (see, for instance, Hanushek & Woessmann, 2012; Oreopoulos & Salvanes, 2011; Riddell & Song, 2011). At the individual level, developing skills enables workers to understand and perform better, and improve economic processes. This productivity-enhancing effect of skills increases a person's wages or allows him or her to escape unemployment and find a job in the first place (e.g., Hanushek & Woessmann, 2014). At the macroeconomic level, better skills lead to faster technological progress and facilitate technology adoption (e.g., Benhabib & Spiegel, 2002; Ciccone & Papaioannou, 2009; Nelson & Phelps, 1966).

Skills, however, must be put to effective use. Only when the workforce uses its skills effectively can individuals generate adequate earnings, which, in turn, foster economic growth (OECD, 2012). We refer to skill mismatch when skills possessed by workers are lower or higher than the level of skills required at the workplace. Thus, workers can either be over-skilled, hence possessing more skills than actually needed on the job (skill surplus), or under-skilled, possessing less skills than needed on the job (skill deficit, e.g., Quintini, 2011b).

Skill mismatch can arise from structural changes in the economy. Innovation and technological change are typically skill-biased, thus increasing the demand for certain types of skills (e.g., Tinbergen, 1974, 1975). Individuals who possess skills that allow fast adaptation to such changes have better chances to stay employed or to find new employment once they are laid off. Individuals lacking those skills become unemployed or have to accept jobs that do not match their skill portfolios (Acemoglu & Autor, 2011). Several studies suggest that this depends on whether skills are general in nature, that is, whether they are productive in various occupations and therefore transferrable (Hanushek, Schwerdt, Woessmann, & Zhang, 2014), or whether they are occupation-specific (Acemoglu & Autor, 2011; Gathmann & Schönberg, 2010; Nedelkoska, Neffke, & Wiederhold, 2014; Poletaev & Robinson, 2008).

In addition, skill mismatch is related to certain socio-demographic factors. It is likely that a mismatch occurs early in a professional career (Jovanovic, 1979). Inexperienced workers are often found in temporary and entry-level jobs; here, skill requirements are often lower than workers' skills. As workers gain more experience – and are better able to signal their skills by referring to past work experience – it becomes easier for them to move into jobs in which they can adequately apply their skills (Desjardins & Rubenson, 2011; OECD, 2013a). Moreover, women may be more under-skilled than men at the workplace if they are subject to discrimination in the labor market (Desjardins & Rubenson, 2011), or if taking care of children or older family members forces them to work in part-time jobs that typically require fewer skills (OECD, 2013a). Skill mismatch is also a common phenomenon among immigrants whose qualifications can often not be adequately assessed and recognized when they apply for jobs in the host country (Quintini, 2011b).

Previous research calls for a nuanced picture when assessing the consequences of skill mismatch for the economy. On the one hand, a skill surplus can serve as a skill reserve that can be activated once more advanced technologies are introduced at the workplace. On the other hand, skills that are not used may depreciate. Hence, a skill surplus can eventually lead to a loss of skills and thus to a waste of resources that were used to build up existing skills (Krahn & Lowe, 1998; Schooler, 1984) and to lower enterprise productivity as employee turnover increases (Allen & van der Velden, 2001; OECD, 2012). In addition, a skill deficit can challenge existing skills or help to build them up (Schooler, 1984). However, it can also slow down economic growth, because workers possessing too few skills are less able to adapt to technological changes.

Finally, apart from its macroeconomic effects, skills mismatch also influences outcomes at the individual level. First, mismatch affects workers' wages. Typically, over-skilled workers must expect a wage penalty, compared to workers who possess the same skills and match the requirements of their jobs. This is because only skills actually required at a job are rewarded through wages (Tinbergen, 1956). Under-skilled workers are rewarded for applying a large portion of their skills in the job (a proportion presumably larger than someone who is well-matched) and, thus, receive a wage premium. In addition, skill mismatch has an impact on job satisfaction and the likelihood of workers actively searching for a better match in a new job (Allen & van der Velden, 2001).

However, despite the recent upsurge in interest in skill mismatch, one key challenge remains: How do we adequately measure skill mismatch? The international PIAAC data contain direct measures of adult cognitive skills in various domains, thus providing a unique opportunity to assess skill mismatch in the labor market. In the following section, we present various approaches to measuring skill mismatch, using PIAAC.

Measuring Skill Mismatch

There are essentially two ways to measure skill mismatch: self-reported skill mismatch and direct, objective measures of skill mismatch. Both approaches are predominantly based on methods typically used to measure educational mismatch. Leuven and Oosterbeek (2011) provide a survey of various educational mismatch measures and Quintini (2011a) summarizes skill mismatch measures.

Self-Reported Versus Direct Measures of Skill Mismatch

Most often, self-reports are used to measure skill mismatch. Information on self-reported skill mismatch is obtained by asking workers to what extent their skills correspond to the tasks performed at work (e.g., Allen & van der Velden, 2001; Green & McIntosh, 2007; Mavromaras, McGuinness, & Fok, 2009; Mavromaras, McGuinness, O'Leary, Sloane, & Fok, 2007).[1] Self-report measures have the advantage of being easily implementable in a survey; thus, up-to-date information on skill mismatch can be obtained. However, self-reports are prone to biases. Respondents may have the tendency to overstate the requirements of their workplace and upgrade their position at work (see Hartog, 2000, for education mismatch).

Skill mismatch can also be measured directly, which provides a more objective measure. In all direct skill mismatch measures, workers' skills are compared to skills required at their workplace. For instance, required skills can be measured using the Job Requirement Approach (JRA: Felstead, Gallie, Green, & Zhou, 2007). However, biases can also arise from this approach if respondents overstate their skill use at work. Alternatively, required skills can be measured by obtaining a general, occupation-specific skill level (e.g., Pellizzari & Fichen, 2013), similar to the "Realized Matches" approach applied in education mismatch research (Hartog, 2000; Leuven & Oosterbeek, 2008). Both direct approaches for measuring skill

1 In a similar vein, measures of educational mismatch typically refer to a match between educational qualifications obtained in the past and education required for the job.

mismatch require data on skills actually possessed by the workers. These are typically available in large-scale assessments, such as the International Adult Literacy Survey (IALS), the Adult Literacy and Lifeskills (ALL) Survey, or, most recently, PIAAC. National competency assessments, such as the German National Education Panel Study (NEPS), also provide such information. However, the implementation of large-scale competency assessments is costly. Data on workers' skills are therefore scarce and only available for a limited number of countries and time periods. Nevertheless, direct skill data provide a compelling avenue for measuring skill mismatch.

The PIAAC Data

Overview. Developed by the OECD and implemented between August 2011 and March 2012, PIAAC provides internationally comparable data about skills of the adult population in 24 countries.[2] PIAAC was designed to provide representative measures of cognitive skills possessed by adults aged 16 to 65 years.

Together with information on cognitive skills, PIAAC also offers extensive information on respondents' individual and workplace characteristics, for instance, occupation and skill use at work. This information is derived from a background questionnaire completed by the PIAAC respondents prior to the skills assessment. Using the PIAAC data, we can derive a direct measure of skill mismatch, rather than relying on self-reports, which are prone to biases. Moreover, because PIAAC also contains a measure of self-reported skill mismatch, we can compare direct and self-reported mismatch measures.

Cognitive skills. PIAAC provides measures of cognitive skills in three domains: literacy, numeracy, and problem solving in technology-rich environments. These skills were measured on an infinite scale. By default, respondents had to work on the assessment tasks by using a computer. Respondents without sufficient computer experience were assessed in pencil-and-paper mode.[3] This paper focuses on numeracy mismatch. The average numeracy skill in the three countries at the

2 Countries that participated in PIAAC are Australia, Austria, Belgium (Flanders), Canada, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Russian Federation, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), and the United States.

