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Skills mismatch, productivity and policies

EVIDENCE FROM THE SECOND WAVE OF PIAAC

Muge Adalet McGowan, Dan Andrews

JEL Classification: I20, J20, J24, J61, O40

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SKILLS MISMATCH, PRODUCTIVITY AND POLICIES: EVIDENCE FROM THE SECOND WAVE OF PIAAC

ECONOMICS DEPARTMENT WORKING PAPERS No. 1403

By Muge Adalet McGowan and Dan Andrews

English - Or. English

ABSTRACT/RÉSUMÉ

Skills Mismatch, Productivity and Policies: Evidence from the Second Wave of PIAAC

This paper extends earlier OECD work exploring the link between skills mismatch, productivity and policies to include the countries in the second wave of *OECD Survey of Adult Skills*, with a special focus on New Zealand. We find that the percentage of workers who are mismatched in terms of skills is 28% in New Zealand, slightly over the OECD average of 25%. The share of over-skilling is at the OECD average of 18%, while the share of under-skilling - at around 10% - is also above the OECD average of 7%. The results suggest that improving the allocation of skills to OECD best practice could be associated with an increase in productivity of around 7% in New Zealand.

JEL Classification: O40, I20; J20, J24, J61.

Keywords: productivity, reallocation, human capital, skill mismatch, education, framework policies, labour mobility.

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Inadéquation des compétences, productivité et politiques publiques: observations à partir de la deuxième vague de PIAAC

Ce papier étend les travaux précédents de l'OCDE explorant la relation entre inadéquation des compétences, productivité et politiques publiques, pour inclure les pays de la deuxième vague de PIAAC (Programme de l'OCDE pour l'évaluation internationale des compétences des adultes), avec une attention particulière portée au cas de la Nouvelle-Zélande. Nous trouvons que le pourcentage de travailleurs dont les compétences ne sont pas adaptées à celles requises est de 28% en Nouvelle-Zélande, ce qui est légèrement supérieur à la moyenne de l'OCDE de 25%. La proportion de travailleurs surqualifiés est de 18%, ce qui correspond à la moyenne de l'OCDE, tandis que la part de travailleurs sous-qualifiés – d'environ 10% - est supérieure à la moyenne de l'OCDE de 7%. Les résultats suggèrent qu'une amélioration de la distribution des compétences au niveau des meilleures pratiques de l'OCDE pourrait être associée à une augmentation de la productivité d'environ 7% en Nouvelle-Zélande.

Classification JEL: O40, I20, J20, J24, J61.

Mots-clés : productivité, redéploiement, capital humain, inadéquation des compétences, éducation, politiques-cadres, mobilité de la main-d'œuvre.

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SKILLS MISMATCH, PRODUCTIVITY AND POLICIES: EVIDENCE FROM THE SECOND WAVE OF PIAAC

By Müge Adalet McGowan and Dan Andrews[1]

1. Introduction

Raising productivity growth is highly dependent on a country's ability to innovate and adopt new technologies, which requires an effective supply of human capital. 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). In this context, the ability of economies to efficiently deploy their existing stock of human capital will become increasingly important. However, skills mismatch indicators derived from the OECD Survey of Adult Skills, a product of the Programme for the International Assessment of Adult Competencies (PIAAC), show that on average across countries, around one-quarter of workers report a mismatch between their existing skills and those required for their job, implying that there is considerable scope to improve the efficiency of human capital allocation in OECD countries. Furthermore, skills mismatch has the potential to explain a non-trivial share of cross-country labour productivity gaps (Adalet McGowan and Andrews, 2015a), and differences in skill mismatch across countries are associated with differences in the policy environment (Adalet McGowan and Andrews, 2015b).

This paper extends our earlier analysis of the relationship between skills mismatch, productivity and public policies to include seven additional countries, including New Zealand, for which PIAAC results were recently released (OECD, 2016). We find that the percentage of workers who are mismatched in terms of skills at 28% in New Zealand, is slightly greater than the OECD average of 25%. The share of over-skilling is around the OECD average at 18%, while the share of under-skilling at around 10% is also above the OECD average of 7%. The results suggest that improving the allocation of skills to OECD best practice could be associated with an increase in productivity of around 7% in New Zealand.

The inclusion of the additional countries in the cross-country analysis yields similar results to those in Adalet McGowan and Andrews (2015b), which covered 22 countries from the first wave of PIAAC results. After controlling for individual and job characteristics, skills mismatch is found to be lower in countries with well-designed framework conditions that promote efficient reallocation and housing policies that do not impede residential mobility. Lower mismatch is also associated with higher participation in lifelong learning and better managerial quality. While New Zealand performs well in many of the policies found to be associated with skill mismatch, there is scope to improve the allocation of skills by moving policies to the OECD best practice.

