ABSTRACT

Labour market mismatch and labour productivity: Evidence from PIAAC data

This paper explores the link between skill and qualification mismatch and labour productivity using cross-country industry data for 19 OECD countries. Utilising mismatch indicators aggregated from micro-data sourced from the recent OECD *Survey of Adult Skills* (PIAAC), the main results suggest that higher skill and qualification mismatch is associated with lower labour productivity, with over-skilling and under-qualification accounting for most of these impacts. A novel result is that higher skill mismatch is associated with lower labour productivity through a less efficient allocation of resources, presumably because when the share of over-skilled workers is higher, more productive firms find it more difficult to attract skilled labour and gain market shares at the expense of less productive firms. At the same time, a higher share of under-qualified workers is associated with both lower allocative efficiency and *within-firm* productivity – i.e. a lower ratio of high productivity to low productivity firms. While differences in managerial quality can potentially account for the relationship between mismatch and *within-firm* productivity, the paper offers some preliminary insights into the policy factors that might explain the link between skill mismatch and resource allocation.

JEL Classification: O40; I20; J20; J24.

Keywords: Productivity; reallocation; human capital; skill mismatch; qualification mismatch; education; allocation of talent; managerial quality.

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The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

LABOUR MARKET MISMATCH AND LABOUR PRODUCTIVITY: EVIDENCE FROM PIAAC DATA

By Müge Adalet McGowan and Dan Andrews[1]

1. Introduction

1. Cross-country differences in GDP per capita generally reflect differences in labour productivity (Figure 1). In turn, these labour productivity gaps are largely a function of differences in multi-factor productivity and the human capital pool that a country has at its disposal. While increases in the stock of highly educated workers have significantly boosted labour productivity over the past 50 years, the rate of increase in the stock of human capital is projected to slow (Braconier et al., 2014; Fernald and Jones, 2014). At the same time, the increasing economic importance of knowledge is projected to raise the returns to skills, thus underpinning further increases in earning inequalities within countries over coming decades (Braconier et al., 2014). In this context, the ability of economies to efficiently deploy their existing stock of human capital will take on heightened significance in order to combat the slowing growth and rising inequality that these projections imply.

2. According to the OECD *Survey of Adult Skills (*PIAAC), however, roughly one-third of workers in OECD countries are over- or under-qualified for their job, while one-sixth report a mismatch between their existing skills and those required for their job (OECD, 2013). At a first glance, this implies that there is considerable scope to improve the efficiency of human capital allocation in OECD countries. The potential gain to aggregate productivity from doing so is unclear, however, given that the existing literature typically does not estimate the direct effect of mismatch on productivity, but rather infers it indirectly from wages, job satisfaction and other correlates of productivity (Hartog, 2000). Moreover, the few studies in the literature that directly examine the relationship between mismatch and productivity are country-specific (Mahy et al., 2013), and thus it is unclear how generalizable their conclusions are to other countries.

3. Accordingly, this paper utilises cross-country data to explore the *direct* relationship between skill and qualification mismatch – aggregated from PIAAC micro-data – and industry-level labour productivity indicators, constructed from firm-level data. Another key novelty of the paper is that it studies the channels that link mismatch to productivity. To this end, it employs a decomposition which reveals that differences in aggregate labour productivity at any point in time will reflect two factors. First, average differences in *within-firm* productivity – measured by the unweighted average of firm productivity, irrespective of each firm's relative size – which is increasing in the ratio of high productivity to low productivity firms within an industry. Second, the extent to which, all else equal, it is the more productive firms that command a larger share of industry employment (*i.e.* allocative efficiency), which will be the outcome of the shift in resources across firms in previous periods (see Olley and Pakes, 1996). While the former component has been the subject of much research, reflecting a number of *within-firm* factors (*e.g.* managerial quality; intangible assets), researchers are increasingly linking the efficiency of resource allocation within industries to aggregate performance.

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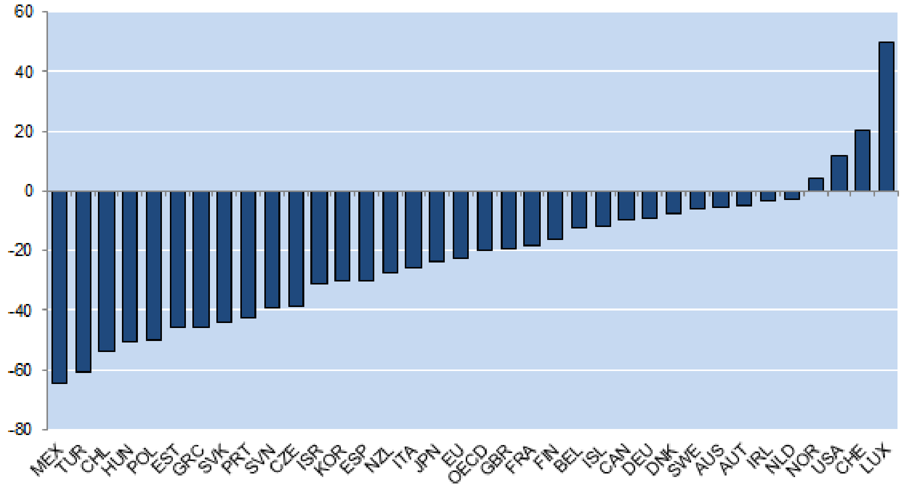
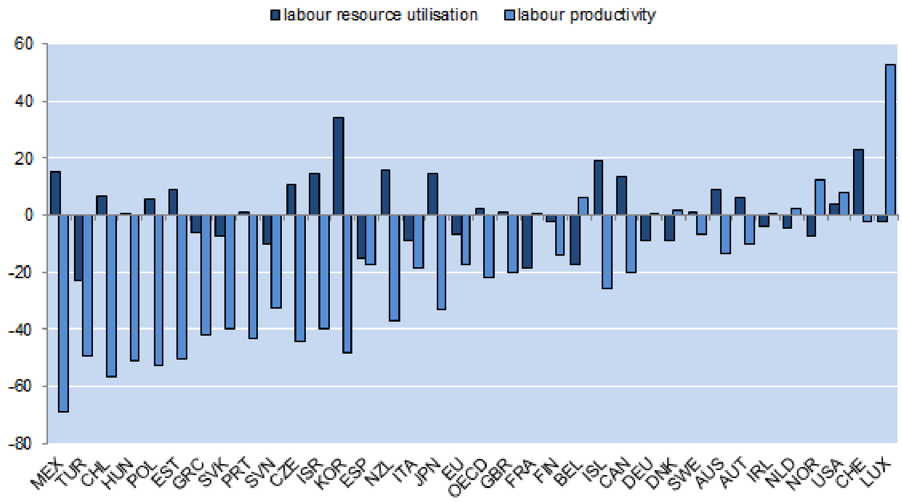
Figure 1. Large differences in income per capita are mostly accounted for by labour productivity gaps

OECD countries, 2013

Panel A: % GDP per capita difference compared with the upper half of OECD countries (2013 PPPs)



Panel B: % difference in labour resource utilisation and labour productivity



Notes: The sum of the percentage difference in labour resource utilisation and labour productivity do not add up exactly to the GDP per capita difference since the decomposition is multiplicative. Labour productivity is measured as GDP per hour worked. Labour resource utilisation is measured as the total number of hours worked per capita.

Source: OECD (2015), *Going for Growth*.

4. To the best of our knowledge, the existing literature only allows for the possibility for mismatch to affect *within-firm* productivity. From the perspective of any given firm, hiring an over-skilled and over-qualified worker may be beneficial for productivity, assuming there are no adverse effects on job satisfaction and the higher wages do not more than offset any associated productivity gains. From the perspective of the economy as a whole, however, the impacts may be very different. Assuming that wages do not adjust to these frictions in the short-run, mismatch could have reallocation effects. This could be the case if there are other relatively more productive firms in the economy that could potentially employ the mismatched workers more efficiently, but these firms find it difficult to gain market shares due to lack of skilled and well-qualified labour. In this case, the more productive firms remain smaller than otherwise, lowering aggregate productivity relative to a situation where workers are reallocated to achieve a more

efficient match. By allowing for the possibility that mismatch affects productivity through its impact on resource allocation, this paper connects research on mismatch to an emerging literature which focuses on resource misallocation as a potential explanation for why some countries are more productive than others.[2]

5. We analyse both skill and qualification mismatch since their determinants and impact on productivity may be different (Allen and Van der Velden, 2001). Specifically, we employ two main approaches: *i)* consider qualification and skill mismatch and their components separately; and *ii)* take into account the overlap between the types of mismatch, to allow for the possibility that some workers that are over-skilled might also be over-qualified, for example. The first approach is possible since the overlap between qualification and skill mismatch is low, with on average only one-tenth of workers mismatched in terms of both. The second approach is useful as it paints a more nuanced picture of the links between mismatch and productivity, although the results should be treated with caution as the additional categories create additional pressure from a degrees of freedom perspective, given the relatively small sample size.

6. To summarise, using both approaches, we find that higher qualification and skill mismatch is associated with lower labour productivity, although the exact channel varies across the different types of mismatch. The results are consistent with a body of existing evidence which emphasises that under-qualification and under-skilling are associated with lower productivity *within* the affected firms. At the same time, however, new insights emerge, which suggests that mismatch can adversely affect labour productivity via the allocation of employment across firms of varying productivity levels.

7. While higher skill mismatch is associated with lower productivity, this largely reflects the strong negative correlation between over-skilling and productivity; by contrast, the under-skilled component of mismatch – assuming that the worker is well-matched in terms of qualifications – does not appear to bear on productivity. Furthermore, the negative correlation between over-skilling and labour productivity results from its effect on allocative efficiency; that is, in industries with a higher share of over-skilled workers, the more productive firms find it more difficult to attract suitable labour, in order to expand their operations. The effect is also economically significant. For example, if interpreted causally, the estimates suggest that Italy – a country with high skill mismatch and low allocative efficiency – could potentially close one-fifth of its gap in allocative efficiency with the United States if it were to reduce its level of mismatch within each industry to that corresponding to the OECD best practice. Hence, the allocation of skills can potentially account for a non-trivial share of cross-country labour productivity gaps, which provides a complement to recent analysis finding that the *level* of skill use (constructed from PIAAC data) can explain 30-40% of the cross country variation in aggregate labour productivity (OECD, 2013).

8. The paper also explores the link between qualification mismatch and productivity, although this type of mismatch may be somewhat less relevant to the extent that it does not take into account skills gained or lost beyond the formal qualifications (Desjardins and Rubenson, 2011). In contrast to skills, the negative relationship between qualification mismatch and productivity is largely driven by the under-qualified component of mismatch, while over-qualification by itself – assuming that the worker is well-matched in terms of skills – is not statistically significant. Furthermore, under-qualification is related to productivity through both lower allocative efficiency and *within-firm* productivity – that is, a higher share of under-qualified workers is associated with a lower ratio of high productivity firms to low productivity firms, within an industry.

9. Controlling for the overlap between skill and qualification mismatch yields two main additional insights. First, a higher share of workers who are both over-qualified and over-skilled is positively associated with *within-firm* productivity, but negatively correlated with allocative efficiency. These findings imply that while having workers with a combination of over-skilling and over-qualification might

2 See Hsieh and Klenow (2009); Bartelsman et al. (2013) and Andrews and Cingano (2014).

be good for the firms who employ these workers, this does not necessarily translate into higher aggregate productivity because it may constrain the growth of other relatively more productive firms that could more efficiently utilise these workers. Second, the negative relationship between under-qualification and *within-firm* productivity is entirely driven by workers who are both under-qualified and under-skilled. However, additional analysis suggests that differences in managerial quality can potentially account for this relationship between under-qualification and under-skilling, and *within-firm* productivity. This suggests that a more efficient matching of qualifications and skills to jobs is one of the possible channels through which higher managerial quality increases productivity, as shown in the seminal work of Bloom and Van Reenen (2007).

10. These results are suggestive, but should be treated with caution because they are based on a relatively small sample size. Moreover, they only identify correlations, as opposed to causal effects, and it is possible that there may be more scope to reduce mismatch in industries with more efficient reallocation. While further research is clearly required, the analysis nonetheless highlights a number of important policy issues. First, given its correlation with productivity, mismatch is a relevant structural indicator that should be monitored in cross-country structural surveillance exercises. Second, policymakers should be concerned with not only increasing the stock of human capital, but also allocating the existing pool more efficiently. This is particularly important given the benefits of human capital-augmenting policies take a long time to be realised, while improving the allocation of human capital will enhance the 'bang-for-the-buck' (*i.e.* productivity impact) of such policies.

11. While the paper primarily focuses on the establishing a link between mismatch and productivity, the question of what drives mismatch remains. The link between managerial quality, mismatch and *within-firm* productivity uncovered in this paper reaffirms the importance of policies that improve managerial performance, such as pro-competitive product market regulations. That mismatch is also linked to productivity through the reallocation channel, however, suggests that a broader set of policies also warrant consideration.

12. The paper proceeds as follows. The next section defines the mismatch indicators and discusses the channels that link mismatch to productivity. Section 3 discusses data measuring productivity and mismatch and presents some descriptive cross-country evidence on differences in skill and qualification mismatch across industries. Section 4 outlines the empirical methodology used to estimate the relationship between productivity and mismatch, and then discusses the baseline results, robustness tests and extensions to the analysis. Section 5 identifies some potential policy factors that may shape mismatch, while the final section offers some concluding thoughts.

2. Mismatch and labour productivity

13. While the centrality of human capital accumulation for economic growth has been firmly established (Romer, 1989), evidence on the importance of the efficient allocation of human resources to jobs is only beginning to emerge. One strand of research takes a broad perspective, emphasising the adverse effects of gender and racial discrimination and lack of equality of opportunity for the allocation of talent and ultimately productivity performance (see Box 1 for details). While the consequences for productivity of discrimination, for example, are relatively clear to the extent that it can result in blatant occupational mismatch – such as restrictions on women entering certain professions – human capital misallocation can also take more subtle forms, such as a mismatch of worker's skills and/or qualifications to jobs.

Box 1. Talent allocation and growth

A recent literature has highlighted the negative effects on productivity of labour market discrimination restricting the allocation of talent. Hsieh et al. (2013) augment the traditional Roy (1951) model of occupational choice such that barriers to occupational choice, relative mobility across occupations and relative returns to occupational skills affect the occupational distribution. They find that reductions in barriers to occupational choice facing women and racial minorities in the United States can explain 15-20% of growth in aggregate output per worker over the period 1960 to 2008. Using a cross-country approach, Cuberes and Teignier (2014) find that the exclusion of females from entrepreneurship leads to a 12% drop in average output per worker.