3 Problem solving in technology-rich environments was measured only in a computer-based mode and was an international option. Cyprus, France, Italy, and Spain did not implement the problem-solving domain.

focus of this paper (Germany, Austria, and the United States) is 267 points, with a standard deviation of 53 points.[4]

The role of plausible values. In PIAAC, skills are a latent variable that is estimated using item-response-theory models (IRT). Because IRT was applied, not all respondents worked on the same set of assessment items and did not receive items covering every skill domain in PIAAC (Kirsch & Yamamoto, 2013). To derive skill information for each respondent and every competency domain, the remaining competency scores for each individual are imputed. To account for possible errors due to imputation, 10 plausible values, instead of only one individual proficiency score, are derived for each respondent and each skill domain. Hence, competency scores in PIAAC represent a competency distribution rather than an individual score (von Davier, Gonzalez, & Mislevy, 2009).

Whereas using the average of the 10 plausible values generally provides an unbiased estimate of a person's skills, the associated standard errors are underestimated, because the uncertainty in skills is not accounted for. Another approach often applied is to use only one plausible value, typically the first one. This also leads to underestimated standard errors, though to a lesser extent. However, the resulting estimates may differ, depending on the plausible value used in the analysis (Rutkowski, Gonzalez, Joncas, & von Davier, 2010).

Existing skill mismatch measures (with the exception of the self-report) neglect the fact that no single proficiency score – neither the first plausible value nor the average of all 10 plausible values – can be assigned to a specific respondent. Allen, Levels, and van der Velden (2013), for instance, use only the first plausible value to compare individual skills with the skills used at the workplace. As we will show in Section 6, replacing the first with another plausible value changes the magnitude of the coefficients on skill mismatch in a Mincer regression. An improved measure of skill mismatch should therefore account for all 10 plausible values, because indivdual proficiency scores do not adequately represent the individual skill level.[5]

Job Requirement Approach. In addition to the assessment of cognitive skills, PIAAC surveys skills required at the job. To measure job requirements, respondents are asked which skills they use(d) at their current or last workplace and to which extent they use(d) them. This Job Requirement Approach is based on

4 This is very close to the mean (standard deviation) of numeracy skills for all countries that participated in PIAAC: 268 points (53 points). We excluded only the Russian Federation in these calculations because the Russian data are preliminary and may still be subject to change. Additionally, they are not representative of the entire Russian population because they do not include the population of the Moscow municipal area (OECD, 2013b).

5 In Hanushek, Schwerdt, Wiederhold et al. (2014), where the authors measure returns to cognitive skills, using either only the first plausible value or all of them did not affect the results. They thus used only the first plausible value, which greatly reduced the computational burden.

previous work by Felstead et al. (2007). Information on skill use can be compared to the assessed skill level, to decide whether skills possessed by the workers match the skills required at their workplace.

Additional variables. The extensive background questionnaire in PIAAC offers additional information about respondents. It covers education, labor market status, information on the current or most recent job, skills used at the workplace and at home, as well as personal background information. When testing the relationship between skill mismatch and individual earnings (see Section 5), we use years of schooling, gender, and years of work experience as control variables.

Skill Mismatch Measures in PIAAC

As outlined above, PIAAC offers the opportunity to derive direct and objective measures of skill mismatch. However, the PIAAC background questionnaire also includes a skill mismatch self-report, which we additionally examine and include in our analyses. Direct skill mismatch measures discussed here include those derived by Quintini (2012), Allen et al. (2013), the OECD (2013a), and Pellizzari and Fichen (2013), as well as a new measure developed by the authors of this paper.

Whereas direct skill mismatch measures can, technically, be derived for all three proficiency domains in PIAAC, we focus only on numeracy mismatch. We do this because numeracy skills are most likely to be comparable across countries. Moreover, previous research has demonstrated the high relevance of numeracy for wages (e.g., Hanushek, Schwerdt, & Wiederhold et al., 2014; Klaukien et al., 2013). The measures presented here can easily be applied to literacy skills as well. However, greater care must be taken when analyzing skill mismatch related to problem solving in technology-rich environments.[6]

The skill mismatch measures presented in this section are summarized in Table 1.

6 The sample of PIAAC respondents who took part in the problem-solving assessment may be subject to selection effects. In addition, when comparing assessed skills with skill use at work (see Section 3), it is important to remember that the corresponding skill-use index covers only a narrow aspect of this domain (OECD, 2013a).

Table 1 Characteristics of different measures of numeracy mismatch in PIAAC

	Measure	Computation	Variables	Consideration of PVs	Pro	Contra
Self-reported measure	Self-report in PIAAC	Categories (well-matched, under-skilled, over-skilled) based on answers to two skill mismatch questions in PIAAC BQ	Skill mismatch self-report (F_Q07a, F_Q07b)	n/a	Can be easily administered in other surveys; refers to general mismatch and not to a specific proficiency domain	Based on self-reported information, which can be biased (e.g. Hartog, 2000); fourth category resulting from combination of both questions "under-skilled as well as over-skilled" is not interpretable; category "well-matched" rather small (e.g., 3.1 % in Germany)
Skill-use-based measures	Quintini (2011), following Krahn and Lowe (1998)	Level of numeracy skill use compared to proficiency level: proficiency level equals numeracy skill use level: well-matched; proficiency level lower than numeracy skill use level: under-skilled, proficiency level higher than numeracy skill use level: over-skilled	Numeracy skill use (G_Q03b G_Q03c G_Q03d G_Q03f G_Q03g G_Q03h); numeracy (PVNUM)	Proficiency level included, not specified whether derived from one PV or from average of all 10 PVs	Can be easily computed	Proficiency and skill use are measured on different scales and should not be compared without standardization; one proficiency level assigned to individuals instead of 10; skill use at work is likely to be overrated by employees (Hartog, 2000); arbitrary cut-off points (one skill level); mismatch restricted to relevant proficiency domain (e.g., numeracy)

Table 1 Characteristics of different measures of numeracy mismatch in PIAAC (cont.)

	Measure	Computation	Variables	Consideration of PVs	Pro	Contra
Skill-use-based measures	Allen, Levels, and v. d. Velden (2013)	Three steps 1) PVNUM1 and mean of numeracy skill use standardized to compare different scales 2) Standardized skill use level subtracted from standardized skill level 3) Individuals with resulting value lower than 1.5 points above or below 0: ”well-matched”, individuals with value less than -1.5: ”under-skilled”, individuals with value greater than 1.5: ”over-skilled”	Numeracy skill use (G_Q03b G_Q03c G_Q03d G_Q03f G_Q03g G_Q03h); numeracy (PVNUM)	PVNUM1	Can be easily computed; numeracy skill use and skill level are standardized to compare the different scales	Only one PV used instead of 10; skill use at work is likely to be overrated by employee (Hartog, 2000); arbitrary cut-off points (1.5 SD); mismatch restricted to relevant proficiency domain (e.g., numeracy)
Realized-matches	OECD (2013a)	Three steps 1) Respondents classified as well-matched based on self-report in PIAAC BQ (see above) 2) Proficiency range for well-matched defined for each country based on self-reported well-matched respondents per occupation	Skill mismatch self-report (F_Q07a, F_Q07b); One-digit ISCO (ISCO1C); numeracy (PVNUM)	Average of ten plausible PVs	Theory-driven approach to define skill mismatch based on workers who are well-matched	Large computational effort; neglects heterogeneity within occupations; base population derived using self-report, which can be biased, resulting in a small N (see above); average of PVs instead of 10 PVs;

Table 1 Characteristics of different measures of numeracy mismatch in PIAAC (cont.)