The paper proceeds as follows. The next section defines the mismatch indicators and presents some industry-level evidence on the links between mismatch and productivity. Section 3 outlines the empirical methodology, baseline results, robustness tests and the economic significance of the effects of policies on mismatch. Section 4 concludes.

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2. Skills mismatch and productivity

2.1 Measuring skills mismatch

The Survey of Adult Skills assesses the proficiency of adults aged between 16 and 65 in literacy, numeracy and problem solving in technology-rich environments in OECD member and partner countries (see Box A1 in the Appendix for details). The first round, conducted between 2008 and 2013, included Australia, Austria, Belgium (Flanders), Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Russian Federation, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland) and the United States. The second round that took place between 2012 and 2016, added Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey[2]. Besides the level of skills, information was collected on the background of respondents, their education and labour market experience, their skill use at work and at home plus indicators of well-being. The Survey has a number of advantages over comparable datasets as it extends the number of countries, sample size per country and the range of assessed skills.

Skills mismatch can be measured in several ways, each with their advantages and disadvantages (see Box 1). One is through self-assessment by asking workers to compare their skills level and that required for their job. Another approach is to compare the skills levels – as measured by proficiency scores – to skills use at work. A final approach, developed in OECD (2013) and employed in this analysis, combines information on self-reported skills mismatch and quantitative information on skills proficiency following Adalet McGowan and Andrews (2015a):

- 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)[3].
- Using this scale of proficiency scores of well-matched workers, minimum and maximum threshold values – based on the 10th and 90th percentile, for example – are identified, which effectively provide the bounds that define what it is to be a well-matched worker[4].
- 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.

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2. In the following empirical analysis, Indonesia, Singapore and the Russian Federation are not included.

3. Literacy is defined as the ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals and to develop one's knowledge and potential.

4. OECD (2013) uses different threshold values based on the 5th and 95th percentiles.

Box 1. Alternate approaches to measuring skills mismatch

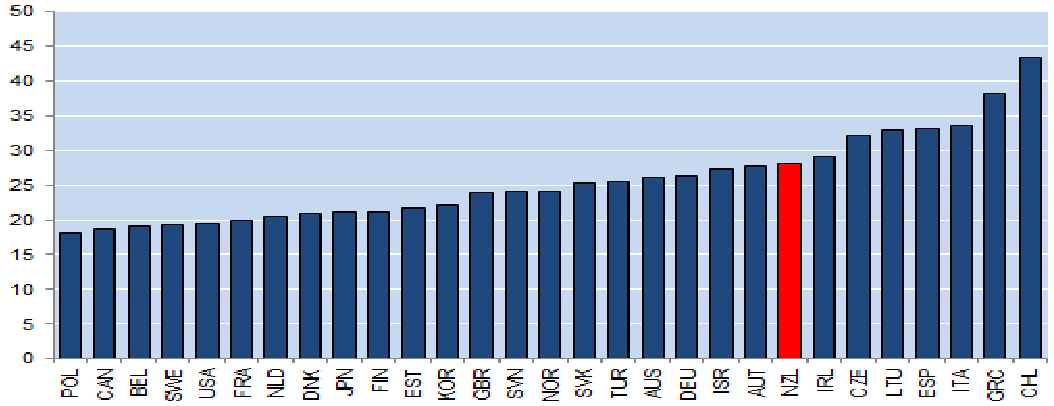
There are several ways to measure skills mismatch. One is to ask workers to assess themselves on their skill level and that required for their job. While this self-assessment method addresses the issue of partial measurement of skills (such as those based only on numeracy or literacy), it does not identify specific skills deficits or excesses. Furthermore, there is some evidence that skills 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. Another approach is to directly measure the skills of individual workers, most commonly, literacy and numeracy, and to compare them with skills use at work (CEDEFOP, 2010; Desjardins and Rubenson, 2011). Such measures are subject to two main drawbacks. First, they assume that skills use can be a proxy for job requirements. Second, skills proficiency and skills use are based on different theoretical concepts and are hard to measure on the same scale. In fact, skills proficiency and skills use are calculated by using structurally different types of information as the indicators of skills proficiency are based on cognitive tests, whereas those of skills use exploit survey questions on the frequency with which specific tasks are carried out. A final approach is to combine information on self-reported skills mismatch and skills 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 skills requirements. However, it does carry a number of advantages, to the extent that it addresses the drawbacks associated with the other approaches outlined above (See Pelizzari and Fichen (2013) for a more detailed description of the construction of this skills mismatch indicator).