Barriers to equality of opportunity, reflected in low intergenerational mobility, are another potential source of talent misallocation to the extent that talented children of poor parents may never reach their full potential. The relationship between parental or socio-economic background and offsprings' educational and wage outcomes is positive and significant (Causa and Johannson, 2009). Using PIAAC data, OECD (2014) finds that despite some improvements in access to education, in most countries, 40-50% of adults have the same educational attainment as their parents. Furthermore, skill proficiency levels are also correlated with the education of the parents (Huber and Stephens, 2014). An example of such barriers causing a misallocation of talent and inefficiency is family firms, where the person who inherits the firm might not be a good manager (Pica and Rodriguez Mora, 2005), while Hassler and Rodriguez Mora (2000) show that management driven by talent instead of inheritance improves the allocation of talent, resulting in higher innovation and growth. Indeed, Bloom and Van Reenen (2007) show that family-owned firms are typically less well-managed, particularly those managed by the oldest son of the founder.

Financial market frictions can also affect the allocation of talent. Caselli and Gennailoi (2005) show that credit market imperfections may prevent the transfer of control of productive assets from the untalented rich to the talented poor and the severity of the misallocation of talent will depend on the degree of concentration on the goods market such that increased competition would improve the allocation of talent. Other barriers to misallocation of talent include lack of competition and restrictions on firm size. Furthermore, factors that might influence the occupational choice of talented people such that they are skewed towards rent-seeking sectors at the expense of research or entrepreneurship may also engender a misallocation of talent.

2.1 Measuring mismatch

14. A good match between the skills demanded by firms and those acquired in education and on the job is important for promoting strong and inclusive growth. While there is a variety of approaches to measuring qualification and skill mismatch in the literature (see Box 2), in this paper we adopt the following definitions based on data from the OECD *Survey of Adult Skills* (see Section 3.2):

- *Qualification mismatch*: a benchmark of "appropriate" qualifications required to get the job is created, based on the following question: "If applying today, what would be the usual qualifications, if any, that someone would need to get this type of job?". If the person has a qualification (measured by the International Standard Classification of Education (ISCED) level corresponding to their highest qualification) above (below) this benchmark, they are classified as over-qualified (under-qualified).

- The measure of *skill mismatch* is based on qualitative information – *i.e.* a self-assessment of mismatch – that is verified by quantitative information on skill proficiency. This approach – adopted in OECD (2013) – involves three steps:

  - First, the (literacy) proficiency scores of workers who report themselves as well-matched – *i.e.* those who neither feel they have the skills to perform a more demanding job nor feel the need for further training in order to be able to perform their current job satisfactorily – are used to create a quantitative scale of the skills required to perform the job for each occupation (based on 1-digit ISCO codes).

- Second, using this scale of proficiency scores of well-matched workers, minimum and maximum threshold values – based on the 5^{th} and 95^{th} percentile, for example – are identified, which effectively provide the bounds that define what it is to be a well-matched worker.
- Third, respondents whose scores are lower (higher) than this minimum (maximum) threshold in their occupation and country, are classified as under- (over-) skilled. By contrast, respondents whose proficiency scores reside within these bounds are not counted as mismatched, regardless of whether they self-report as being well-matched or mismatched.

Box 2. Alternate approaches to measuring mismatch

Qualification mismatch

There are several approaches to measuring qualification mismatch. One is to compare the qualification level of a worker according to the International Standard Classification of Education (ISCED) level and the required qualification level corresponding to his/her occupation code according to the International Standard Classification of Occupations (ISCO) (Chevalier, 2003). A second approach is to calculate the modal qualification of workers in each occupation and country (Mendes de Oliveira et al., 2000). This measure has some drawbacks as it assumes that all jobs within an occupation have the same education requirements and combines current and past qualification requirements, suffering from cohort effects.

A final approach is based on workers' opinions on the match between their jobs and education, which is the definition used in this paper (Battu et al., 2000; Dorn and Sousa-Poza, 2005). This type of self-reported measures can be subject to biases due to the wording of the question or the impact of external variables, some of which may be country-specific (Dumont and Monso, 2007). However, they have the advantage of being job-specific rather than suffering from the caveats associated with the other measures.[1]

Skill mismatch

There are also several ways to measure skill mismatch. One is to ask workers to assess themselves on their skill level and that required for their job. While this self-assessment method addresses the issue of partial measurement of skills (such as those based only on numeracy or literacy), it does not identify specific skill deficits or excesses. Furthermore, there is some evidence that skill deficits are hard to measure using this method (Allen and van der Velden, 2001). Indeed, PIAAC data show that the incidence of under-skilling is much lower than that of over-skilling (Table A1 in Appendix A). Another approach is to directly measure the skills of individual workers, most commonly, literacy and numeracy, and to compare them with skill use at work (CEDEFOP, 2010; Desjardins and Rubenson, 2011). Such measures are subject to two main drawbacks. First, they assume that skill use can be a proxy for job requirements. Second, skill proficiency and skill use are based on different theoretical concepts and are hard to measure on the same scale. In fact, skill proficiency and skill use are calculated by using structurally different types of information as the indicators of skill proficiency are based on cognitive tests, whereas those of skill use exploit survey questions on the frequency with which specific tasks are carried out.

A final approach is to combine information on self-reported skill mismatch and skill proficiency as developed in OECD (2013) – which is exploited in this paper. The main limitation of this measure is that it uses 1-digit occupation codes because of sample size, thus assuming that all jobs with the same occupation code have the same skill requirements. However, it does carry a number of advantages, to the extent that it addresses the drawbacks associated with the other approaches outlined above.[2]

1. OECD (2014b), which also utilises the definition adopted in this paper, reports that qualification mismatch indicators calculated using the other two approaches yield similar country rankings and incidences of mismatch of the same magnitude.

2. See Pelizzari and Fichen (2013) for a more detailed description of the construction of this skill mismatch indicator and Allen et al. (2013) and Levels et al. (2014) for a criticism and an analysis based on an alternative skill mismatch indicator using skill use and proficiency data from PIAAC.

15. Qualification mismatch may not reflect skill mismatch, even though qualifications have been extensively used as a proxy for skills. Although qualification mismatch is easier to measure and broader in its coverage of skills (even though it is measured indirectly), it does not take into account: *i)* skills gained or lost beyond the formal qualifications (Desjardins and Rubenson, 2011); *ii)* differences in the quality and orientation of various education and training systems; and *iii)* on-the-job learning or adult learning/training. Hence, using qualification mismatch as an indicator of skill mismatch has been criticised

(Green and McIntosh, 2007; Mavromaras et al., 2009). Skill mismatch is more precise as it takes into account skill gain or loss, but its definition is narrower as it concentrates on one aspect of skills such as literacy or numeracy.

16. With these definitions in mind, roughly one-third of workers in OECD countries experience qualification mismatch, while one-sixth of workers are affected by skill mismatch calculated using the 5th percentile thresholds (OECD, 2013) – a figure that rises to one-fourth when we consider a 10th percentile threshold. While we interpret this as evidence of inefficiencies in the allocation of skills and qualifications, it is important to recognise that some of this mismatch reflects temporary factors that will not necessarily carry important implications for productivity. Indeed, imbalances between the demand for and supply of different skills will inevitably arise, due to economic shocks, imperfect information about opportunities in the labour market and improvements in technology and organisational practices (Robst, 1995; Sicherman, 1991). While this implies that the natural rate of mismatch will be above zero, empirical evidence suggests that mismatch is relatively persistent (Mavromaras et al., 2012 and 2013), possibly reflecting frictions affecting: *i*) the response of the supply of skills to demand; *ii*) firms' recruitment and training; and *iii*) intergenerational and geographical mobility. Moreover, persistent differences in the incidence of mismatch across socio-demographic characteristics might suggest that there are barriers to allocating at least part of the labour force more efficiently. In this context, these measures of mismatch are potentially important structural indicators, and it is thus natural to relate them to productivity.

2.2 Mismatch and productivity

17. The existing literature on the impact of mismatch on productivity draws on two main approaches, which can yield varying conclusions. The first strand of research relies on human capital theory – and more specifically, the observation that wages equal marginal productivity in competitive equilibrium – and thus infers the impact of mismatch on productivity through its estimated effect on wages. The second strand of the literature focuses on the impact of mismatch on job satisfaction in order to indirectly estimate the productivity impact of mismatch. In both cases, the effect of mismatch on productivity is not directly estimated. Furthermore, the existing research tends to be country-specific and ignores some of the possible channels that link mismatch to aggregate productivity.

2.2.1 Indirect evidence of the impact of mismatch on productivity is inconclusive

18. The first approach, based on human capital theory, posits that over- (under-) qualified/skilled workers should be inherently more (less) productive at their jobs and that the associated gap in wages should reflect these different levels of productivity. Indeed, these predictions are generally borne out in the research that studies the impact of mismatch on wages (see Mahy et al., 2013 for a summary). For instance, across a sample of OECD countries, Quintini (2011a) estimates that over-qualified workers earn around 4% more than well-matched workers in similar jobs. In other words, a tertiary graduate who holds a job requiring only an upper secondary qualification will earn less than if he were in a job requiring a tertiary qualification, but more than an upper secondary graduate in a job requiring upper secondary qualifications. Similarly, under-qualified workers earn on average around 17% less than workers who are well-matched in similar jobs.[3] Recent analysis based on PIAAC data has shown that skill levels can explain part of the wage effects of qualification mismatch, but the extent depends on the institutional setting, for example, in

3 Hence, an upper secondary graduate in a job requiring tertiary qualifications will earn more than an upper secondary graduate in a job requiring upper secondary qualifications but less than a tertiary graduate in a job requiring tertiary qualifications. The latter comparison of workers with the same skills in different jobs is based on assignment theory that emphasises both individual and job characteristics for mismatch analysis (Sattinger, 1993).

countries with weak employment protection legislation, a larger part of the observed effects can be accounted for by skills (Levels et al., 2014).

19. An alternate approach is to infer the impact of mismatch on productivity through its relationship with other correlates of firm productivity (*e.g.* job satisfaction, absenteeism and turnover) but the conclusions are less clear-cut. Over-qualified or over-skilled workers would have an incentive to move to a job that better reflects their education and skills, suggesting that they experience reduced job satisfaction, which would in turn decrease job effort, increase absenteeism and lower productivity (Green and Zhu, 2010; Battu et al., 1999). Quintini (2011a) finds that being over-qualified reduces job satisfaction compared with well-matched workers with the same level of qualification, but the effect is not significant compared with well-matched workers with the same job.

20. Low job satisfaction can also lead to higher job turnover such that over-qualified and over-skilled workers are more likely to change jobs or engage in on-the-job training than well-matched workers with similar qualifications or jobs (Quintini, 2011b; Sloane et al., 1999; Verhaest and Omey, 2006). High job turnover can be a barrier to the accumulation of firm-specific human capital, as neither the employee nor the employer would have high incentives to invest in them. Indeed, there is evidence that over-qualified workers are less likely to take part in training than well-matched workers with the same qualifications (Hersch, 1991; Verhaest and Omey, 2006), while the opposite results hold when compared to well-matched workers in the same job (Büchel, 2002).

21. There is some evidence that the effect of skill mismatch on job satisfaction is stronger than that of qualification mismatch, with over-skilling having a negative effect on satisfaction (Allen and van der Velden, 2001). Despite the evidence of some relationship between mismatch and job satisfaction, the correlation between job satisfaction and qualitative measures of job performance is only modest (the correlation coefficient is around 0.3) which casts some doubt on the reliability of using job satisfaction to assess the effect of mismatch on productivity (Judge et al., 2001).

22. A range of other studies also provide indirect evidence in favour of the proposition that the allocation of skills has important economic consequences. Industry-level studies from specific countries demonstrate that skill shortages – as measured by surveys of firms' perceptions – have sizeable adverse impacts on productivity growth (Haskel and Martin, 1993), technological adoption and tangible and intangible investment (Forth and Mason, 2006).[4] It is important to note, however, that the source of skill shortages in these studies is unclear, and may not necessarily be related to under-skilling or over-skilling. Moreover, there is evidence that the perception of employers and employees differ, with employers being less likely to report skill gaps (McGuinness and Ortiz, 2014).[5]

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4 Using industry-level data for the United Kingdom, Haskel and Martin (1993) find that increases in skill shortages reduced productivity growth by 0.7% per annum between 1980 and 1986. Bennett and McGuinness (2009) find hard-to-fill and unfilled vacancies reduced output per worker levels by between 65-75% in affected firms in Northern Ireland, while Tang and Wang (2005) provide similar evidence for Canada. Nickell and Nicolitsas (2000) find that a permanent 10 percentage point increase in the share of companies in a firm's industry reporting skilled labour shortages leads to a permanent 10% reduction in its fixed capital investment and a temporary 4% reduction in R&D expenditure.

5 At the same time, other studies calculate the costs of skill gaps in terms of vacancies and unemployment, which have been estimated to range from 7-8% of GDP for a number of European countries (Marsden et al., 2002).

2.2.2 Direct evidence of the impact of mismatch on productivity is limited

23. For our purposes, the main methodological shortcoming of the existing literature is that they do not directly address the link between mismatch and productivity, but instead focus on indirect links through wages and job satisfaction (Hartog, 2000). Indeed, direct evidence on the impact of mismatch on firm productivity is very limited. The most relevant study uses linked employer-employee data for Belgium and finds a positive impact of over-qualification on firm productivity and a negative one for under-qualification (Mahy et al., 2013). Furthermore, the effect of over-qualification on productivity is stronger for firms with a higher share of high-skilled jobs and that are in high-tech or knowledge-based industries. Using a similar dataset, Kampelman and Rycx (2012) also show that additional years of over-qualification increase the productivity of firms, while under-qualification has the reverse effect. While these studies from Belgium represent an important advance in the literature, it is unclear whether the conclusions can be extended to other countries.