Measure		Computation	Variables	Consideration of PVs	Pro	Contra
		3) Respondents re-assigned to categories (well-matched, under-skilled, over-skilled) according to defined band-width				Respondents reassigned into mismatch categories according to proficiency range, irrespective to their self-reported information; mismatch restricted to relevant proficiency domain (e.g., numeracy)
Realized-matches	Alternative measure	Four steps 1) Average skill level and SDs computed in each country per occupation 2) Cut-off points for match and mismatch defined for each occupation as 1.5 SD from mean 3) Skill mismatch defined based on cut-off points for each PV for each person (results in 10 skill mismatch variables per person) 4) Average of estimates resulting from 10 skill mismatch variables included in analysis	Two-digit ISCO (ISCO2C); numeracy (PVNUM)	PVNUM1-10	Includes all PVs according to IRT; does not rely on self-reported information, which can be biased	Large computational effort; neglects heterogeneity within occupations; arbitrary cut-off points (1.5 SD); mismatch restricted to relevant proficiency domain (e.g., numeracy)

Notes. BQ = background questionnaire; IRT = item response theory; PV = plausible value; PVNUM = plausible value for numeracy; SD = standard deviation.

Table 2 Self-reported skill mismatch in the PIAAC background questionnaire

		Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?	
		Yes	No
Do you feel that you need further training in order to cope well with your present duties?	Yes	Over-skilled as well as under-skilled	Under-skilled
	No	Over-skilled	Well-matched

Note. Variables in the PIAAC background questionnaire are: F_Q07a and F_Q07b.

Self-reported Skill Mismatch in PIAAC

The self-report on skill mismatch in PIAAC consists of two questions in the PIAAC background questionnaire (OECD, 2013b):

- 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?
- Do you feel that you need further training in order to cope well with your present duties?

Each of the questions had to be answered with "yes" or "no" and the combination of both answers provides the self-reported skill mismatch of the respondent (see Table 2).

As shown in Table 2, the combination of both questions leads to four categories, where only the three categories under-skilled, well-matched, and over-skilled are meaningful. It is not entirely clear how we should interpret the remaining category "over-skilled as well as under-skilled". This category may refer to different sets of skills. For example, respondents could consider their mathematical skills when asked whether they have the skills to cope with more demanding tasks at work and confirm. When asked whether they needed further training to cope with their duties, they may have considered their negotiation skills. Furthermore, respondents might feel that they are able to generally cope with more demanding work tasks, but at the same time feel the need for continuously maintaining and developing their skills through training. This is, in particular, the case for highly educated workers who generally have a positive attitude towards education.

Because the answers to these two questions can be interpreted in different ways, we must assume that this measure cannot adequately reflect the construct of skill mismatch. The self-reported measure in PIAAC should therefore *not* be used for measuring skill mismatch.

Skill Mismatch According to Quintini (2012)

Quintini (2012) suggests a PIAAC-based measure of skill mismatch that combines information on skills used at the workplace, using the JRA (Felstead et al., 2007), and competencies assessed in PIAAC. This measure is developed following a previous approach developed by Krahn and Lowe (1998) with data from IALS.

To derive this measure, Quintini grouped skill use and the respective skill proficiency measure into four categories each (level 1 through 4/5). If the levels of skill use and possessed skills are identical, the respondent is well-matched in his or her job. Respondents are under-skilled when their level of skill use is higher than their personal skill level and over-skilled when their skill-use level is lower than their personal skill level.[7]

Krahn and Lowe (1998) assess the validity of their measure and find that using any deviation of skill use from the worker's possessed skills to define mismatch is arbitrary. Whereas Quintini (2012) defines a deviation between skill level and skill use by one level as mismatch, a deviation of two levels defines mismatch for Krahn and Lowe (1998). Hence, agreement on the exact definition of mismatch is lacking. Also, in both studies, skill use is measured by self-reports, which are frequently prone to bias (Hartog, 2000). Allen et al. (2013) point out that skill use and skill level in PIAAC are measured in two different ways and a comparison of these two constructs is not meaningful. In addition, a single plausible value is used to define the numeracy skill level, although how this individual score is derived is not specified. However, a single skill score, irrespective of how it is derived, does not entirely reflect an individual's competency level in PIAAC (Rutkowski et al., 2010; von Davier et al., 2009).

Skill Use in Relation to Skill Level by Allen et al. (2013)

Allen et al. (2013) suggest an alternative, and improved, approach to measure skill mismatch, based on the work of Krahn and Lowe (1998) and Quintini (2012). In a first step, they standardize the average of numeracy skill use and the first plausible value of the numeracy domain, to make both measures comparable.[8] Allen et al. (2013) define mismatch as a deviation of skill use and individual skill level by at least 1.5 standard deviations. Thus, if the difference between standardized numeracy skill use and standardized skill score is below 1.5 standard deviations,

7 Krahn and Lowe (1998) and Desjardins and Rubenson (2011) further disaggregate "well-matched" workers. In Quintini (2012), however, the "well-matched" category corresponds to the other measures presented in this paper.

8 Employed respondents rate their numeracy skill use at their workplace on a six-item scale. A five-point rating scale, ranging from "never" to "every day", was used to measure the respondents' assessments. These are averaged across items to derive a single skill-use score for each employed respondent.

the respondent is defined as being under-skilled. If the difference is larger than 1.5 standard deviations, the respondent is over-skilled. Respondents who are neither over- nor under-skilled are defined as being well-matched.

By standardizing the measures of numeracy skill level and skill use before comparing them, Allen et al. (2013) address an important disadvantage of the measures developed by Krahn and Lowe (1998) and Quintini (2012). However, like the previous authors, Allen et al. (2013) assign an individual skill score to the respondent, even though such an individual skill score does not entirely reflect the respondent's actual competency. Furthermore, self-reported skill use can be overestimated by the respondent (Hartog, 2000). In addition, one can argue that using a bandwidth of 1.5 standard deviations to define mismatch is arbitrary and other boundaries should be considered. The authors argue that this definition of mismatch is "fairly extreme" (p. 10). This is to ensure that workers identified as being mismatched possess skill levels that are indeed unusually high or low, compared to workers facing similar job requirements.

Skill Mismatch by the OECD (2013a) and Pellizzari and Fichen (2013)

In its *Skills Outlook*, the OECD (2013a) presents a new direct measure of skill mismatch that is discussed in detail by Pellizzari and Fichen (2013). This measure follows the "Realized Matches" approach (cf. Hartog, 2000; Leuven & Oosterbeek, 2011).

In a first step, the authors look at respondents who are well-matched, according to the self-report in PIAAC (see above). For this group of workers, they derive a competency bandwidth by country and occupation.[9] To account for outliers, respondents in the top and bottom 5 % of the skill distribution in each occupation are excluded when deriving the bandwidth. Moreover, to obtain a sufficient number of respondents in the well-matched category, only occupations at the one-digit ISCO level were used.[10] Individuals whose skill levels are below/above this bandwidth are considered to be under-skilled/over-skilled. Individuals whose skills are within the bandwidth are labeled well-matched. Importantly, all respondents are assigned

9 In PIAAC, the respondents reported their occupation verbally by naming the profession and describing their work tasks in detail. This information was then recoded into the International Standard Classification of Occupations (ISCO-08, International Labour Organization, 2012).

10 ISCO 0 (armed forces) and ISCO 6 (skilled agricultural, forestry, and fishery workers) were eliminated from the analysis and the categories ISCO 1 (managers) and ISCO 2 (professionals) were combined, due to the small number of observations in these categories.

a level of skill mismatch that is based on the average of their 10 plausible values in numeracy.