2.2 Cross-country differences in skills mismatch are significant

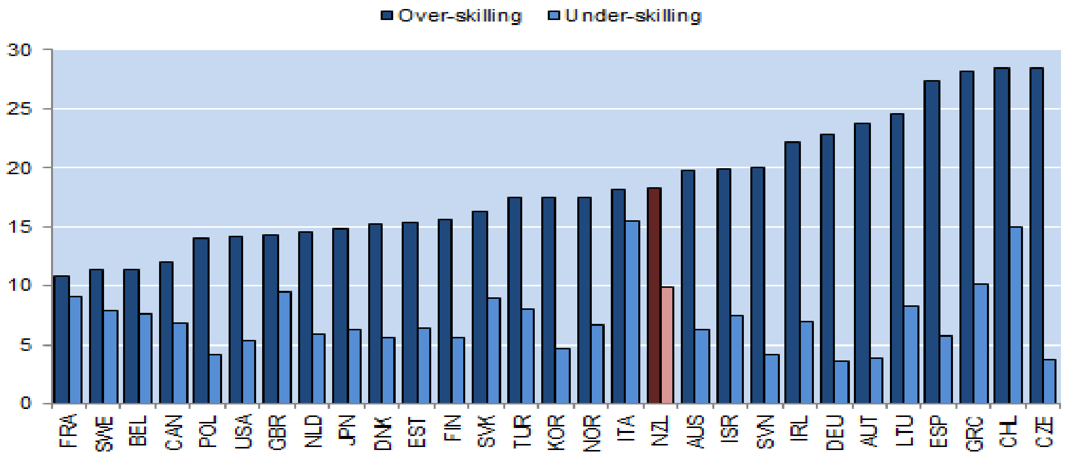
Indicators of skills mismatch suggest that there is considerable scope to improve the efficiency of human capital allocation in OECD economies. For example, on average across countries, roughly one-quarter of workers report a mismatch between their existing skills and those required for their job; i.e. they are either over- or under-skilled. Moreover, important cross-country differences emerge, with the incidence of skills mismatch ranging from around 40% in Greece and Chile to less than 20% in Sweden and the United States (Figure 1, Panel A). In New Zealand, the incidence of skills mismatch at 28% is slightly above the OECD average. Across OECD countries, over-skilling is generally more common than under-skilling, on average roughly two and a half times (Panel B). In New Zealand, the share of over-skilling is around the OECD average at 18%, while the share of under-skilling at around 10% is also above the OECD average of 7%.

Figure 1. Cross-country differences in skill mismatch

Panel A: Percentage of workers with skill mismatch; selected OECD countries, 2011-12*



Panel B: Components of skill mismatch; selected OECD countries, 2011-12*



Note: The figure shows the percentage of workers who are either over- or under- skilled for a sample of 11 market industries: 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. 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. * For Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Slovenia and Turkey, the data was collected in 2014-2015.

Source: OECD calculations based on the *Survey of Adult Skills* (2012 and 2015).

2.3 Skill mismatch and cross-country gaps in labour productivity

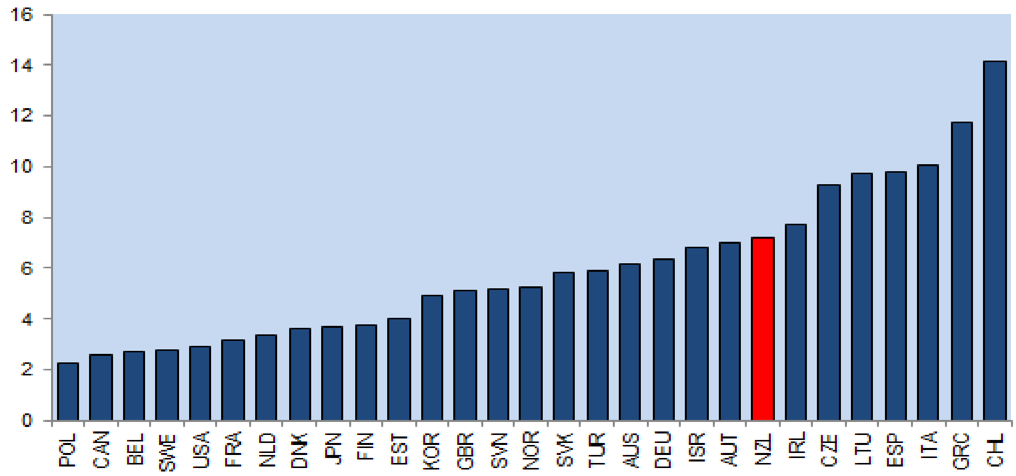
Using an industry-level analysis, Adalet McGowan and Andrews (2015a) shows that higher skills mismatch is associated with lower labour productivity performance, with over-skilling being particularly costly. The negative association between over-skilling and labour productivity is driven through the channel of less efficient resource allocation. From the perspective of any given 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, the impacts may be very different. Assuming that wages do not adjust to these frictions in the short run, mismatch could have reallocation effects, if skilled labour is clogged up in low productivity firms. 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 set of matches.