2.2.3 Mismatch can affect aggregate productivity through reallocation effects

24. A key feature of the existing literature is its exclusive focus on the impact of mismatch on *within-firm* productivity, but the impact on aggregate productivity may very well be different. From the perspective of a single firm, hiring an over-skilled worker may be beneficial for productivity, assuming there are no adverse effects on job satisfaction and the higher wages do not more than offset any associated productivity gains. From the perspective of the economy as a whole, however, over-skilling in any given firm could be harmful to productivity to the extent that there exist relatively more productive firms that could more efficiently utilise these skills but find it difficult to expand due to a lack of suitable labour.[6] In an economy where firms are relatively homogenous, the potential gains to aggregate productivity from such a reallocation of mismatched workers would be relatively small. In practice, however, the degree of heterogeneity in firm performance is striking, which creates considerable scope for productivity-enhancing reallocation. For example, even within narrowly defined industries in the United States, firms at the 90th percentile of the TFP distribution are twice as productive as firms at the 10th percentile (Syverson, 2004).[7] Moreover, the distribution of firm productivity is typically not clustered around the mean (as would be the case with a normal distribution) but is instead characterised by many below-average performers and a smaller number of star performers. From this perspective, mismatch could also potentially influence aggregate productivity through the channel of resource allocation: that is, the allocation of employment across firms of varying productivity levels.

25. Given the tendency for highly productive firms to coexist with low productivity firms within narrowly-defined industries, the recent literature has focused on resource misallocation as a potential explanation for why some countries are more productive than others (Bartelsman et al., 2013; Hsieh and Klenow, 2009). A key observation is that in well-functioning economies, a firm's relative position in the productivity and size distributions is positively correlated, which means that on average relatively more productive firms should be larger (see Olley and Pakes, 1996). Research on firm dynamics reveals large cross-country differences in the efficiency of resource allocation, which suggests that some economies are more successful at channelling resources to highly productive firms than others. For example, in the United States, manufacturing sector labour productivity is 50% higher due to the actual allocation of employment across firms, compared to a hypothetical situation where labour is uniformly allocated across firms, irrespective of their productivity (Bartelsman et al., 2013). While a similar pattern holds for some countries of Northern Europe such as Sweden, it turns out that static allocative efficiency is considerably lower in other OECD economies, particularly those of Southern Europe (Andrews and Cingano, 2014).

6 In this case, aggregate productivity could improve via a reallocation of workers toward these firms.

7 The same is true with respect to the firm size distribution, with many small firms co-existing with a smaller number of very large firms (Bartelsman et al., 2013).

26. In fact, it is increasingly being recognised that the growth potential of innovative firms is inversely related to the amount of resources that are absorbed by other less productive firms. In a heterogeneous firm model calibrated to US data, Acemoglu et al. (2013) show that policy intervention such as R&D tax subsidies are only truly effective when policy-makers can encourage the exit of "low-type" incumbent firms, in order to free-up R&D resources (*i.e.* skilled labour) for innovative "high-type" incumbents and entrants.[8] Along the same lines, mismatch could make it more difficult for the most productive firms in an economy to attract suitable labour and expand, thus lowering aggregate productivity. Indeed, such an explanation could potentially draw on four observations: *i*) there is a fixed pool of highly skilled workers; *ii*) more productive firms employ a higher share of high skilled workers than less productive firms; *iii*) to the extent that over-skilling implies that high skilled workers are clogged up in low productivity firms, the effective pool of labour that the most productive firms can draw workers from is reduced; *iv*) which in turn makes it more difficult for the most productive firms to attract employment and expand, thus lowering allocative efficiency. Of course, this assumes that the adjustment in wages in the short run is not sufficiently large to facilitate a reallocation of mismatched workers from less productive to more productive firms, via mechanisms such as poaching. Indeed, this assumption seems reasonable to the extent that there are frictions that affect the efficiency of labour reallocation, arising from policy-induced frictions (*e.g.* labour market regulations; see Hopenhayn and Rogerson, 1993) or structural factors that prevent geographical mobility across regions.

3. Data description

3.1 Productivity indicators

27. With this in mind, we follow the emerging literature on firm dynamics and decompose weighted average productivity at the industry level into: *i*) *within-firm* or unweighted average productivity, which captures the fraction of 'better' relative to 'worse' firms; and *ii*) the extent to which, all else equal, it is the more productive firms that command a larger share of aggregate employment (*i.e.* allocative efficiency). More formally, we employ the cross-sectional decomposition of productivity developed by Olley and Pakes (1996). An index of productivity in industry j, defined as the weighted average of firm-level productivity ($P_j = \sum_{i \in j} \theta_i P_i$) can be written as:

$$\sum_{i \in j} \theta_i P_i = \bar{P}_j + \sum_{i \in j} (\theta_i - \bar{\theta}_j)(P_i - \bar{P}_j) \quad (1)$$

where $\bar{P}_j = 1/N_j \sum_{i \in j} P_i$ is the *within-firm* productivity mean, θ_i is a measure of the relative size of each firm (measured by the firm employment share) and $\bar{\theta}_j$ is the average share at the industry level. This allows the decomposition of aggregate productivity (P_j) into a moment of the firm productivity distribution (the unweighted mean) and a joint moment with the firm size distribution reflecting the extent to which firms with higher efficiency also have a larger relative size (the Olley-Pakes covariance term or allocative efficiency).

28. In this framework, a positive allocative efficiency reflects an increase in the industry productivity index due to an actual allocation of employment across firms within an industry relative to the case in which employment is randomly allocated, which would imply that weighted average and *within-firm* (unweighted) average productivity are equal. Another advantage of this approach is that focusing on the relative contribution of allocative efficiency to the observed aggregate productivity level only involves

8 This reflects the idea that low-type firms – despite their lack of innovativeness – still employ skilled labour to cover the fixed costs of operation, such as management and back-office operations. One implication is that a R&D subsidy will be fully capitalised into the high-skilled wage rate – without a concomitant rise in innovation output (as suggested by Goolsbee, 1998) – unless the effective supply of high skilled labour can rise to meet additional demand via downsizing and/or exit of "low-type" firms.

comparing productivity levels of firms in the same industry and countries, such that most of the measurement problems are controlled for (Bartelsman et al., 2009). By contrast, measurement problems can make comparisons of the levels of weighted average productivity or *within-firm* (unweighted) average productivity across sectors or countries problematic, although the inclusion of country and industry fixed effects in the regression specifications can potentially control for these problems. Finally, this decomposition could be performed at various levels of aggregation – *e.g.* the country level or at the 1 or 2-digit industry level – but we adopt a 1-digit industry classification to better align with the mismatch data.

29. While there are several potential sources of industry-level productivity data for OECD countries (*e.g.* OECD STAN or EU KLEMS), firm-level data are required to perform the decomposition outlined above. Following Andrews and Cingano (2014), we use a harmonised cross-country dataset, where the underlying firm level data are sourced from ORBIS, a commercial database provided to the OECD by Bureau Van Dijk.[9] ORBIS has a number of drawbacks such as the representativeness of firms in certain industries and underrepresentation of small and young firms. Hence, in order to improve representativeness, the ORBIS firm sample is aligned with the distribution of the firm population from the Structural Demographic Business Statistics (SDBS) collected by the OECD and Eurostat, based on confidential national business registers.[10] This post-stratification procedure is of course based on the assumption that within each specific cell, ORBIS firms are representative of the true population – an assumption that may be problematic if the nature of selection varies across countries.[11] Labour productivity is calculated using an operating revenue turnover-based measure of labour productivity as value-added data are not available for all firms, but as outlined in Andrews and Cingano (2014), the correlation between the two measures is reasonably high. Finally, we follow a common data cleaning practice by excluding firms with one employee and firms in the top and bottom 1% of the labour productivity distribution.

3.2 Mismatch data and sample composition

30. The measures of qualification and skill mismatch, introduced in Section 2.1, are assembled from micro-data contained in the *OECD Survey of Adult Skills* (PIAAC), which is described in more detail in Box 3. To align with the industry level productivity indicators discussed in Section 3.1, the share of workers that are well-matched, over-qualified/skilled and under-qualified/skilled are aggregated to the 1-digit industry level. Although PIAAC has 2-digit industry level identifiers, there are often not enough observations within each 2-digit industry cell to ensure sufficiently reliable estimates, so only 1-digit industries are considered.[12]

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9 See Pinto Ribeiro et al. (2010) for details on the construction of the data, which includes financial and balance sheet information on tens of millions of firms worldwide.

10 The post-stratification procedure applies re-sampling weights based on the number of employees in each SDBS country-industry-size class cell to ‘scale up’ the number of ORBIS observations in each cell so that they match those observed in the SDBS (see Gal, 2013). For example, if SDBS employment is 30% higher than ORBIS employment in a given cell, then the 30% ‘extra’ employment is obtained by drawing firms randomly from the pool of ORBIS firms, such that the ‘extra’ firms will make up for the missing 30%. See Gal (2013) and Andrews and Cingano (2014) for more details on the cleaning and construction of the data sample.

11 To the extent that post-stratification weights do not address the issue of how accurately industry level productivity indicators are measured when the underlying number of available units is small, this issue will be addressed empirically by weighting OLS regression estimates by the number of available observations in each country-industry cell.

12 On average across countries in our sample, there are 407 observations in each 1-digit industry, while there are only 117 observations on average in 2-digit industries, but the variance around this average is very large.

Box 3. OECD Survey of Adult Skills (PIAAC)

The survey is based on a background questionnaire administered to households representing the population aged between 16 and 65 in 24 countries: Australia, Austria, Belgium (Flanders), Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), the United States, Cyprus[*] and the Russian Federation. The data were collected in 2011-12 and published in the autumn of 2013.[1] On average, across countries, 77.5% of participants were assessed on a computer, while the rest took the paper-based assessment.

PIAAC has extensive information on skill use at work and at home and background variables such as educational attainment, employment status, job, socio-economic background and personal characteristics. It was also designed to measure key cognitive and workplace skills and provides indicators on the proficiency of individuals in literacy, numeracy and problem-solving in technology-rich environments, measured on a 500-point scale. These data allow a more in-depth assessment of skills compared to previous surveys as they include more dimensions in capturing key information-processing competencies defined as:

- *Literacy:* 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.

- *Numeracy*: 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.

- *Problem-solving in technology rich environments:* the ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks.[2]

There are two main issues that need to be taken into consideration when these data are used.[3] First, the three skill domains were not directly assessed for each respondent due to time constraints, but PIAAC uses matrix-sampling design to assign the assessment exercises to individuals and *Item Response Theory* to combine the individual responses to get a comprehensive view of each skill domain across the country. However, such aggregation can lead to biased estimates due to measurement error. Hence, a multiple imputation methodology was utilised to generate 10 "plausible values" for each respondent for each skill domain and the subsequent analysis takes a mean of these values. Second, complex sampling designs that vary across countries were administered in the data collection. In order to get a consistent approach to sampling variance calculation, a replication technique (the Jacknife Repeated Replication) is used to compute sampling error. The estimates presented in this paper take these weights into account through the use of the "PIAAC Tool" macro. [4]

1. PIAAC is being implemented in 9 additional countries (Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey) in 2014 and the results will be available in 2016.

2. Using the problem-solving indicator is problematic as the average score does not take into account the large and variable proportion of participants who did not take that part of the assessment either due to not being able to use a computer or due to refusal.

3. For more details, see OECD (2013), *Technical Report of the Survey of Adult Skills* (PIAAC), Paris.

4. The macro is available at http://www.oecd.org/site/piaac/publicdataandanalysis.htm.

*1.Footnote by Turkey
The information in the document with reference to « Cyprus » relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognizes the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Turkey shall preserve its position concerning the "Cyprus issue".

2. Footnote by all the European Union Member States of the OECD and the European Union

The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in the documents relates to the area under the effective control of the Government of the Republic of Cyprus.

31. Before aggregation, however, we cleaned the data in the following ways. First, as outlined in Section 2.1, threshold values are applied to the scale of proficiency scores of well-matched workers in order to provide the bounds that define what it is to be a well-matched worker. OECD (2013) uses the 5th and 95th percentile rather than the actual minimum and maximum to create benchmarks. To test the robustness of the results, other thresholds, namely 10th/90th percentile and 2.5th/97.5th percentile, are also

considered. The correlation between these various measures is reasonably high but far from perfect (Table A2 in Appendix A). Given these similarities, results are not reported for the 2.5th/97.5th percentile definition. Although the 5th percentile cut-off works well in the analysis of the overall indicator of skill mismatch in each country, a less extreme measure of mismatch based on a more generous threshold (*e.g.* 10th/90th percentile) is used when analysing the links between productivity and mismatch at the industry level. Second, only employees holding just one job and who are not self-employed are considered. Finally, due to the small sample size, ISCO codes 0 (armed forces) and 6 (skilled agricultural and fishery workers) are dropped while ISCO codes 1 (managers) and 2 (professionals) are merged together.

32. While PIAAC covers 24 countries, the final sample is based on the overlapping 19 countries and 11 1-digit market sector industries for which productivity data are available. More specifically, the country sample includes Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Slovak Republic, Spain, Sweden, the United Kingdom, and the United States.[13] The industries covered are manufacturing; electricity, gas, steam and air conditioning supply; water supply; construction; wholesale and retail trade; transportation and storage; accommodation and food service activities; information and communication; real estate activities; professional, scientific and technical activities, and administrative and support service activities. This results in a dataset of 205 country-industry cells, which is relatively small. Thus, the results should be viewed with some caution.

3.3 Cross-country differences in mismatch

33. There is significant variation across countries and industries in the degree of both qualification and skill mismatch (OECD, 2013). These differences are also reflected in calculations based on the sample used in this paper.[14] On average, qualification mismatch (at 36%) is more common than skill mismatch at 24% (Figure 2).[15] As documented in Figure A1 in Appendix A, being over-qualified is on average roughly twice as common than being under-qualified, while being over-skilled is on average roughly two and a half times more common than being under-skilled.

34. It is important to control for both types of mismatch when analysing the links between mismatch and labour productivity to the extent that the overlap between qualification and skill mismatch is quite low, suggesting that qualifications are not a good proxy for skills in literacy. For example, on average, 14% of over-qualified workers are also over-skilled, with the overlap ranging from 7% in Estonia to 25% in Ireland, while the overlap between under-qualified and under-skilled workers is even less at 5% of respondents (OECD, 2013).

35. Finally, in Table A3 in Appendix A, the extent to which the country and industry dimensions of the data explain the overall variance in mismatch is explored. With the exception of over-qualification, most of the variance is explained by cross-country factors, which raises the possibility that policy factors

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13 Although Australia, Canada and Ireland are excluded from the econometric analysis due to a lack of reliable productivity data, they are included in the results presented in Sections 3.3 and 4.4.