The results of this skill-mismatch measure should be interpreted with great caution. As stated above, the self-report used in the PIAAC background questionnaire cannot adequately reflect whether or not a respondent's skills match the skills required at his or her workplace. Moreover, only a small proportion of respondents report being well-matched (see Table 3). Thus, even though the definition of bandwidths is based on the one-digit ISCO level and is therefore very broad, the number of observations within one occupation is often still small. For some occupations in some countries, the bandwidth is based on only very few observations.[11] However, Allen et al. (2013) argue that the derived occupation-level 5th to 95th percentile ranges do not differ systematically from those based on the full sample. Thus, the restriction of using only well-matched workers to derive occupation-specific bandwidths could also be neglected. Allen et al. (2013) further criticize the OECD approach to measuring skill mismatch for neglecting heterogeneity within occupations, because the OECD defines one bandwidth for all respondents within an occupation. In addition, the average of all 10 plausible values is used to assign individual proficiency scores. However, as explained above, the average of plausible values does not reflect individual competency and, when used in analyses, underestimates associated standard errors to an even greater extent than if only one of the ten plausible values is used (Rutkowski et al., 2010).

An Alternative Measure to Compute Skill Mismatch

We propose an alternative measure for calculating skill mismatch that also follows the "Realized Matches" approach, improving on the measure by the OECD (2013a) and Pellizzari and Fichen (2013). We also define bandwidths for each occupation according to the average skill level and, thus, avoid using self-reported information about skill use that may be biased. Also, as Allen et al. (2013) argue, skill levels of workers who report being well-matched in PIAAC do not differ substantially from those of workers in general. Thus, we define boundaries between matched and mismatched workers for each occupation, based on the total population of workers in a country. The resulting increase in the number of observations allows us to use the more detailed two-digit ISCO categorization to derive bandwidths within occupations. To reduce measurement error, we eliminated a few occupations to reach a minimum number of observations by country-occupation cell of 30. Like Allen et al. (2013), we calculate the mean proficiency score for each occupation in each

11 The authors base further steps on at least 10 observations per occupation. However, whenever the sample is reduced (as done in this paper, by looking at full-time employees only), the number of observations decreases on the occupation level.

country and add/subtract 1.5 standard deviations to define the corridor of being well-matched. Contrary to other measures discussed here, we take into account all 10 plausible values for each individual by repeating the above procedure for all plausible values. However, as a result of this procedure, respondents can be categorized simultaneously as well-matched *and* mismatched. Therefore, to calculate estimates, for example, percentages of workers who are mismatched as well as regression coefficients, we take the average of the results computed with each plausible value to derive our final estimate. By applying this procedure, we derive more reliable estimates of skill mismatch than previous studies that use the PIAAC data.

When choosing between different measures of skill mismatch, researchers need to know which measure is most suitable and, especially, most valid for their types of analyses. Following Groves, Fowler, Couper, Singer, and Tourangeau (2004), a measure is valid when the operationalization (in our case the skill mismatch measure) corresponds to the construct of interest (in our case existing skill mismatch). To derive recommendations regarding which measure to use when analyzing skill mismatch, we compare them in a Mincer regression on earnings (Mincer, 1974). The next section describes the Mincer regression in more detail.

Empirical Approach

The aim of this paper is to compare various skill-mismatch measures in PIAAC. After having described the measures in the preceding section, we now attempt to judge their validity by looking at differences in outcomes, namely, the proportion of matched and mismatched workers and the relationship between skill mismatch and earnings in a Mincer regression model (Mincer, 1974).

Empirical Model

When examining the relationship between various measures of skill mismatch and earnings, we rely on a Mincer-type regression model. The Mincer regression is probably the most widely used empirical model in economic research.[12]

The regression equation reads as follows:

$$\text{In } y_i = \beta_0 + \beta_1 C_i + \beta_2 U_i + \beta_3 O_i + \beta_4 S_i + \beta_4 G_i + \beta_6 E_i + \beta_7 E_i^2 + \varepsilon_i \qquad (1)$$

where y_i is the (pre-tax and pre-transfer) hourly wage of individual i. To correct for outliers, we trimmed wages in Germany by removing the highest and lowest 1 % of observed earnings. Due to data restrictions, we do not have access to con-

12 See Heckman, Lochnern, & Todd (2006) for a recent review of the literature.

tinuous wage information for Austria and the U.S. Instead, we used information on the median wage of each decile, which allowed us to assign the decile median to each survey participant belonging to the respective decile of the country-specific wage distribution (Hanushek, Schwerdt, & Wiederhold et al., 2014, apply a similar procedure). *C* is the individual's numeracy skills, *U* is a dummy variable for being under-skilled, *O* a dummy variable for being over-skilled, represented by 10 plausible values[13], *S* is the number of years of schooling (average or most usual time that it takes to complete a qualification), *G* is a dummy variable taking the value 1 for female and 0 for male. We also include a quadratic polynomial in work experience, *E*, to account for positive but diminishing returns of experience on earnings.[14] ε is the stochastic error term.

Sample

For each country participating in PIAAC, a sample of at least 5,000 adults[15] was surveyed. We use sampling weights to obtain nationally representative estimates. Moreover, to account for the complex sample design, we use replicate weights in all estimations.[16]

Our analysis only includes persons who were employed full-time at the time of the survey. Like Hanushek, Schwerdt, Wiederhold et al. (2014), we define full-time employees as those who work 30 hours or more per week. We exclude students and apprentices. Students who work while studying are unlikely to have a job that makes proper use of their skills. Apprentices are typically paid lower wages than equivalent workers who have completed their vocational education. In addition, the self-employed are excluded from the sample, because this group typically includes extreme outliers regarding hourly earnings.

Country Selection

Of the 24 countries surveyed in PIAAC, we focus on Austria, Germany, and the U.S. Our main analysis uses the German PIAAC data. However, to check whether our results can be generalized to other country economies, we compare the results

13 Numeracy is 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 (Gal et al., 2009).

14 Numeracy skills and work experience squared are divided by 100, to facilitate exposition.

15 In countries that did not implement the skill domain problem solving in technology-rich environments, at least 4,500 adults were assessed (Mohadjer, Krenzke, & Van de Kerchove, 2013a).

16 Detailed information on the sampling processes in PIAAC is presented in Mohadjer, Krenzke, & Van de Kerchove (2013b).

for Germany with those from Austria and the U.S. We chose Austria because its education system is similar to that in Germany, particularly with respect to its emphasis on vocationally oriented education.[17] In the U.S. education system, on the contrary, skills are less specific to a particular occupation but more general in their applicability. This general education arguably provides students with broad knowledge and basic skills in mathematics and communication, which can serve as a foundation for further learning on the job.[18] Moreover, social and labor market institutions differ vastly between Austria/Germany and the U.S.

Results

In this section, we present the results of our analyses. First, we focus on existing measures of skill mismatch, comparing the percentages of well-matched and mismatched workers in Germany, Austria, and the U.S. and the relationship between mismatch and earnings. We then show that the measure developed by Allen et al. (2013) produces quite different results, depending on the plausible value used in the analyses. Finally, we present results for our newly developed skill mismatch measure and compare them with an adjusted version of the Allen et al. (2013) measure that accounts for all 10 plausible values.

Existing Measures: Percentages of Mismatched Workers

The percentages of mismatched workers differ widely between the skill mismatch measures (see Table 3). For example, the percentage of well-matched workers in Germany ranges from below 4 % in the PIAAC self-report to 84 % in the measure reported by the OECD (2013a) and Pellizzari and Fichen (2013). The percentage of under-skilled workers ranges between 4 %, using the self-report measure, and 30 %, using the measure suggested by Quintini (2012). Finally, for over-skilled workers, the percentages for Germany vary between 8 %, according to Allen et al. (2013), and 46 %, according to the self-reports. We observe similar differences in the percentage of mismatched workers in Austria and the U.S. These findings suggest that different skill mismatch measures will also result in quite different distributions of skill mismatch across subgroups; indeed, we observe such differences for gender, age, and education.[19]

17 See Woessmann (2014) for an extensive discussion of the link between education and individual earnings.

18 Using the IALS data, Hanushek, Schwerdt, Woessmann et al. (2014) show that, at entry-age, employment rates are higher for people who gained vocational education. However, this turns around later, when people with a general education degree have substantially higher employment rates.