Indeed, Adalet McGowan and Andrews (2015a) finds that 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. At the same time, skills mismatch has the potential to explain a non-trivial share of cross-country labour productivity gaps. For example, Italy – a country with high skills mismatch and low allocative efficiency – could boost its level of labour productivity by around 10% and 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 (Figure 2).

More speculatively, the same exercise can be extended to countries that are not in the empirical analysis linking mismatch to productivity due to lack of productivity data, but are included in the PIAAC sample. Applying the coefficient estimates from that analysis suggests that lowering the skills mismatch to best practice could be associated with an increase in allocative efficiency of 7.2% for New Zealand. It is not possible to calculate how much reducing skills mismatch can explain cross-country productivity gaps for New Zealand due to a lack of publicly available firm-level productivity data.

Figure 2. 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 outcome based on lowering the skills mismatch in each country to the best practice. 1-digit industry level mismatch indicators are aggregated using a common set of weights based on the industry employment shares for the United States. The estimated coefficient of impact of mismatch on productivity is based on a sample of 19 countries for which both firm-level productivity and mismatch data are available (Austria, Belgium, the 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). The estimated gains to allocative efficiency for the other countries should be interpreted with caution to the extent that they are not included in the econometric analysis due to missing productivity data.

Source: OECD calculations based on the *Survey of Adult Skills* (2012 and 2015).

3. Empirical model and results

The estimates above suggest that skills mismatch is one factor that may contribute to explaining cross-country differences in labour productivity. Hence, it is important to consider what factors explain it. According to the theoretical and empirical literature, mismatch will be shaped by two key factors: i) individual and workplace/job characteristics (e.g. age, migrant status, firm size); and ii) policy-induced distortions to labour mobility (see Adalet McGowan and Andrews (2015b) for a detailed discussion on the literature on these different factors).

3.1 Empirical model

The link between individual background characteristics and mismatch is investigated by estimating the following binomial logit specification for New Zealand:

$$SMM_i = \Phi(\delta_1 + \delta_2 I_i + \epsilon_i) \qquad (1)$$

where Φ is the normal distribution, i denotes an individual and SMM_i denotes the probability that an individual i is mismatched (SMM=1 if an individual i is over- or under-skilled; we also estimate separate models for over-skilling and under-skilling). The explanatory variables include a vector of individual characteristics, I, which are likely to influence mismatch. These include: age category (15-24, 25-34, 35-44, 45-54 and 55-65), gender (1 if the person is male, 0 otherwise), nationality (1 if national, 0 if foreign born), marital status (1 if married, 0 otherwise), education (categorical variable measuring if the person has lower secondary, upper secondary, post-secondary or tertiary education), firm size (1-10, 11-50, 51-250, 251-999 and 1000+ employees), contract type (indefinite, fixed and temporary agency/apprenticeship/no contract), full-time (1 if the person is employed full-time, 0 otherwise) and organisation type (1 if private firm, 0 if public sector or NGO).

The empirical approach also exploits cross-country variation in policies and institutions to assess the role of policy settings in explaining skills mismatch. To consider these policies, the following cross-country specification is estimated:

$$SMM_{i,c} = \Phi(\delta_1 + \delta_2 I_{i,c} + \delta_3 P_c + \delta_4 C_c + \epsilon_{i,c}) \qquad (2)$$

where SMM is a measure of whether individual i in country c is over- or under-skilled, I denotes the vector of individual characteristics outlined above, P denotes country-specific policies (see Table A1 in Annex for the list of policies) and C denotes country-specific control variables, including total national income.