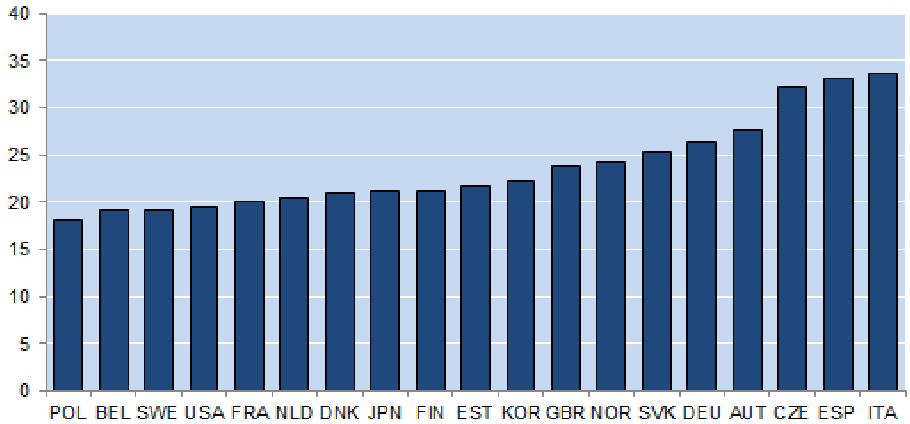
14 The percentage of workers with skill and qualification mismatch reported may vary somewhat from the aggregate values in OECD (2013) due to three main reasons. First, only workers in the industries for which productivity data are available are considered. Second, threshold values based on a top and bottom 10 per cent definition are utilised to construct the skill mismatch indicator. Finally, in order to abstract from differences in industrial structures across countries, the 1-digit industry level mismatch indicators are aggregated using a common set of weights, based on industry employment shares for the United States.

15 Figure C1 in Appendix C is an extension of Figure 2 to include countries that are not in our sample, but are included in the PIAAC sample.

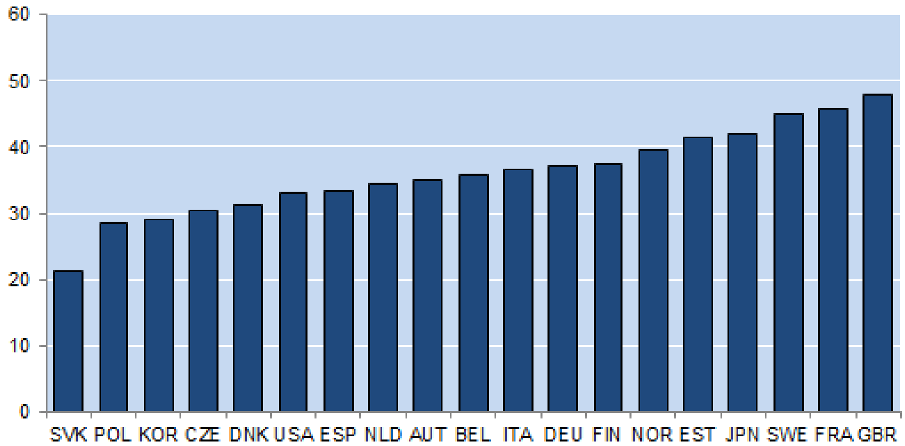
may explain mismatch. Technological factors that are reflected in industry-specific effects are an important determinant of over-qualification.

Figure 2. Incidence of qualification and skill mismatch

Panel A: Percentage of workers with skill mismatch



Panel B: Percentage of workers with qualification mismatch



Note: The figures are calculated from the cross-country industry data from the sample described in Section 3.2. Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled), as defined in Section 2. Under - (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10th (90th) percentile of the scores of the well-matched workers in each occupation and country. In order to abstract from differences in industrial structures across countries, the 1-digit industry level mismatch indicators are aggregated using a common set of weights based on industry employment shares for the United States.

Source: OECD calculations based on the *Survey of Adult Skills* (2012).

4. Empirical model and results

4.1 Empirical model

36. To explore the link between mismatch and labour productivity, we estimate an industry level regression of the following form:

$$prod_{s,c}^{j} = \alpha + \beta_1 Mismatch_{s,c}^{k} + \delta_s + \delta_c + \varepsilon_{s,c} \qquad (2)$$

where: *prod* is a measure of labour productivity (weighted productivity, *within-firm* productivity and allocative efficiency) in country *c* and industry *s*, while *Mismatch* refers to the measures of qualification and skill mismatch and their components (under-skilled/qualified and over-skilled/qualified). The model controls for country and industry fixed effects, while standard errors are clustered at the country level. Including country fixed effects controls for omitted time-invariant country-specific factors that might affect labour productivity, while industry fixed effects control for common industry-specific technological factors, such as differences in the extent of natural competition across industries. Following Andrews and Cingano (2014), OLS regression estimates are weighted by available observations in each country-industry cell to control for outliers arising from the small number of observations in some cells.

37. The literature exploring the determinants of qualification and skill mismatch and their economic consequences suggest that skill and qualification mismatch can have different implications for productivity and there is no real consensus on which one can be more costly (Allen and van der Velden, 2001). For example, some studies claim that just looking at qualification mismatch exaggerates the adverse economic effects since only over-qualified workers who are also over-skilled should be considered a *real mismatch* (Green and Zhu, 2010). In order to address these concerns as well as take into account the fact that there is little overlap between the two types of mismatch (see Section 3.3), we include both qualification and skill mismatch in the baseline specification.[16] However, including these terms separately yields similar results.

38. In addition to the baseline specification, several other alternatives are considered based on the literature between mismatch and productivity.

- First, given the importance of competition for productivity, a Herfindahl index (calculated as $\sum_{i=1}^{N} s_i^2$ where s_i is the market share of firm *i* and *N* is the number of firms in an industry, using ORBIS data) is added to the baseline specification as a measure of market power, such that a higher value might be associated with lower competitive pressures. The use of the Herfindahl index to proxy competitive pressures reflects practical considerations. Alternative indicators, – *e.g.* mark-ups or product market regulation indices – while conceptually superior, are not readily available at the corresponding industry classification used in this paper.

- Second, as an extension to the baseline model, it is also possible to control for the overlap between skill and qualification mismatch by creating additional categories of mismatch – *e.g.* the share of workers who are both over-skilled and over-qualified – which is explored in detail in Appendix B. There are nine possible categories: *i*) over-qualified and under-skilled; *ii*) over-qualified and over-skilled; *iii*) over-qualified and well-matched in terms of skills; *iv*) under-qualified and under-skilled; *v*) under-qualified and over-skilled; *vi*) under-qualified and well-matched in terms of skills; *vii*) over-skilled and well-matched in terms of qualifications; *viii*) under-skilled and well-matched in terms of qualifications; and *ix*) well-matched in terms of both skills and qualifications (Table B1 in Appendix B). Looking at these additional categories can provide additional insight into the relationship between mismatch and productivity.

- Third, a new measure of managerial quality, based on the average literacy scores of managers in each country-industry cell using PIAAC data, is also included.

39. The analysis is undertaken with a view to establish a robust correlation between mismatch and labour productivity and should not be interpreted as causal for a number of reasons. First, in sectors with more reallocation, there is more scope to reduce mismatch. Second, there may be other factors that affect both mismatch and productivity. For example, better managed firms are more productive (Bloom and Van Reenen, 2010), while they may also be less susceptible to mismatch to the extent that better managers may

16 This is possible since the correlation between skill and qualification mismatch is low.

be more effective at: *i*) screening potential job applicants; *ii*) developing new work practices to more effectively integrate new technologies; *iii*) internally reallocating over-skilled/qualified workers to more productive uses within the firm; and *iv*) taking remedial measures and/or removing under-skilled/qualified workers from organisations. This raises the possibility that part of the correlation between mismatch and productivity could be due to managerial ability, which we explore in more depth in Section 4.3.3.

4.2 Baseline results

40. Table 1 shows the baseline results for three measures of industry productivity performance: weighted average productivity, allocative efficiency and *within-firm* productivity. The odd number columns include the aggregated mismatch variables (qualification and skill mismatch) while the even numbered columns decompose these measures into their constituent parts (e.g. under- and over-qualified/skilled). In the odd-numbered columns, the coefficients should be interpreted as the estimated impact of increasing the share of mismatched workers at the expense of the omitted category: the share of well-matched workers. In the even-numbered columns that include the respective components of mismatch, the coefficients should be interpreted as the impact on productivity of an increase in the share of a given category (*e.g.* over-skilled workers), at the expense of the omitted category (*i.e.* well-matched workers), holding constant all other components of mismatch (*i.e.* the share of under- and over-qualified and under-skilled workers). The results are shown for the 10th percentile definition of skill mismatch, while those using the 5th percentile definition are broadly similar (Table A4 in Appendix A). The estimates suggest that both qualification and skill mismatch are associated with lower labour productivity, though in each case, the mechanism varies.

Table 1. Baseline results of the link between mismatch and labour productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		*Within-firm* Productivity	
Over-qualified workers		0.0039 (0.009)		0.0005 (0.005)		0.0033 (0.005)
Under-qualified workers		-0.0216*** (0.007)		-0.0087* (0.005)		-0.0129** (0.005)
Over-skilled workers		-0.0094** (0.003)		-0.0124*** (0.004)		0.0030 (0.003)
Under-skilled workers		-0.0047 (0.004)		0.0016 (0.003)		-0.0063 (0.004)
Workers with qualification mismatch	-0.0077* (0.004)		-0.0070* (0.003)		-0.0007 (0.003)	
Workers with skill mismatch	-0.0036 (0.002)		-0.0045* (0.002)		0.0010 (0.001)	
AdjR2	0.887	0.901	0.601	0.636	0.924	0.930
Observations	205	205	205	205	205	205

1. The dependent variables are as defined in (1), computed for 2007. All specifications include country and industry fixed effects and are clustered by country. Observations are weighted by industry size—number of firms. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

2. Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled). Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10th (90th) percentile of the scores of the well-matched workers in each occupation and country.

41. Higher skill mismatch is associated with lower weighted average labour productivity, although the effect is not statistically significant (Column 1). However, higher skill mismatch has a negative relationship with allocative efficiency – the ability of more productive firms to attract resources to grow

(Column 3). By contrast, skill mismatch is uncorrelated with the *within-firm* productivity component (Column 5), which is important given that the existing literature predicts that skill mismatch should be related to productivity through this *within-firm* channel.

42. The aggregated measure of skill mismatch in Column 1 hides a strong and statistically significant negative relationship between the share of over-skilled workers and labour productivity (Columns 2 and 4), while the under-skilled component of skill mismatch, assuming that the worker is well-matched in terms of qualifications, is uncorrelated with labour productivity. Columns 4 and 6 show that the negative relationship between over-skilling and weighted average labour productivity is entirely realised through the channel of allocative efficiency, which suggests that that a higher incidence of over-skilling makes it more difficult for the most productive firms to gain market shares at the expense of less productive firms. In terms of economic significance, a one standard deviation increase in over-skilling – roughly equivalent to the difference in mismatch between Italy and the United States in Figure A1 – is associated with a 6% reduction in allocative efficiency and a 4% decrease in overall labour productivity.[17]

43. A higher percentage of workers with qualification mismatch is associated with lower labour productivity, with the coefficient in Column 1 implying that a one standard deviation increase in qualification mismatch – roughly equivalent to the difference between Estonia and the United States in Figure 2, Panel B – is associated with a 5% reduction in weighted average labour productivity.[18] Column 2 shows that the main source of this effect is under-qualified workers, while over-qualification, assuming that the worker is well-matched in terms of skills, is uncorrelated with labour productivity. With respect to economic magnitudes, the results suggest that a one standard deviation increase in the percentage of under-qualified workers – roughly equivalent to the difference in mismatch between Denmark and Belgium in Figure A1 – would be associated with a 10% decrease in overall labour productivity.[19]

44. Closer inspection reveals that the negative relationship between under-qualification and labour productivity is realised through both lower allocative efficiency and *within-firm* productivity, where the latter is predicted by the existing literature. The *within-firm* productivity component (Column 6) reflects the fact that in industries with a higher share of under-qualified workers, there is a lower ratio of high productivity to low productivity firms – which is consistent with research from Belgium (Mahy et al., 2013). A one standard deviation increase in the share of under-qualified workers – roughly equivalent to the difference in mismatch between Denmark and Belgium in Figure A1 – is associated with a 6% reduction in labour productivity. Under-qualification is also related to labour productivity through the channel of allocative efficiency, although the coefficient is only statistically significant at the 10% level. The economic impact is slightly more modest: a one standard deviation increase in under-qualification is associated with a 4% reduction via the allocative efficiency channel (Column 4).

4.3 Extensions and robustness tests

4.3.1 Controlling for market competition

45. Table 2 explores the robustness of the baseline results to controlling for the extent of competition which may influence both mismatch and labour productivity (Rodriguez Mora, 2007; see Box 1). More

17 Calculated as β*standard deviation of the percentage of over-skilled workers*100, that is, -0.0094*5.1*100 for productivity and -0.0124*5.1*100 for allocative efficiency.

18 Calculated as β*standard deviation of the percentage of workers with qualification mismatch*100, that is 0.079*6.6*100.

19 Calculated as β*standard deviation of the percentage of under-qualified workers*100, that is -0.0216*4.9*100 for productivity, -0.0087*4.9*100 for allocative efficiency and -0.0129*4.9*100 for within-firm productivity.

specifically, the baseline specification, which includes country and industry fixed effects, is augmented with a measure of market power, proxied by the Herfindahl index as described in Section 4.1. Results show that once the extent of market competition is controlled for, the main results remain intact, with coefficients very similar to the baseline specification. In addition, the negative relationship between skill mismatch and labour productivity becomes statistically significant at the 10% level (Column 1). Furthermore, as expected, less competition is correlated with lower weighted productivity and allocative efficiency.

Table 2. Mismatch and labour productivity: controlling for market competition

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		*Within-firm* Productivity	
Over-qualified workers		0.0049 (0.008)		0.0014 (0.005)		0.0035 (0.005)
Under-qualified workers		-0.0224*** (0.007)		-0.0094** (0.004)		-0.0131** (0.005)
Over-skilled workers		-0.0102** (0.004)		-0.0130*** (0.004)		0.0028 (0.003)
Under-skilled workers		-0.0057 (0.004)		0.0008 (0.003)		-0.0065 (0.004)
Workers with qualification mismatch	-0.0074* (0.004)		-0.0068* (0.004)		-0.0007 (0.003)	
Workers with skill mismatch	-0.0042* (0.002)		-0.0050** (0.002)		0.0009 (0.001)	
Herfindahl index	-3.1614*** (0.871)	-3.5212*** (1.099)	-2.6904*** (0.488)	-2.8232*** (0.665)	-0.4710 (0.543)	-0.6980 (0.591)
AdjR2	0.895	0.911	0.636	0.675	0.923	0.930
Observations	205	205	205	205	205	205

1. The dependent variables are as defined in (1), computed for 2007. All specifications include country and industry fixed effects and are clustered by country. Observations are weighted by industry size—number of firms. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

2. Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled). Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10^{th} (90^{th}) percentile of the scores of the well-matched workers in each occupation and country.