19 Results available from the authors upon request.

Table 3 Share of mismatched workers by definition of skill mismatch

		Mismatch measures (Numeracy)			
Country	Mismatch category	Self-report	Quintini (2012)	Allen et al. (2013)	OECD (2013a)
Germany	Under-skilled	3.93	30.42	8.36	2.88
		(0.46)	*(0.84)*	*(0.60)*	*(0.35)*
	Well-matched	3.48	33.96	83.70	84.09
		(0.38)	*(0.87)*	*(0.78)*	*(0.71)*
	Over-skilled	45.81	35.61	7.94	13.02
		(1.11)	(1.02)	(0.58)	(0.69)
Austria	Under-skilled	2.96	23.83	8.65	1.80
		(0.36)	*(0.95)*	*(0.55)*	*(0.29)*
	Well-matched	4.03	34.55	83.03	86.62
		(0.42)	*(0.90)*	*(0.68)*	*(0.74)*
	Over-skilled	53.39	41.61	8.32	11.57
		(0.97)	*(0.98)*	*(0.50)*	*(0.68)*
USA	Under-skilled	2.33	44.71	9.65	4.54
		(0.30)	*(1.09)*	*(0.55)*	*(0.42)*
	Well-matched	5.35	31.63	81.24	86.51
		(0.47)	*(0.98)*	*(0.85)*	*(0.67)*
	Over-skilled	71.84	23.66	9.11	8.95
		(1.09)	*(0.91)*	*(0.72)*	*(0.62)*

Notes. Full-time employees between 16 and 65 years of age, excluding students and apprentices. Standard error in parentheses. Percentages in self-reported measure do not add up to 100 % due the fourth category "under-skilled and over-skilled" that is not reported here. The OECD measure excludes members of the armed forces (ISCO 0) and skilled agricultural, forestry, and fishery workers (ISCO 6). *Data source:* OECD (2013c) and Rammstedt et al. (2014).

Measures: Relationship Between Numeracy Mismatch and Earnings

We now investigate the relationship between skill mismatch and individual earnings. In Figure 1, the length of each bar represents the coefficient magnitude resulting from an estimation of the Mincer regression in Equation (1) for each measure of skill mismatch[20] in numeracy and country.[21] The exact coefficient and level of significance are displayed next to each bar. Similar to previous findings on education mismatch (Hartog, 2000) and skill mismatch (Allen et al., 2013), workers with a surplus/deficit of skills receive wage penalties/premiums, compared to workers with the same skills who are well-matched. However, the result that over-skilled workers suffer a wage penalty shows up more systematically in our data than the wage premium for under-skilled workers. Moreover, the magnitudes of these relationships vary substantially according to the measure of skill mismatch. Considering the wage premium for being under-skilled, the OECD (2013a) measure provides the largest range: from insignificant in Germany and the U.S. to 16 % in Austria. On the other hand, the wage premiums for the Quintini (2012) measure are the smallest and, in fact, never significant.

The coefficients on over-skilling also differ widely across the measures. We further observe pronounced country differences regarding the mismatch estimates. In Germany and the U.S., we obtain very high wage penalties when using the OECD (2013a) measure, whilst, in Austria, penalties are smallest with this measure. The U.S. stands out as having by far the largest wage penalty for over-skilled workers; the coefficient implies a decrease in earnings of 23 % when a worker is over-skilled, using the OECD mismatch measure. In terms of magnitude, the self-reported mismatch measure always yields the smallest earnings penalty for over-skilling. This result is probably due to the fact that, across all measures, the self-report yields by far the largest percentage of over-skilled workers (see Table 3).

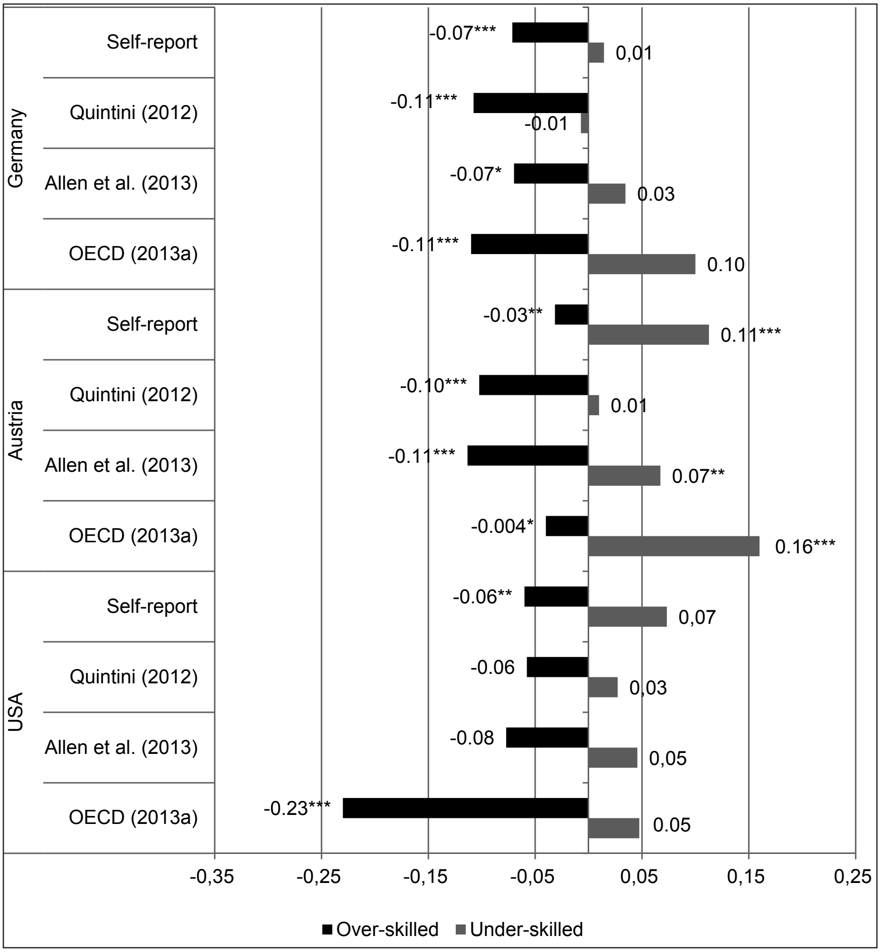
Note that sample sizes differ across the regression models. This is due to omitted cases in professions with a low number of well-matched workers (OECD measure) and to missing values in the background questionnaire (self-reported measure). However, the R^2 do not differ notably across the regression models, when we use a common sample for all measures.[22]

As described above (see Section "*The Role of Plausible Values*"), calculations involving proficiency scores should, ideally, take all 10 plausible values into account. Thus far, however, we performed the Mincer regressions with the original measures that use the average of all plausible values (OECD, 2013a; Pellizzari &

20 We consider the results pertaining to our own mismatch measure in a separate section below.

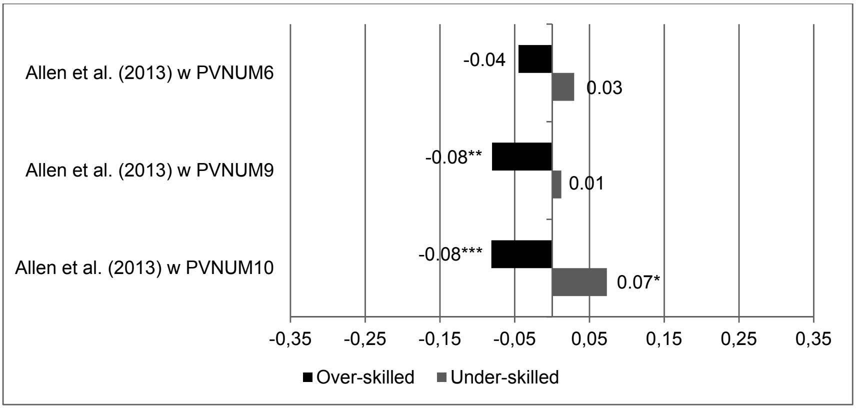
21 See Tables A.1-A.4 for detailed results.