4.3.2 Controlling for the overlap between qualification and skill mismatch

46. On average, there is little overlap between qualification and skill mismatch across OECD countries, with only 9% of workers mismatched on both skills and qualifications. Nevertheless, it is useful to exploit this overlap in order to shed more light on the possible channels and to test the robustness of the baseline results. This might also help explain why over-skilling – but not over-qualification – should matter for allocative efficiency, while under-qualification – but not under-skilling – should matter for *within-firm* productivity. However, the results from this analysis should be interpreted with caution for two main reasons. First, increasing the potential number of categories of mismatch decreases the number of observations within each industry cell. Second, the higher number of variables in the regression analysis creates additional pressure from a degrees of freedom perspective, given the already small sample size.

47. While a detailed discussion of the results from this exercise is contained in Appendix B, a few key results warrant further discussion. First, the results for the overall mismatch measures highlight the robustness of the baseline model: while there is a negative relationship between having only qualification or only skill mismatch and labour productivity, the correlation of labour productivity with the share of respondents with *both* skills and qualifications mismatch is insignificant. Second, Table 3 reports the

results from including the overlap of the different components of qualification and skill mismatch, where the omitted category is the share of workers who are well-matched in terms of both skills and qualifications (these results can be compared to the even-numbered columns of Table 2). While these results are also broadly consistent with the baseline results, they paint a more nuanced picture. The negative relationship between under-qualification and labour productivity, which was shown to be significant in the baseline results, is mainly driven by under-qualified workers, who are well-matched in terms of skills (term 6). The main channel of this effect is allocative efficiency. However, column (3) of Table 3 also shows that the negative relationship between under-qualification and *within-firm* productivity observed in the baseline results is entirely driven by workers who are both under-qualified and under-skilled (term 4) such that increasing their share at the expense of well-matched workers in terms of qualifications and skills is associated with lower *within-firm* productivity.

Table 3. Mismatch and labour productivity: controlling for the overlap between the components of qualification and skill mismatch

	(1) Weighted Productivity	(2) Allocative Efficiency	(3) *Within-firm* Productivity
1. Over-qualified and under-skilled	**-0.0322*** (0.017)	-0.0263 (0.023)	-0.0059 (0.022)
2. Over-qualified and over-skilled	0.0157 (0.010)	**-0.0126***** (0.004)	**0.0282**** (0.011)
3. Over-qualified and well-matched (skill)	-0.0032 (0.009)	-0.0003 (0.006)	-0.0029 (0.005)
4. Under-qualified and under-skilled	-0.0166 (0.020)	0.0151 (0.015)	**-0.0317**** (0.014)
5. Under-qualified and over-skilled	0.0093 (0.018)	0.0044 (0.017)	0.0048 (0.023)
6. Under-qualified and well-matched (skill)	**-0.0200***** (0.004)	**-0.0191***** (0.005)	-0.0009 (0.006)
7. Over-skilled and well-matched (qualification)	**-0.0207***** (0.004)	**-0.0129***** (0.004)	-0.0078 (0.005)
8. Under-skilled and well-matched (qualification)	0.0046 (0.004)	-0.0040 (0.003)	0.0086 (0.005)
Herfindahl index	**-3.3932***** (1.067)	**-2.8125***** (0.677)	-0.5807 (0.513)
AdjR2	0.916	0.704	0.936
Observations	205	205	205

1. The dependent variables are as defined in (4), computed for 2007. All specifications include country and industry fixed effects and are clustered by country. Observations are weighted by industry size—number of firms. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

2. Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10th (90th) percentile of the scores of the well-matched workers in each occupation and country.

48. Third, with respect to over-skilling, Table 3 shows that a higher share of over-skilled workers who are well-matched in terms of qualification (term 7) is negatively correlated with allocative efficiency, which is consistent with the baseline estimates. This suggests that being only over-skilled (*i.e.* not over-qualified at the same time) might have a larger impact on productivity than just being over-qualified (*i.e.* not over-skilled at the same time). Fourth, a key result is that a higher share of workers who are both over-qualified and over-skilled (term 2) is positively associated with *within-firm* productivity, but negatively correlated with allocative efficiency. These findings imply that while having workers with a combination of over-skilling and over-qualification might be good for the firms who employ these workers, this does not necessarily translate into an increase in the economy-wide labour productivity to the extent that this

constrains the growth of other relatively more productive firms that could more efficiently utilise these skills.

4.3.3 Controlling for managerial quality

49. Recent research has shown that higher managerial quality improves firm and aggregate productivity (Bloom et al., 2012 and 2013a). The benefits of superior management practices on productivity are largely realised through *within-firm* effects, such as the use of modern HR practices (*e.g.* monitoring) and organisational restructuring to promote more efficient technological adoption, as opposed to higher allocative efficiency. While this literature has not specifically analysed the nexus between managerial quality and mismatch, it is plausible that better managers will also be more effective at matching the qualifications, knowledge, skills and competencies of a worker to those required by a job (see Section 4.1 for more details).

50. In order to analyse the links between managerial quality, mismatch and productivity, we consider several options. First, the relationship between a new measure of managerial quality (proxied by the average literacy scores of managers in each industry and country) and the various measures of mismatch and productivity, is considered.[20] Consistent with the channels discussed above, Table A6 in Appendix A shows that higher managerial quality is associated with higher labour productivity through the *within-firm* (unweighted) productivity channel, while the relationship of managerial quality with allocative efficiency is not significant. Furthermore, managerial quality is correlated with under-skilling and under-qualification (Table A7, Panel A in Appendix A), which have a significant and negative relationship with *within-firm* labour productivity (see Tables 1 and 3).

51. Consistent with the above prediction, Table 4 shows that managerial quality is correlated with labour productivity through the *within-firm* productivity channel. More interestingly, the impact of under-qualification on *within-firm* productivity becomes insignificant, suggesting that most of the effect is accounted for by differences in managerial quality. Controlling for managerial quality in regressions using the overlap of the components of mismatch also shows that most of the impact of under-qualification and under-skilling is due to differences in managerial quality (see Appendix B). Similar results are obtained when the different measures of mismatch are instrumented using the managerial quality indicator. Indeed, the second stage estimates in Panel B of Table A7 (see Appendix A) indicate that the relationship between *within-firm* productivity and under-qualification is predominantly explained by the variation in under-qualification that is predicted by managerial quality.[21] In terms of economic significance, a one standard deviation increase in managerial quality – roughly equivalent to moving from the sample average to the high level in Sweden – is associated with a 9% increase in *within-firm* productivity.

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20 Managerial quality indicators from the World Management Survey (WMS) data (see Bloom et al., 2012) are not utilised to the extent that they are only available for a subset of countries and industries in our sample. However, many of the countries that rank highly according to the WMS data also perform well according to the PIAAC data (e.g. Japan, Germany, Sweden and to a less extent, the United States).

21 This exercise is undertaken purely to demonstrate the idea that mismatch is a potential channel through which managerial quality may influence productivity. Of course, these results should be interpreted with caution to the extent that the exclusion restriction is clearly violated given that management may affect productivity through channels other than mismatch.

Table 4. Mismatch and labour productivity: controlling for managerial quality

	(1) Weighted Productivity	(2) Allocative Efficiency	(3) *Within-firm* Productivity
Over-qualified workers	0.0060 (0.008)	-0.0001 (0.006)	0.0061 (0.006)
Under-qualified workers	-0.0195*** (0.007)	-0.0122** (0.006)	-0.0073 (0.005)
Over-skilled workers	-0.0108*** (0.004)	-0.0124*** (0.004)	0.0016 (0.003)
Under-skilled workers	-0.0038 (0.004)	-0.0016 (0.003)	-0.0022 (0.004)
Herfindahl index	-3.6242*** (1.073)	-2.7424*** (0.696)	-0.8818* (0.461)
Mean scores of managers	0.0028 (0.002)	-0.0030 (0.002)	0.0059** (0.003)
AdjR2	0.911	0.680	0.935
Observations	201	201	201

1. The dependent variables are as defined in (1), computed for 2007. All specifications include country and industry fixed effects and are clustered by country. Observations are weighted by industry size—number of firms. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

2. Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled). Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10^{th} (90^{th}) percentile of the scores of the well-matched workers in each occupation and country.

4.3.4 Other sensitivity tests

52. The baseline results reported in Table 1 are broadly robust to a number of sensitivity tests. Instead of using ORBIS data from 2007, estimations using data for 2005 and 2006 as well as an average of 2005-07 yield similar results. The baseline coefficients are also broadly robust to excluding one country and industry from the sample at a time and to changing the omitted category, which is the share of well-matched workers in the baseline specification.[22] Finally, given the large literature on the relationship between skill levels and productivity, the baseline results are robust to including the mean proficiency score for each industry, which turns out to be positively correlated with productivity.

53. Although industry fixed effects play a relatively small role in explaining cross-country industry variation in mismatch, we also explored whether the link between mismatch and productivity varied according to the technological characteristics of the industry. For example, it could be of interest to policymakers if mismatch disproportionately affected productivity in emerging knowledge-based capital (KBC)-intensive sectors, which are expected to become increasingly important for economic growth. To test this hypothesis, we interacted the mismatch indicators with measures of sectoral R&D, KBC and ICT intensity, using data from the United States. However, this analysis did not yield any meaningful results, possibly reflecting the fact that there was insufficient variation at the 1-digit level in these indicators.

4.4 Skill mismatch and cross-country gaps in labour productivity

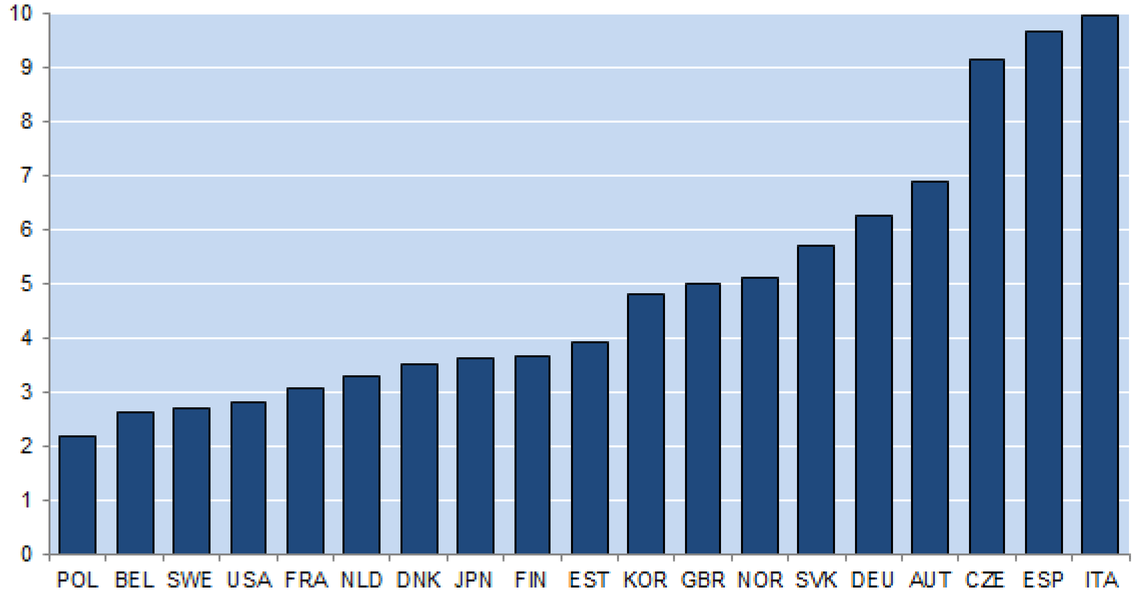
54. Assuming the relationship is causal, the economic significance of the results can be illustrated by estimating the potential gain to labour productivity under a counterfactual scenario where skill mismatch in each country is reduced to the best practice level in each industry. We concentrate on skill mismatch rather

22 The analysis in Table A5 in Appendix A repeats the exercise using over-qualified and over-skilled workers or under-qualified and under-skilled workers as the omitted category and yields broadly similar results.

than qualification mismatch to the extent that qualifications become less relevant for workplace performance over time, than skills (see OECD, 2013). In turn, these 1-digit industry level mismatch indicators are aggregated using industry employment shares for the United States as weights to calculate the weighted average difference in the actual and the counterfactual productivity in each country. Aggregation based on United States employment shares is performed for practical purposes, to the extent that employment data on the ISIC Rev. 4 industry classification basis – on which the industry identifiers in PIAAC are defined – are not yet available for seven countries in the sample. However, the choice between using country-specific or United States employment shares in the aggregation does not materially affect the results, at least for the 11 countries (other than the US) in the sample for which ISIC Rev. 4 data are available (see Figure A2 in Appendix A). This result is consistent with the fact that the industry fixed effects play a relatively small role in explaining the cross-country industry variation in skill mismatch (Table A3).

Figure 3. Counterfactual productivity gains from reducing skill mismatch

Simulated gains to allocative efficiency from lowering skill mismatch to the best practice; per cent



Note: The chart shows the difference between the actual allocative efficiency and a counterfactual allocative efficiency based on lowering the skill mismatch in each country to the best practice level of mismatch. Both the actual and counterfactual numbers are calculated by aggregating 1-digit industry level mismatch indicators using a common set of weights based on the industry employment shares for the United States. For example, lowering the skill mismatch to best practice leads to a simulated gain of around 10% in Italy and 3% in the United States.

Source: OECD calculations based on the *Survey of Adult Skills* (2012).

55. Figure 3 plots the simulated gains to allocative efficiency from lowering skill mismatch to the best practice.[23] If interpreted causally, this exercise suggests reducing skill mismatch in countries such as Italy and Spain to the best practice level would be associated with an increase in allocative efficiency of around 10%, which would account for about roughly one-fifth of the gap in non-farm business sector

23 This exercise focuses on allocative efficiency (AE) as opposed to weighted productivity (WP) to the extent that fewer cross-country or cross-sector comparability issues arise with respect to the former, compared to the latter (see Section 3.1). Moreover, the link between skill mismatch and WP is realised through AE, while the mismatch-AE relationship is also more precisely estimated than the mismatch-WP link.

allocative efficiency between Italy and the United States (or Sweden), for example.[24] From this perspective, skill mismatch has the potential to explain a non-trivial share of cross-country labour productivity gaps.