22 Results of this comparison are available upon request from the authors.



Notes. Bars resulting from least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. The OECD measure excludes members of the armed forces (ISCO 0) and skilled agricultural, forestry, and fishery workers (ISCO 6). See Section "Empirical Approach" for details of the Mincer regression and Tables A.1 to A.4 for regression results. Significance levels: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Figure 1 Coefficients of various skill-mismatch measures in a mincer regression



Notes. Bars resulting from least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. See Section "Empirical Approach" for details of the Mincer regression and Table A.5 for regression results. Significance levels: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Figure 2 Mincer-regression coefficients of skill-mismatch measure of Allen et al. (2013) with three different plausible values for Germany

Fichen, 2013) or only the first plausible value (Allen et al., 2013; Quintini, 2012) to assign individual proficiency scores. To assess the importance of uncertainty in skill scores when analyzing skill mismatch, we calculated the measure suggested by Allen et al. (2013) with the remaining nine plausible values in the same Mincer regression model, as described above. In Figure 2, we present the regression results for plausible values 6, 9, and 10 for Germany.[23] We observe that the results for each alternative plausible value differ to a considerable extent. The increase in earnings if a worker is under-skilled ranges from being insignificant (PVNUM6 and 9) to 7 % (PVNUM10). The earnings decrease for over-skilled workers ranges from being insignificant (PVNUM6) to 8 % (PVNUM9 and PVNUM10).

Refined Measures of Skill Mismatch

Next, we present results from our newly developed skill mismatch measure that takes all 10 plausible values into account. Moreover, as described above, this measure only uses objective skill scores and does not rely on any self-reported information. In Table 4, we present the percentages of well-matched, over-skilled, and

23 See Tables A.5 for detailed results.

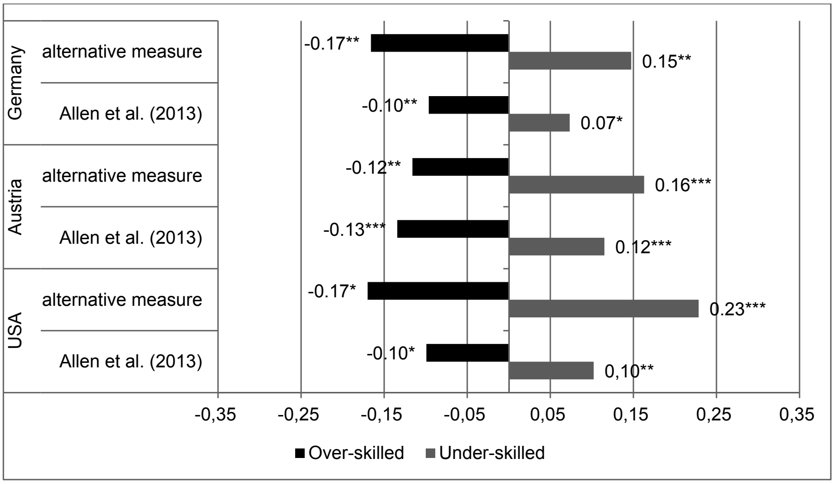
Table 4 Share of mismatched workers by definition of skill mismatch taking all plausible values into account

		Mismatch measures (Numeracy)	
Country	Mismatch category	Allen et al. (2013)	alternative measure
Germany	Under-skilled	8.46	7.39
		(0.66)	*(0.76)*
	Well-matched	83.55	87.23
		(0.93)	*(1.00)*
	Over-skilled	7.99	5.37
		(0.69)	*(0.70)*
Austria	Under-skilled	8.86	6.91
		(0.68)	*(0.62)*
	Well-matched	83.15	87.50
		(0.89)	*(0.86)*
	Over-skilled	7.99	5.59
		(0.59)	*(0.61)*
USA	Under-skilled	9.79	7.65
		(0.66)	*(0.65)*
	Well-matched	80.76	86.70
		(0.94)	*(0.87)*
	Over-skilled	9.45	5.65
		(0.71)	*(0.53)*

Notes. Full-time employees between 16 and 65 years of age, excluding students and apprentices. Standard error in parentheses. The alternative measure excludes workers in professions with less than 30 observations per country (at two-digit ISCO level). *Data source:* OECD (2013c) and Rammstedt et al. (2014).

under-skilled workers according to this measure. For comparison, we also present percentages of workers using the Allen et al. (2013) measure with all plausible values. We focus further analyses on these two measures, because we see both as improvements, compared to previously described skill mismatch measures (i.e., those of OECD, 2013a; Pellizzari & Fichen, 2013; Quintini, 2012).

The percentage of mismatched workers differs only slightly between the two measures, with somewhat large differences regarding the share of over-skilled workers. Especially in the U.S., the percentage of over-skilled workers derived with the adjusted measure of Allen et al. (2013) (9 %) is almost 70 % larger than that derived by the alternative measure (6 %). Generally, the percentage of well-matched workers is lower for the adjusted Allen et al. (2013) measure vis-a-vis our own



Notes. Bars resulting from least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. The alternative measure excludes workers in professions with less than 30 observations per country (at two-digit ISCO level). See Section "Empirical Approach" for details of the Mincer regression and Tables A.6 and A.7 for regression results. Significance levels: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Figure 3 Mincer-regression coefficients of various skill mismatch measures taking all plausible values into account

measure. Compared to their original measure, the adjusted measure of Allen et al. (2013) leads to slight changes in the percentage of mismatched workers. In particular, the standard errors increase, because uncertainty increases when all plausible values are taken into account.

When using both measures in a Mincer regression, coefficients for being over-skilled and under-skilled again differ (see Figure 3).[24] Considering the wage premium for being under-skilled, our measure consistently produces larger estimates than the refined measure of Allen et al. (2013), ranging from 15 % in Germany (Allen et al.: 7 %) to 23 % in the U.S. (Allen et al.: 10 %). For Germany and the U.S., our measure also shows larger wage penalties for over-skilled workers, namely 17 % (Allen et al.: 10 %), whilst the wage penalty is similar to that yielded by the refined Allen et al. (2013) measure for Austria (12 % vs. 13 %). Importantly, in contrast to the results shown in Figure 1, all coefficients using any of these two skill-mismatch measures are significant at 10 % or better.

24 See Tables A.6 and A.7 for detailed results.

Interestingly, wage premiums for under-skilled workers are smaller or equal to wage penalties of over-skilled workers when the refined measure of Allen et al. (2013) is used. Applying our alternative skill-mismatch measure produces a larger wage premium for under-skilled workers in Austria and the U.S., compared to the wage penalty incurred by over-skilled workers. In Germany, the alternative measure indicates that the wage premium for under-skilled workers is slightly lower than the wage penalty for over-skilled workers.

Again, we report different sample sizes for each measure, because we had to omit cases in professions with less than 30 workers when computing the alternative skill mismatch measure. This results in the reduction of sample sizes by up to 184 cases in Germany. Although the coefficient estimates differ between the two measures, the R^2 are again similar for both measures, when they are compared within the same sample.[25] This implies similar predictive validities of both measures, even though the magnitude of the coefficients differs.

We performed several further checks to test the robustness of these results. For instance, we performed the regression separately for men and women. While the coefficients for skill mismatch become slightly larger in the regression models that contain only male workers, they become insignificant for women, which is due to a smaller sample size. Moreover, we restricted the sample to prime-age workers who, as Hanushek, Schwerdt, Wiederhold et al. (2014), for instance, argue, should be less often mismatched than entry-age workers. Doing so, we, again, find only slight changes compared to our original regression model.[26]

Discussion

Differences in Results Across Skill Mismatch Measures

Although the underlying data were the same in all analyses, the percentages of mismatched workers resulting from different measures vary substantially. While the self-reported measure suggests a very small percentage of well-matched workers, the measures proposed by Allen et al. (2013) and the OECD (2013a) yield a percentage of well-matched workers well above 80%. The higher percentages resulting from the latter two measures seem to be much closer to reality than the self-reported measure, because it is hard to imagine that the majority of workers are mismatched in their jobs. The substantial differences in these results already imply that researchers must carefully consider their choice of skill mismatch measure.

We also compared the relationship between the various skill mismatch measures and earnings in a Mincer regression. Although the results indeed confirm

25 Results of this comparison are available on request from the authors.

26 Results of this comparison are available on request from the authors.

the commonly found relationship between mismatch and earnings (cf. Allen et al., 2013; Hartog, 2000) – namely, under-skilled workers earn a wage premium and over-skilled workers incur a wage penalty – the coefficient magnitudes differ widely between the skill mismatch measures.

One problem with existing skill mismatch measures is that, in assigning a single skill score to each respondent, they neglect important assumptions of IRT. No individual skill score, neither the first of 10 plausible values nor the average of all 10 plausible values, captures the uncertainty in a respondent's skill level in PIAAC. This becomes apparent when, as a simple example, we compare the measure developed by Allen et al. (2013) with three different plausible values.

To overcome this problem, we calculated skill mismatch variables per respondent for all 10 plausible values and took the average of the resulting statistics. While this procedure can, in principle, be applied to all direct measures presented in this paper, we derived results based on this approach only for the measure suggested by Allen et al. (2013), as an improved version of the measure by Quintini (2012), and for the alternative measure we propose in this paper, as an improved version of the OECD measure (OECD, 2013a; Pellizzari & Fichen, 2013).

Comparing our results to the original measure of Allen et al. (2013) reveals differences in Mincer regression coefficients and standard errors. This suggests that whether only one plausible value or whether the mean of all plausible values is used has consequences when the implications of skill mismatch are investigated.

Although results differ for the various skill mismatch measures, the general pattern appears similar: earnings increase when workers are under-skilled and decrease when workers are over-skilled. Previous research finds that wage premiums for being under-skilled are usually smaller than wage penalties for being over-skilled (e.g., Allen et al., 2013; Hartog, 2000). Depending on the extent of skills not used when workers are over-skilled, the drop in earnings can be relatively large. When workers are under-skilled, on the other hand, the skill level they possess limits their productivity and prevents large wage premiums. We are able to replicate these findings using the redefined measure of Allen et al. (2013); however, when using our alternative measure, wage premiums for under-skilled workers are larger than wage penalties for over-skilled workers in Austria and the U.S., but not in Germany. These results resemble previous evidence obtained for education mismatch: there are country-specific differences in the pattern of penalties and rewards related to skill mismatch (cf. Hartog, 2000). Interestingly, we find a large difference between the two measures for under-skilled workers in the U.S. and Germany, but only small differences in Austria. Further research is required to investigate the causes of these differences in parameter estimates. Nevertheless, the predictive validity of both measures (as inferred by the R^2 of the Mincer models) is the same.

The sample size, when applying our measure (as well as the OECD measure), is reduced, compared to the other measures. This is due to omitting cases from the sample in professions with fewer respondents than the defined threshold. This procedure not only complicates the computation of both measures and is prone to error but it also reduces the representativeness of both measures, because they do not represent the entire population of the analyzed countries. This is especially true for the alternative measure that omits 184 cases for Germany, compared to measures based on comparing skill scores and skill use.

Limitations of the Presented Direct Skill Mismatch Measures

A major disadvantage of all direct skill mismatch measures discussed in this paper is that they focus on only one skill domain, in our case numeracy. Although it is possible to derive additional measures for literacy or problem-solving mismatch, these measures will only shed limited light on actually existing mismatches, because they only cover the cognitive dimension of skills. Ideally, we would like to extend the scope of skill mismatch to other, non-cognitive skills, e.g., extraordinary sales or management talents; however, these are not assessed in PIAAC. We are neither able to measure occupation-specific skills nor any resulting mismatch.[27] In general, looking at only one skill domain – although informative – does not provide a complete picture of skill mismatch.

Conclusions

This paper contributes to existing research on skill mismatch in several ways. First, we review existing measures of skill mismatch and assess their differences in various empirical applications. Second, we discuss the validity of each measure, with a main focus on methodological aspects, such as the wording of the questions in the PIAAC questionnaire of the self-report on skill mismatch and the use of plausible values when considering cognitive skills in the analysis. Third, we develop a new measure of skill mismatch that avoids some weaknesses of existing measures. One major improvement is that all plausible values are taken into account, accurately reflecting the uncertainty in individual skills, as assessed in PIAAC. Moreover, this measure only relies on actually tested skills, neglecting subjective responses on skill use at the workplace, which are prone to misreporting.

Our results indicate that the percentage of mismatched workers in the population, as well as wage implications of being mismatched, differ widely between the measures. Possible sources of these differences may be biases in response behav-

27 See Nedelkoska, Neffke, & Wiederhold (2014) for a discussion of the implication of occupation-specific skill mismatch.

ior, especially when self-reports are used in the calculations, and methodological errors, such as relying on very small samples (i.e., number of respondents by occupations) upon which further computations are based.

Whenever large-scale assessment data are used, one has to carefully consider methodological particularities, such as complex sample design and uncertainty in skill scores expressed through multiple plausible values per individual. Thus, researchers measuring skill mismatch must pay great attention to their choice of measure and its computation. We strongly advise against using the self-report surveyed in the PIAAC background questionnaire because it cannot adequately reflect the respondent's actual perception of match or mismatch. Rather, we recommend the use of direct skill mismatch measures, such as the revised measure of Allen et al. (2013) or our own measure. If an invalid measure of skill mismatch is applied, the resulting policy implications will surely be misleading.

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Appendix

Table A.1

Mincer regressions with Self-reported skill-mismatch

Dependent variable: Gross hourly earnings (log)	Germany	Austria	USA
Constant	0.82***	1.03***	1.07***
	(0.08)	*(0.06)*	*(0.07)*
Numeracy/100	0.23***	0.18***	0.18***
	(0.02)	*(0.02)*	*(0.03)*
Over-skilled	-0.07***	-0.03**	-0.06**
	(0.02)	*(0.01)*	*(0.03)*
Under-skilled	0.01	0.11***	0.07
	(0.05)	*(0.03)*	*(0.06)*
Years of education	0.06***	0.06***	0.07***
	(0.00)	*(0.00)*	*(0.01)*
Gender (female)	-0.12***	-0.11***	-0.15***
	(0.02)	*(0.01)*	*(0.02)*
Work experience	0.03***	0.03***	0.04***
	(0.00)	*(0.00)*	*(0.00)*
Work experience squared/100	-0.04***	-0.03***	-0.06***
	(0.01)	*(0.01)*	*(0.01)*
R^2	0.35	0.44	0.38
Observations	2368	2330	2063

Notes. Least squares regressions weighted by sampling weights. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. See Section "Empirical Approach" for details of the Mincer regression. Standard errors in parentheses. Significance levels: *** $p < 0.01$. ** $p < 0.05$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Table A.2

Mincer regressions with skill-mismatch according to Quintini (2012)