56. More speculatively, the same exercise can be extended to countries that are not in our sample due to lack of productivity data, but are included in the PIAAC sample (Figure C2 in Appendix C). The estimates suggest that lowering the skill mismatch to best practice would be associated with an increase in allocative efficiency of 8% for Ireland, 6% in Australia and 2% for Canada. Of course, it is not possible to calculate how much reducing skill mismatch can explain cross-country productivity gaps for these countries due to a lack of productivity data.

5. Policy discussion

57. If interpreted causally, the estimates in this paper suggest that mismatch is one factor that may contribute to explaining cross-country differences in labour productivity. However, the question remains as to what are the policy and structural factors that determine mismatch. While this is addressed in more detail in a companion paper (see Adalet McGowan and Andrews, 2015), this section provides some preliminary insights into the types of policies that may be relevant. To the extent that mismatch is related to productivity through more than one channel, it is important to consider policies that work through both *within-firm* and *between-firm* factors.

58. As discussed in the previous section, differences in managerial quality can potentially account for the strong association between under-qualification and *within-firm* productivity. From a policy perspective, the question then becomes what determines managerial quality. Recent research (see Bloom et al., 2014) identifies four possible explanations: *i*) competition; *ii*) regulations affecting product and labour markets; *iii*) ownership structure (*e.g.* managerial quality is highest in MNEs and lowest in family managed firms); and *iv*) education. It is also possible that policies may shape the ability of managers to reduce mismatch within firms at any given level of managerial quality. For example, using Microdata from PIAAC, Adalet McGowan and Andrews (2015) find that the negative correlation between skill mismatch and managerial quality is lower in countries with more stringent employment protection legislation (EPL). This suggests that stringent firing regulations may thwart the ability of managers to reduce mismatch for any given level of managerial quality.

59. While improvements in the quality of management can lead to high productivity within firms, from the perspective of the economy as a whole, these gains will be maximised when the most effective managers command a larger share of the economy's resources. Indeed, this is the case on average across OECD countries, with larger firms tending to have better managers than smaller firms (Figure 4, Panel A).[25] However, some interesting cross-country differences emerge, with the monotonic pattern (observed in Figure 4, Panel A) particularly pronounced in Sweden, while there is no apparent relationship between managerial quality and firm size in Poland (Figure 4, Panel B).[26] These findings, which suggest that some countries are more successful at channelling resources to better managers than others, are broadly consistent with evidence from Bloom et al. (2013b), which use data from the *World Management Survey* to measure the core managerial practices in the areas of: monitoring, targets and incentives.

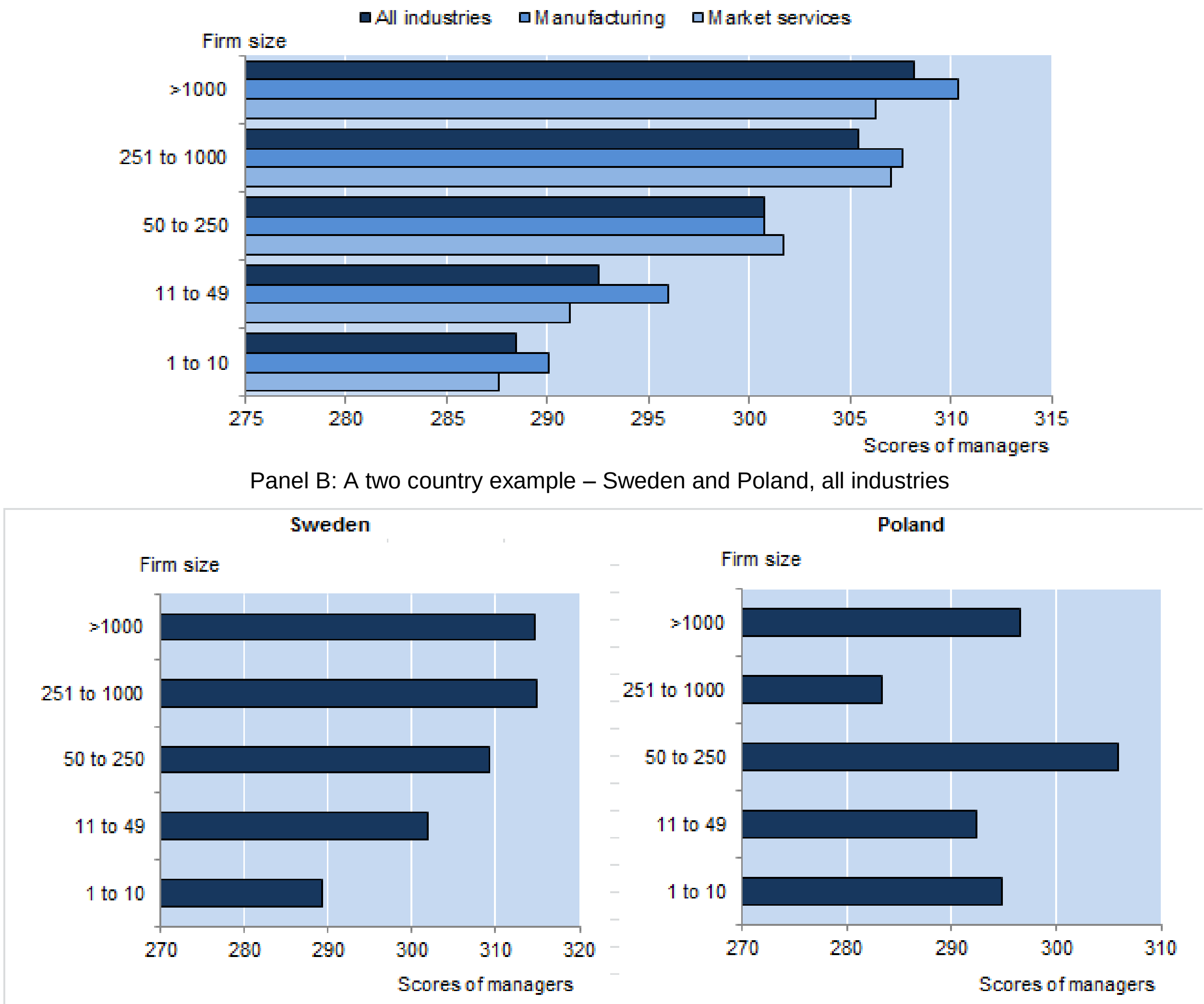
24 This is calculated as: the difference between the gains to allocative efficiency from lowering skill mismatch to best practice in Italy and the United States (7.13 = 9.96-2.83) divided by the difference between business sector allocative efficiency in the United States and Italy (0.38=0.37- (-0.01)).

25 This analysis complements that in OECD (2014b) that uses PIAAC data to show that larger firms are better at rewarding skills and adjusting rewards after hiring as actual skills of workers are revealed.

26 These patterns are symptomatic of differences in the efficiency of resource allocation across the two economies (Andrews and Cingano, 2014).

Figure 4. Managerial quality across industries and firm size

Panel A: Average across selected OECD economies; industry break-down



Notes: Firm size is measured as the number of employees at the firm. Average scores of managers refer to the average of the proficiency scores (in literacy) of managers in each country. Panel A is an unweighted average of the scores of managers in the 22 OECD countries in the PIAAC sample (see Box 3).

Source: OECD calculations based on the *Survey of Adult Skills* (2012).

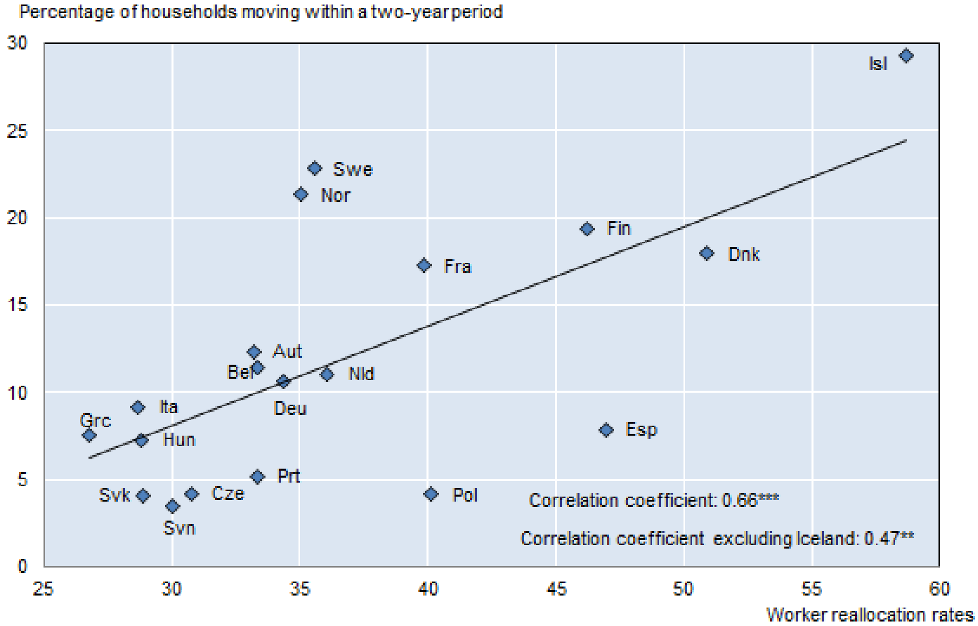
60. The strong negative relationship between skill mismatch (*i.e.* over-skilling) and labour productivity via the allocative efficiency channel suggests that research on the policy determinants of skill mismatch should focus particularly on those policy factors that impose frictions to the efficient reallocation of labour. Previous research has highlighted the adverse effects of stringent regulations affecting product and labour markets and bankruptcy legislation that excessively penalises business failure on the efficiency of resource allocation (Andrews and Cingano, 2014). These same policy distortions also appear to be positively correlated with skill mismatch (Adalet McGowan and Andrews, 2015), suggesting that skill mismatch is a potential channel through which framework policies may impact labour productivity. Moreover, policies that distort reallocation mechanisms – *e.g.* stringent EPL – tend to disproportionately raise the incidence of skill mismatch amongst young people. Indeed, labour market fluidity is particularly important for the job prospects of youth, since it provides scope to improve the quality of job-worker

matching, which is naturally lower amongst young people due to their lack of experience (Davis and Haltiwanger, 2014).

61. Low residential mobility may pose another barrier to the efficient reallocation of labour. Across OECD countries, there is a positive correlation between residential mobility and worker reallocation rates (Figure 5), which is significant to the extent that skill mismatch is related to productivity via the reallocation channel. Indeed, policy interventions in housing markets, such as high transaction costs or pro-tenant rental market regulations, have been shown to reduce residential mobility (Andrews et al., 2011), and these policies are also positively correlated with skill for mismatch (Adalet McGowan and Andrews, 2015). Moreover, high transaction costs and strict rental market regulations are associated with disproportionately higher mismatch amongst youth. Such policies might be more relevant for young people since they have a naturally higher propensity to move (Caldera Sánchez and Andrews, 2011) and may have fewer resources to finance the higher moving costs that these policies imply.

Figure 5. Residential mobility and worker reallocation rates

Selected OECD countries



Notes: Worker reallocation rates are country averages of reallocation rates (hiring and firing rates) expressed in percentage of total dependent employment (adjusted for industry composition). The data are sourced from OECD (2010) and refer to 2000-07 except for Austria, Iceland, Slovenia: 2002-07; Canada, Denmark, France, Germany, Italy, Portugal, Sweden and the United States: 2000-06; the Czech Republic: 2001-07; Greece, Hungary, Ireland, Spain: 2000-05; Norway: 2000-04; Poland: 2004-05; the Slovak Republic: 2002-06; and Turkey: 2007. Residential mobility data are from Andrews et al. (2011) based on 2007 EU-SILC Database, on HILDA for Australia, AHS for the United States and SHP for Switzerland. *** denotes statistical significant at 1% level; ** denotes statistical significant at 5% level.

Source: Andrews et al. (2011) and OECD (2010), *Employment Outlook*, Paris.

6. Conclusion

62. This paper explores the link between skill and qualification mismatch and labour productivity using cross-country industry data for 19 OECD countries. Utilising mismatch indicators aggregated from micro-data sourced from the recent *OECD Survey of Adult Skills*, the main results suggest that higher skill and qualification mismatch is associated with lower labour productivity, with over-skilling and under-qualification accounting for most of these impacts. The channels that link these respective components of mismatch to productivity vary. A novel result is that higher skill mismatch is associated with lower labour

productivity through a less efficient allocation of resources, presumably because when the share of over-skilled workers is higher, more productive firms find it more difficult to attract skilled labour and gain market shares at the expense of less productive firms. At the same time, a higher share of under-qualified workers is associated with both lower allocative efficiency and *within-firm* productivity – *i.e.* a lower ratio of high productivity to low productivity firms. Additional analysis shows that a higher share of workers who are both over-qualified and over-skilled is positively associated with *within-firm* productivity, but negatively correlated with allocative efficiency. Furthermore, the negative relationship between under-qualification and *within-firm* productivity is entirely driven by workers who are both under-qualified and under-skilled. While this finding is consistent with previous research in this area, additional analysis suggests that differences in managerial quality can potentially account for the relationship between under-qualification and under-skilling, and *within-firm* productivity.

63. The analysis does not address the causal impact of mismatch on productivity as in sectors with more reallocation, there is more scope to reduce mismatch. Nevertheless, the finding of a robust negative correlation between mismatch and productivity suggests that mismatch is a relevant structural indicator that is worthy of monitoring in cross-country structural surveillance exercises. At the same time, the analysis highlights the value of cross-country micro-data sources such as the *OECD Survey of Adult Skills* to understanding the sources of cross-country differences in living standards.

64. More generally, this paper adds further weight to the idea that policymakers should not only be concerned with increasing the stock of human capital, but also with allocating the existing stock of human capital more efficiently. The latter is likely to take on heightened importance over coming decades to the extent that the growth in the stock of human capital is projected to slow, which implies a moderation in economic growth but also an increase in income inequality within countries, given that the demand for skills is likely to increase (Braconier et al., 2014). Moreover, reducing mismatch may be beneficial to growth in the short-to-medium term to the extent that the benefits of human capital-augmenting policies take a long time to be realised, while it may also enhance the ‘bang-for-the-buck’ – *i.e.* the productivity impacts – of such policies in the longer run. Of course, the question of what determines mismatch remains, and a companion paper explores the policy correlates of mismatch using micro-data from PIAAC (see Adalet McGowan and Andrews, 2015).