Dependent variable: Gross hourly earnings (log)	Germany	Austria	USA
Constant	0.73***	0.98***	0.99***
	(0.08)	*(0.06)*	*(0.08)*
Numeracy/100	0.26***	0.21***	0,20***
	(0.03)	*(0.02)*	*(0.04)*
Over-skilled	-0.11***	-0.10***	-0.06
	(0.02)	*(0.02)*	*(0.04)*
Under-skilled	-0.01	0.01	0.03
	(0.02)	*(0.02)*	*(0.02)*
Years of education	0.06***	0.06***	0.08***
	(0.00)	*(0.00)*	*(0.01)*
Gender (female)	-0.11***	-0.11***	-0.15***
	(0.02)	*(0.01)*	*(0.02)*
Work experience	0.03***	0.03***	0.04***
	(0.00)	*(0.00)*	*(0.00)*
Work experience squared/100	-0.04***	-0.03***	-0.06***
	(0.01)	*(0.01)*	*(0.01)*
R^2	0.35	0.45	0.39
Observations	2383	2333	2063

Notes. Least squares regressions weighted by sampling weights. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. See Section "Empirical Approach" for details of the Mincer regression. Standard errors in parentheses. Significance levels: *** $p < 0.01$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Table A.3

Mincer regressions with skill-mismatch according to Allen et al. (2013)

Dependent variable: Gross hourly earnings (log)	Germany	Austria	USA
Constant	0.72***	0.94***	0.99***
	(0.08)	*(0.06)*	*(0.08)*
Numeracy/100	0.25***	0.21***	0.19***
	(0.03)	*(0.02)*	*(0.04)*
Over-skilled	-0.07*	-0.11***	-0.08
	(0.04)	*(0.03)*	*(0.05)*
Under-skilled	0.03	0.07**	0.05
	(0.03)	*(0.03)*	*(0.03)*
Years of education	0.07***	0.06***	0.08***
	(0.00)	*(0.00)*	*(0.01)*
Gender (female)	-0.12***	-0.10***	-0.15***
	(0.02)	*(0.01)*	*(0.02)*
Work experience	0.03***	0.03***	0.04***
	(0.00)	*(0.00)*	*(0.00)*
Work experience squared/100	-0.04***	-0.03***	-0.06***
	(0.01)	*(0.01)*	*(0.01)*
R^2	0.34	0.44	0.38
Observations	2383	2333	2063

Notes. Least squares regressions weighted by sampling weights. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. See Section "Empirical Approach" for details of the Mincer regression. Standard errors in parentheses. Significance levels: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Table A.4

Mincer regressions with skill-mismatch according to the OECD (2013a)

Dependent variable: Gross hourly earnings (log)	Germany	Austria	USA
Constant	0.70***	0.96***	1.01***
	(0.08)	*(0.05)*	*(0.08)*
Numeracy/100	0.29***	0.21***	0.23***
	(0.03)	*(0.02)*	*(0.04)*
Over-skilled	-0.11***	-0.04*	-0.23***
	(0.03)	*(0.02)*	*(0.05)*
Under-skilled	0.10	0.16***	0.05
	(0.08)	(0.05)	(0.06)
Years of education	0.06***	0.06***	0.07***
	(0.00)	*(0.00)*	*(0.01)*
Gender (female)	-0.12***	-0.11***	-0.17***
	(0.02)	*(0.02)*	*(0.02)*
Work experience	0.03***	0.02***	0.04***
	(0.00)	*(0.00)*	*(0.00)*
Work experience squared/100	-0.04***	-0.03***	-0.06***
	(0.01)	*(0.01)*	*(0.01)*
R^2	0.35	0.43	0.39
Observations	2332	2262	2039

Notes. Least squares regressions weighted by sampling weights. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. Members of the armed forces (ISCO 0) and skilled agricultural, forestry, and fishery workers (ISCO 6) excluded. See Section "Empirical Approach" for details of the Mincer regression. Standard errors in parentheses. Significance levels: *** $p < 0.01$. * $p < 0.10$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Table A.5

Mincer regressions with skill-mismatch according to Allen et al. (2013) with three different plausible values

Dependent variable: Gross hourly earnings (log)	Allen (2013) with PVNUM6	Allen (2013) with PVNUM9	Allen (2013) with PVNUM10
Constant	0.73***	0.73***	0.70***
	(0.08)	*(0.08)*	*(0.08)*
Numeracy/100	0.25***	0.25***	0.26***
	(0.03)	*(0.03)*	*(0.02)*
Over-skilled	-0.04	-0.08**	-0.08***
	(0.03)	*(0.04)*	*(0.03)*
Under-skilled	0.03	0.01	0.07*
	(0.03)	*(0.04)*	*(0.04)*
Years of education	0.07***	0.07***	0.07***
	(0.00)	*(0.00)*	*(0.00)*
Gender (female)	-0.12***	-0.12***	-0.12***
	(0.02)	*(0.02)*	*(0.02)*
Work experience	0.03***	0.03***	0.03***
	(0.00)	*(0.00)*	*(0.00)*
Work experience squared/100	-0.04***	-0.04***	-0.04***
	(0.01)	*(0.01)*	*(0.01)*
R^2	0.34	0.35	0.35
Observations	2383	2383	2383

Notes. Least squares regressions weighted by sampling weights. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. See Section "Empirical Approach" for details of the Mincer regression. Standard errors in parentheses. Significance levels: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Table A.6

Mincer regressions with skill-mismatch according to our newly developed skill-mismatch measure

Dependent variable: Gross hourly earnings (log)	Germany	Austria	USA
Constant	0.60***	0.81***	0.85***
	(0.09)	*(0.07)*	*(0.10)*
Numeracy/100	0.30***	0.27***	0.28***
	(0.04)	*(0.03)*	*(0.04)*
Over-skilled	-0.17***	-0.12**	-0.17*
	(0.05)	*(0.04)*	*(0.08)*
Under-skilled	0.15**	0.16***	0.23***
	(0.06)	*(0.05)*	*(0.06)*
Years of education	0.07***	0.06***	0.07***
	(0.00)	*(0.00)*	*(0.01)*
Gender (female)	-0.12***	-0.10***	-0.16***
	(0.02)	*(0.01)*	*(0.02)*
Work experience	0.03***	0.03***	0.04***
	(0.00)	*(0.00)*	*(0.00)*
Work experience squared/100	-0.04***	-0.03***	-0.06***
	(0.01)	*(0.01)*	*(0.01)*
R^2	0.35	0.44	0.39
Observations	2199	2175	1894

Notes. Least squares regressions weighted by sampling weights. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. Workers in professions with less than 30 observations per country (at two-digit ISCO level) excluded. See Section "Empirical Approach" for details of the Mincer regression. Standard errors in parentheses. Significance levels: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).

Table A.7

Mincer regressions with skill-mismatch according to Allen et al. (2013) and taking all plausible values into account

Dependent variable: Gross hourly earnings (log)	Germany	Austria	USA
Constant	0.69***	0.89***	0.96***
	(0.08)	*(0.06)*	*(0.07)*
Numeracy/100	0.27***	0.24***	0.22***
	(0.03)	*(0.02)*	*(0.03)*
Over-skilled	-0.10**	-0.13***	-0.10*
	(0.04)	*(0.03)*	*(0.05)*
Under-skilled	0.07*	0.12***	0.10**
	(0.04)	*(0.03)*	*(0.05)*
Years of education	0.07***	0.06***	0.07***
	(0.00)	*(0.00)*	*(0.01)*
Gender (female)	-0.12***	-0.10***	-0.15***
	(0.02)	*(0.01)*	*(0.02)*
Work experience	0.03***	0.03***	0.04***
	(0.00)	*(0.00)*	*(0.00)*
Work experience squared/100	-0.04***	-0.03***	-0.06***
	(0.01)	*(0.01)*	*(0.01)*
R^2	0.35	0.44	0.39
Observations	2383	2333	2063

Notes. Least squares regressions weighted by sampling weights. Sample: Full-time employees between 16 and 65 years of age, excluding students and apprentices. See Section "Empirical Approach" for details of the Mincer regression. Standard errors in parentheses. Significance levels: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.10$. *Data source*: OECD (2013c) and Rammstedt et al. (2014).