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APPENDIX A

Table A1. Descriptive statistics of mismatch

	Mean	Standard Deviation	Minimum	Maximum	p5	p10	p50	p90	p95
Under-qualified	13.33	7.77	0.00	40.80	1.70	3.50	12.60	23.20	26.80
Over-qualified	21.41	11.13	0.00	58.30	4.60	7.50	20.70	36.20	40.60
Qualification mismatch	34.75	11.73	0.00	62.10	16.20	20.80	34.55	49.10	51.90
5% definition									
Under-skilled	3.39	3.73	0.00	24.20	0.00	0.00	2.50	6.80	10.70
Over-skilled	10.65	6.74	0.00	35.80	0.00	4.00	9.55	20.40	23.80
Skill mismatch	14.05	7.06	0.00	40.30	3.80	6.70	13.25	23.80	26.90
10% definition									
Under-skilled	6.79	5.83	0.00	36.30	0.00	0.00	6.15	12.50	20.00
Over-skilled	17.05	8.53	0.00	49.20	4.70	8.00	15.70	28.60	31.20
Skill mismatch	23.84	9.30	0.00	63.70	11.00	13.90	23.00	34.50	39.00
2.5% definition									
Under-skilled	2.14	3.23	0.00	24.20	0.00	0.00	1.15	5.20	6.20
Over-skilled	7.39	6.53	0.00	35.80	0.00	0.00	5.50	16.60	20.90
Skill mismatch	9.54	7.13	0.00	40.30	0.00	2.30	7.60	20.10	24.10

Note: Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled). Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 2.5th/5th/10th (97.5th/95th/90th) percentile of the scores of the well-matched workers in each occupation and country.

Table A2. Correlations between various measures of skill mismatch

Under-skilled	**5%**	**10%**	**2.5%**
5%	1		
10%	0.748	1	
2.5%	0.871	0.605	1
Over-skilled	**5%**	**10%**	**2.5%**
5%	1		
10%	0.829	1	
2.5%	0.889	0.690	1
Skill mismatch	**5%**	**10%**	**2.5%**
5%	1		
10%	0.761	1	
2.5%	0.874	0.605	1

Note: Workers with skill mismatch refer to the percentage of workers who are either over- or under-skilled. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 2.5th/5th/10th (97.5th/95th/90th) percentile of the scores of the well-matched workers in each occupation and country.

Table A3. Mismatch: analysis of variance

	Skill mismatch	Overskilled	Underskilled	Qualification mismatch	Overqualified	Underqualified
Country effects only	0.327	0.362	0.296	0.313	0.226	0.452
Industry effects only	0.063	0.169	0.104	0.262	0.443	0.095
Country and industry fixed effects	0.390	0.529	0.400	0.577	0.666	0.543
Observations	205	205	205	205	205	205

Note: Adjusted R-squared of fixed effects regressions on qualification and skill mismatch.

Table A4. Mismatch and labour productivity: using the 5% definition of skill mismatch

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		*Within-firm* Productivity	
Over-qualified workers		0.0035 (0.008)		-0.0002 (0.005)		0.0038 (0.006)
Under-qualified workers		-0.0187** (0.007)		-0.0065 (0.005)		-0.0122** (0.004)
Over-skilled workers		-0.0095 (0.007)		-0.0092** (0.004)		-0.0003 (0.005)
Under-skilled workers		0.0010 (0.005)		0.0097* (0.005)		-0.0086 (0.005)
Workers with qualification mismatch	-0.0079* (0.004)		-0.0072* (0.003)		-0.0007 (0.004)	
Workers with skill mismatch	-0.0053 (0.005)		-0.0032 (0.003)		-0.0021 (0.004)	
AdjR2	0.888	0.900	0.595	0.626	0.924	0.929
Observations	205	205	205	205	205	205

1. The dependent variables are as defined in (1), computed for 2007. All specifications include country and industry fixed effects and are clustered by country. Observations are weighted by industry size—number of firms. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

2. Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled). Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 5th(95th) percentile of the scores of the well-matched workers in each occupation and country.

Table A5. Mismatch and labour productivity: using a different base case (well-matched workers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		*Within-firm* Productivity	
Under-qualified workers	-0.0273*		-0.0108		-0.0165**	
	(0.013)		(0.007)		(0.008)	
Well-matched workers (qualification)	-0.0049	0.0226***	-0.0014	0.0094**	-0.0035	0.0132**
	(0.008)	(0.007)	(0.005)	(0.004)	(0.005)	(0.005)
Under-skilled workers	0.0045		0.0138**		-0.0093	
	(0.004)		(0.005)		(0.007)	
Well-matched workers (skill)	0.0102**	0.0057	0.0130***	-0.0008	-0.0028	0.0065
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Overqualified workers		0.0274*		0.0107		0.0167**
		(0.013)		(0.007)		(0.008)
Over-skilled workers		-0.0045		-0.0138**		0.0094
		(0.004)		(0.005)		(0.007)
Herfindahl index	-3.5213***	-3.5162***	-2.8238***	-2.8205***	-0.6975	-0.6957
	(1.097)	(1.099)	(0.665)	(0.664)	(0.590)	(0.593)
Observations	205	205	205	205	205	205
$AdjR^2$	0.911	0.911	0.675	0.675	0.930	0.930

1. The dependent variables are as defined in (1), computed for 2007. All specifications include country and industry fixed effects and are clustered by country. Observations are weighted by industry size—number of firms. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

2. Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled). Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10^{th}(90^{th}) percentile of the scores of the well-matched workers in each occupation and country.

Table A6. The link between managerial quality and labour productivity

	(1)	(2)	(3)
	Weighted Productivity	Allocative Efficiency	*Within-firm* Productivity
Mean scores of manag	0.0042*	-0.0021	0.0063***
	(0.002)	(0.002)	(0.002)
Constant	3.8248***	1.0113	2.8135***
	(0.694)	(0.612)	(0.655)
Observations	201	201	201
AdjR2	0.887	0.574	0.932

1. The dependent variables are as defined in (1), computed for 2007. All specifications include country and industry fixed effects. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

Table A7. Instrumental variables estimation of the link between mismatch, managerial quality and labour productivity

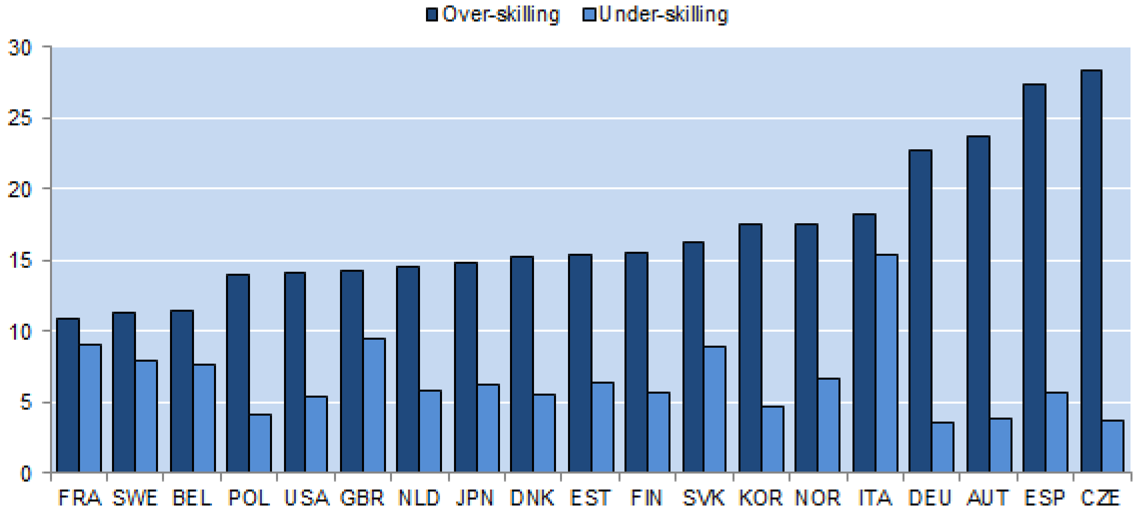
	Panel A: First Stage Regressions – dependent variable: mismatch indicators					
	(1)	(2)	(3)	(4)	(5)	(6)
	Qualification mismatch	*Underqualified*	*Overqualified*	*Skill Mismatch*	*Underskilled*	*Overskilled*
Mean scores of managers	-0.0569 (0.043)	-0.0651** (0.024)	0.0083 (0.031)	-0.0896* (0.048)	-0.1020*** (0.020)	0.0124 (0.036)
Constant	55.0250*** (13.110)	36.4229*** (7.606)	18.6021* (9.375)	56.1689*** (14.429)	34.2382*** (5.985)	21.9306* (10.731)
Observations	201	201	201	201	201	201
AdjR2	0.535	0.525	0.647	0.298	0.350	0.454

	Panel B: Second Stage – dependent variable: labour productivity indicators					
	(1)	(2)	(3)	(4)	(5)	(6)
	Qualification mismatch	*Underqualified*	*Overqualified*	*Skill Mismatch*	*Underskilled*	*Overskilled*
Weighted Productivity	-0.0250* (0.015)	-0.0389** (0.017)	-0.0701 (0.074)	-0.0663 (0.063)	-0.0561* (0.034)	0.3652 (1.490)
Allocative Efficiency	0.0128 (0.014)	0.0199 (0.020)	0.0357 (0.049)	0.0338 (0.064)	0.0286 (0.036)	-0.1862 (0.595)
Within-firm Productivity	-0.0378* (0.022)	-0.0588** (0.024)	-0.1058 (0.109)	-0.1001 (0.122)	-0.0847 (0.058)	0.5514 (2.075)
Observations	201	201	201	201	201	201

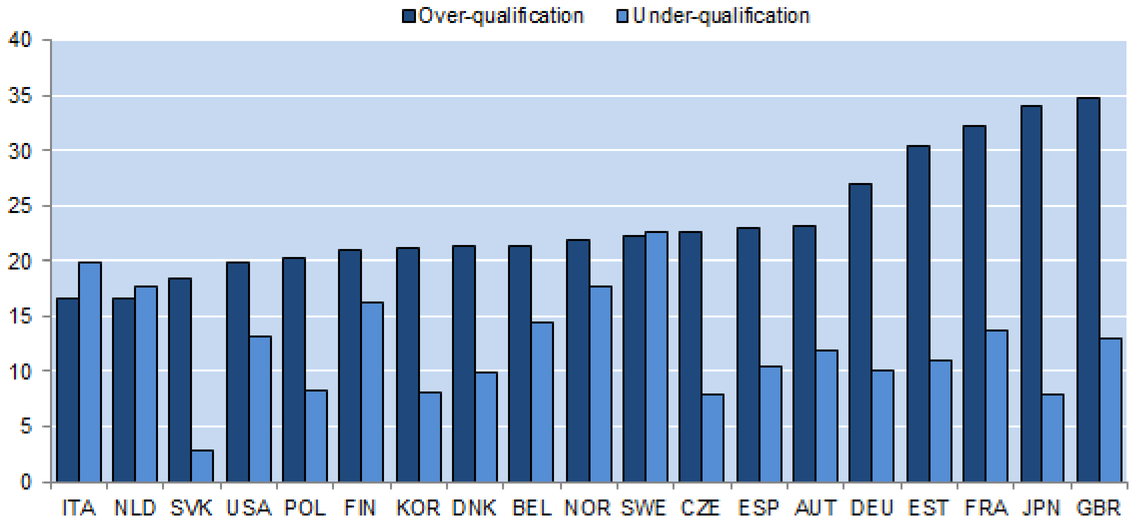
1. The dependent variables in Panel B are as defined in (1), computed for 2007. In each column of Panel B, the relevant mismatch measure is included separately. All specifications include country and industry fixed effects. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

Figure A1. Components of skill and qualification mismatch

Panel A: Under-skilled and over-skilled workers



Panel B: Under-qualified and over-qualified workers

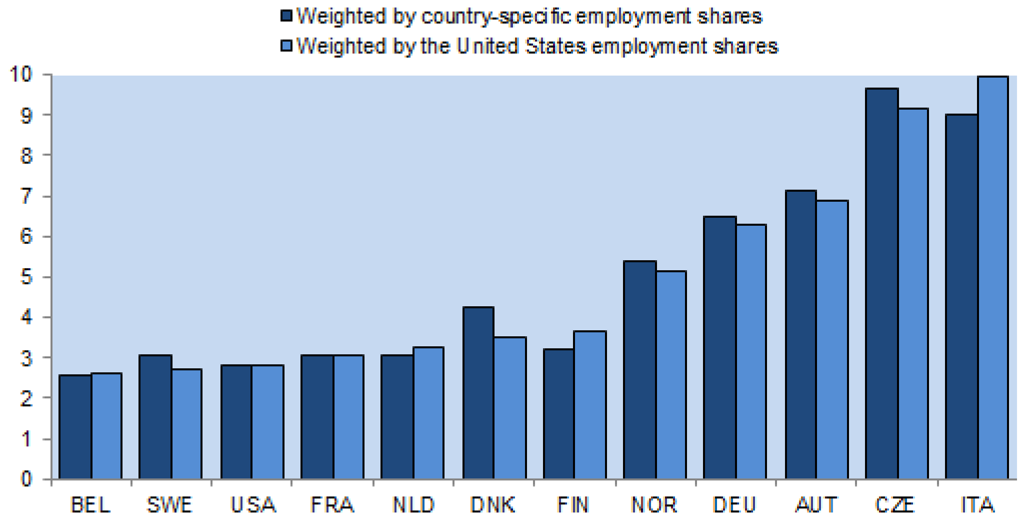


Note: The figures are calculated from the cross-country industry data from the sample described in Section 3.2. Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10th (90th) percentile of the scores of the well-matched workers in each occupation and country. In order to abstract from differences in industrial structures across countries, the 1-digit industry level mismatch indicators are aggregated using a common set of weights based on industry employment shares for the United States.

Source: OECD calculations based on the *Survey of Adult Skills* (2012).

Figure A2. Counterfactual productivity gains from reducing skill mismatch: robustness to aggregation method

Simulated gains to allocative efficiency from lowering skill mismatch to the best practice; per cent



Note: The chart shows the difference between the actual allocative efficiency and a counterfactual allocative efficiency based on lowering the skill mismatch in each country to the best practice level of mismatch. Both the actual and counterfactual numbers for each country are calculated by aggregating 1-digit industry level mismatch indicators both using weights based on their industry employment shares and those for the United States. As noted in Section 4.4, industry weights on the ISIC Rev. 4 basis are not available for the following seven countries in the sample: ESP, EST, GBR, JPN, KOR, POL and SVK.

Source: OECD calculations based on the *Survey of Adult Skills* (2012).

APPENDIX B

1. On average, across OECD countries, only 15% of workers have skill mismatch, despite being well-matched in terms of qualifications, while 27% are only mismatched in terms of qualifications but well-matched in terms of skills. There is little overlap between qualification and skill mismatch, with on average only 9% of workers mismatched on both skills and qualifications. Looking at the different components of mismatch shows that the majority of the overlap is driven by workers who are over-skilled and over-qualified (Table B1). Given the literature that shows that the implications of qualification and skill mismatch may be different for productivity as well as the baseline results presented in the paper, it would be useful to control for this overlap in the regression analysis. However, there are two main issues that make it crucial to interpret these results with extreme caution. First, increasing the potential number of categories of mismatch decreases the number of observations in each industry cell. Second, the higher number of variables in the regression analysis creates additional pressure from a degrees of freedom perspective, given the already small sample size of 205 observations.

Table B1. The overlap between qualification and skill mismatch

Selected OECD countries

	% of workers		% of workers
Over-qualified and under-skilled	1.2	Under-qualified and well-matched (skill)	10.4
Over-qualified and over-skilled	5.0	Over-skilled and well-matched (qualification)	11.0
Over-qualified and well-matched (skill)	16.7	Under-skilled and well-matched (qualification)	4.0
Under-qualified and under-skilled	1.3	Well-matched (skill and qualification)	49.0
Under-qualified and over-skilled	1.5		

Note: Based on the sample of the paper so the figures may vary somewhat from those reported in OECD (2013).

Source: OECD calculations based on the Survey of Adult Skills (2012).

Empirical Model

2. The first specification uses the aggregate definitions of skill and qualification mismatch (as defined in Sections 2 and 3) and estimates an industry level regression of the following form:

$$prod^{j}_{s,c} = \alpha + \beta_1 BOTH_{s,c} + \beta_2 QMM_{s,c} + \beta_3 SMM_{s,c} + \beta_4 HERF_{s,c} + \delta_s + \delta_c + \varepsilon_{s,c} \qquad (3)$$

where: *prod* is a measure of labour productivity (weighted productivity, *within-firm* productivity and allocative efficiency) in country *c* and industry *s*, while *BOTH* refers to the share of respondents with both qualification and skill mismatch, *QMM* to the share with only qualification mismatch and *SMM* to respondents with only skill mismatch. *HERF* refers to a Herfindahl index that measures market power and is included to control for competition.[27] The omitted category is the percentage of workers who are well-matched in terms of both skills and qualifications. The coefficients should be interpreted as the impact on productivity of an increase in the share of a given category (*e.g.* workers with qualification mismatch only) at the expense of the omitted category, holding constant all other categories constant (*i.e.* workers with skill mismatch only and workers who have both skill and qualification mismatch).

3. The second specification uses the overlap between the different components of skill and qualification mismatch and estimates an industry level regression of the following form:

$$prod_{s,c}^{j} = \alpha + \beta_1 OVERLAP_{s,c}^{k} + \beta_2 HERF_{s,c} + \delta_s + \delta_c + \varepsilon_{s,c} \qquad (4)$$

where: *prod* is a measure of labour productivity (weighted productivity, *within-firm* productivity and allocative efficiency) in country *c* and industry *s*, while *OVERLAP* refers to the different combinations of the overlap between qualification and skill mismatch. There are 9 potential categories (k=9): over-qualified and under-skilled; over-qualified and over-skilled; over-qualified and well-matched in terms of skills; under-qualified and under-skilled; under-qualified and over-skilled; under-qualified and well-matched in terms of skills; over-skilled and well-matched in terms of qualifications; under-skilled and well-matched in terms of qualifications; and well-matched in terms of both skills and qualifications. *HERF* is the Herfindahl index, as described above. The omitted category is the share of workers who are well-matched in terms of both skills and qualifications.

4. Similar to the baseline model in the paper, these specifications control for country and industry fixed effects, while standard errors are clustered at the country level. Following Andrews and Cingano (2014), OLS regression estimates are weighted by available observations in each country-industry cell to control for outliers arising from the small number of observations in some cells.

Results

5. Table B2 reports the results from the estimation of equation (3). The results are consistent with those reported in the odd-numbered columns of Table 2, which do not take into consideration the overlap between qualification and skill mismatch for each individual, but instead use aggregate measures of mismatch. More specifically, there is a negative relationship between having only qualification or only skill mismatch and labour productivity. The main channel of this effect is allocative efficiency, the ability of more productive firms to attract more labour. The relationship between having both qualification and skill mismatch and labour productivity is not statistically significant. These results indicate that as discussed in the paper, skill and qualification mismatch measure different aspects of the suitability of a worker for their job and it is useful to consider both to determine their impact on productivity.

27 Calculated as $\sum_{i=1}^{N} s_i^2$ where si is the market share of firm i and N is the number of firms in an industry, using ORBIS data.

Table B2. Mismatch and labour productivity: controlling for the overlap between qualification and skill mismatch

	(1) Weighted Productivity	(2) Allocative Efficiency	(3) *Within-firm* Productivity
Workers with qualification and skill mismatch	0.0025	-0.0044	0.0069
	(0.007)	(0.003)	(0.006)
Workers with only qualification mismatch	**-0.0132****	**-0.0098***	-0.0034
	(0.006)	(0.005)	(0.004)
Workers with only skill mismatch	**-0.0102****	**-0.0084***	-0.0018
	(0.004)	(0.004)	(0.002)
Herfindahl index	**-3.0567*****	**-2.6400*****	-0.4167
	(0.935)	(0.516)	(0.574)
AdjR2	0.902	0.645	0.924
Observations	205	205	205

1. The dependent variables are as defined in (3), computed for 2007. All specifications include country and industry fixed effects and are clustered by country. Observations are weighted by industry size—number of firms. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

2. Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled). Under- (over-) qualified workers refer to the percentage of workers whose highest qualification is lower (higher) than the qualification they think is necessary to get their job today. Under- (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10^{th}(90^{th}) percentile of the scores of the well-matched workers in each occupation and country.

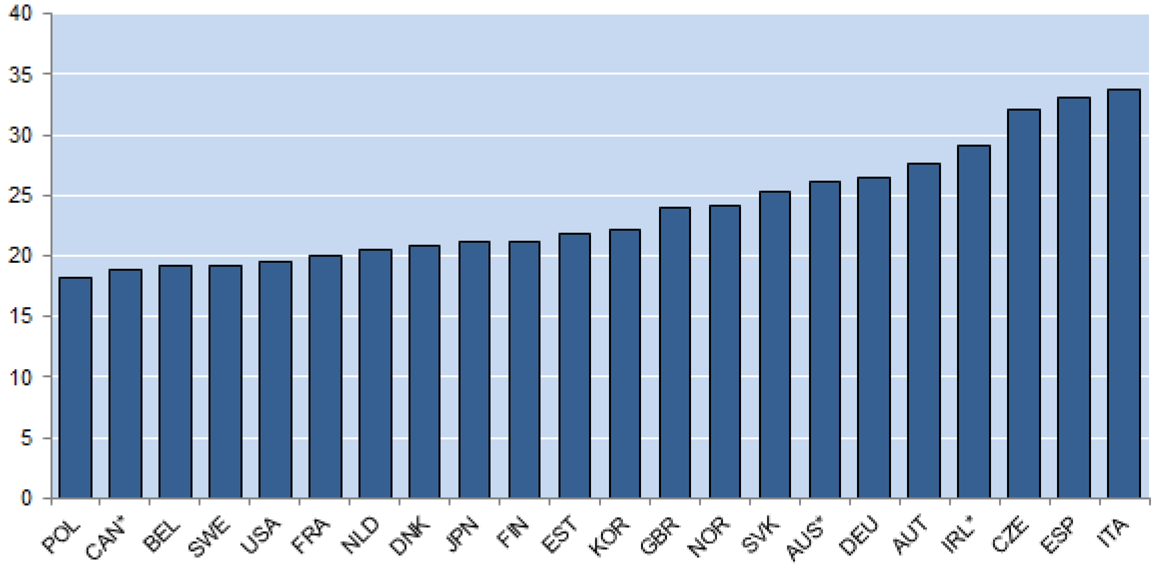
6. Table 3 in Section 4.3.2 reports the results from the estimation of equation (4). Adding the proxy for managerial quality, based on the mean proficiency scores of managers based on PIAAC data, yields similar results to those presented in Table 3.[28] The relationship between managerial quality and *within-firm* productivity is positive, but not statistically significant. Although the main results from Table B3 remain, the impact of under-qualified and under-skilled workers on *within-firm* productivity becomes insignificant when managerial quality is controlled for. This is in line with the baseline results suggesting that most of the impact of under-qualification can be accounted for by differences in managerial quality as discussed in more detail in Section 4.3.3.

28 These results are available from the authors on request.

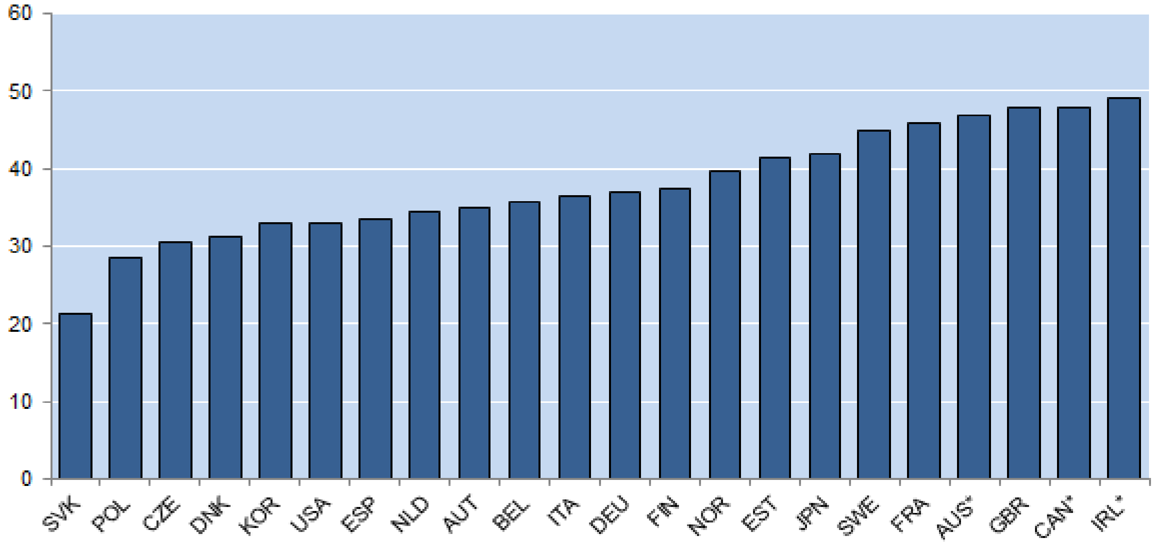
APPENDIX C

Figure C1. Incidence of qualification and skill mismatch: additional countries

Panel A: Percentage of workers with skill mismatch



Panel B: Percentage of workers with qualification mismatch

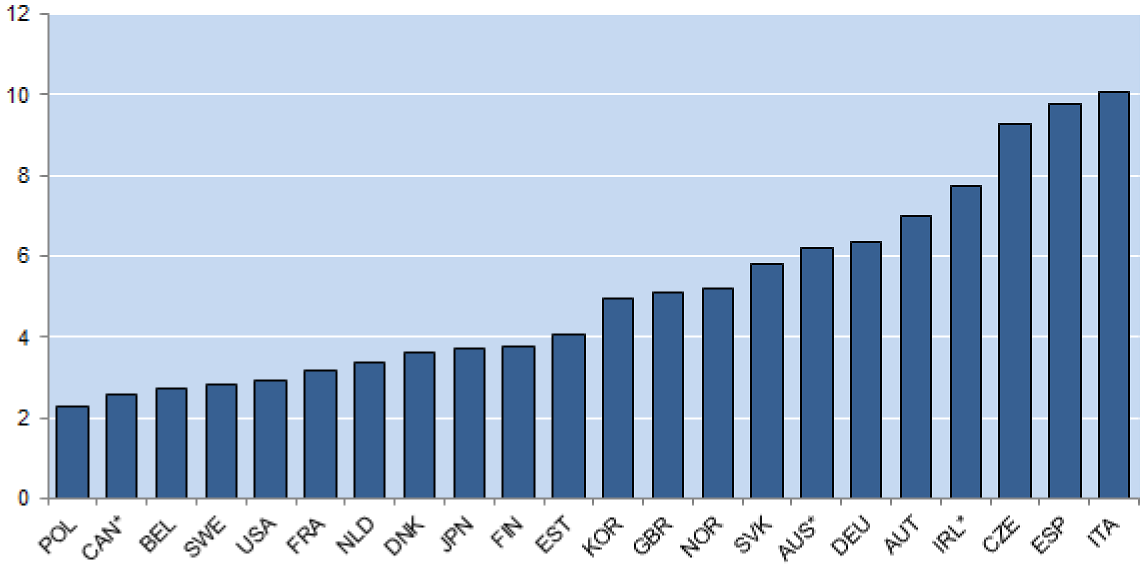


Note: This is an extension of Figure 2 to all the OECD countries in the *Survey of Adult Skills*. * refers to countries that are not in included in the econometric analysis. Workers with qualification (skill) mismatch refer to the percentage of workers who are either over- or under- qualified (skilled), as defined in Section 2. Under - (over-) skilled workers refer to the percentage of workers whose scores are higher than that of the min (max) skills required to do the job, defined as the 10^{th} (90^{th}) percentile of the scores of the well-matched workers in each occupation and country. In order to abstract from differences in industrial structures across countries, the 1-digit industry level mismatch indicators are aggregated using a common set of weights based on industry employment shares for the United States.

Source: OECD calculations based on the *Survey of Adult Skills* (2012).

Figure C2. Counterfactual productivity gains from reducing skill mismatch: additional countries

Simulated gains to allocative efficiency from lowering skill mismatch to the best practice; per cent



Note: The chart shows the difference between the actual allocative efficiency and a counterfactual allocative efficiency based on lowering the skill mismatch in each country to the best practice level of mismatch. Both the actual and counterfactual numbers are calculated by aggregating 1-digit industry level mismatch indicators using a common set of weights based on the industry employment shares for the United States. This is an extension of Figure 3 to all the OECD countries in the *Survey of Adult Skills*. Estimates for Australia, Canada and Ireland should be interpreted with caution to the extent that they are not included in the econometric analysis due to insufficient productivity data.

Source: OECD calculations based on the *Survey of Adult Skills* (2012).