The strong negative relationship between skills mismatch (i.e. over-skilling) and labour productivity via the allocative efficiency channel (Adalet McGowan and Andrews, 2015a) suggests that policy determinants of skills mismatch should focus particularly on those policy factors that impose frictions on the efficient reallocation of labour. Accordingly, in this paper only a subset of potentially relevant policies (framework, housing, education and labour market) for which indicators are readily available are covered, but a range of other policies (e.g. vocational education and training and the matching of available university programmes to labour market needs) that are more difficult to measure may also matter. Of course, policies to increase human capital accumulation, such as investment in higher education, are also important (Braconier et al., 2014).

The estimation of equation (2) treats policies as exogenous factors affecting mismatch, but there may be reason to be concerned about endogeneity. Causation is difficult to establish, given data limitations: i) the data are available only at one point in time; and ii) due to high correlations among the policy variables, the baseline analysis includes the policy variables one at a time. Nevertheless, a number of robust correlations between policy variables and skills mismatch emerge (see below).

3.2 The effect of individual and job characteristics on skill mismatch

Table 1 reports the baseline results of estimating Equation (1) for the probability of skills mismatch (Column 1), over-skilling (Column 2) and under-skilling (Column 3) for New Zealand. Table A2 presents the same results for the pooled cross-country regressions. The reported coefficients are marginal effects and can be interpreted as the impact of a unit change in the explanatory variable on the probability of skills mismatch in New Zealand. These changes are relative to the probability of skills mismatch of the excluded individual: married, male, native-born, young worker with low education attainment, working in a small firm on an indefinite contract.

In New Zealand, there is no significant relationship between gender and skills mismatch (Table 1). Across OECD countries, females are less likely to be mismatched in terms of skills (Table A2, Column 1). Furthermore, this is mainly driven by the fact that females are less likely to be over-skilled (Table A2, Column 2), while the relationship between gender and under-skilling is not significant. Both of these results are contrary to the assumption that women are more likely to be over-skilled/qualified because of family constraints or the wish to improve their work-life balance.

Table 1 shows that the probability of skills mismatch is lower for immigrants in New Zealand (Column 1). Looking at the components of mismatch reveals that immigrants are less likely to be over-skilled (Column 2), while they are more likely to be under-skilled (Column 3)[5]. The heterogeneity of the migrant population could lead to different conclusions on the relationship between being foreign-born and the probability of skills mismatch. However, the relatively low share of migrants in the sample makes a more differentiated analysis of this link difficult.

Many OECD economies, especially those with segmented labour markets, have difficulties in successfully integrating young people into the labour market both by getting them out of unemployment and matching them to the right jobs. Over-skilling could be more common amongst youth since they are more likely to be employed in temporary or entry-level jobs where skill demands could be low (Allen et al., 2013; OECD, 2013). There is some evidence that the degree of mismatch should improve with experience, as workers get more experience and relevant information on job market opportunities (Alba-Ramirez, 1993; Desjardins and Rubenson, 2011). The literature on the links between skills mismatch and other individual characteristics such as gender, marital and migrant status remains inconclusive, but it is important to control for these different aspects of a worker's background that can be linked to their probability of being mismatched.

Consistent with the literature and the results for OECD countries (Table A2), in New Zealand, skills mismatch decreases with age, as workers gain more experience and/or move into jobs that have a better fit with their skills levels (Table 1, Column 1). Additionally, it could be the case that workers whose over-skilling is beneficial for firm productivity are more likely to be promoted to a job matching their skills as they get older. Furthermore, older workers are less likely to be over-skilled (Column 2) and more likely to be under-skilled (Column 3), as skills learned at school tend to depreciate and to become obsolete over time. Young people, on the other hand, are more likely to be over-skilled as they may be in entry-level jobs where skills requirements do not meet their actual skills.

In New Zealand, as the educational attainment of the worker goes up, skills mismatch increases (Table 1, Column 1), whereas the cross-country results show that workers with tertiary education are more likely to have skills mismatch compared to the base category of workers with lower secondary education (Table A2, Column 1). Looking at the components of mismatch shows that over-skilling increases with the level of education for all categories (Column 2), while the opposite is true for under-skilling (Column 3). The higher rates of over-skilling amongst more educated workers could be a result of firm decisions.

4. The relationship between migrant status and over-skilling differs from the finding in the literature that immigrants are more likely to be over-qualified. The low overlap between over-qualification and over-skilling suggests that even if employers are not able to recognise foreign qualifications (resulting in over-qualification), they could be more successful in utilising the skills of the migrant workers effectively.

Table 1. The effect of individual characteristics on skill mismatch: New Zealand

Marginal effects

	(1)	(2)	(3)
	Skill mismatch	Over-skilled	Under-skilled
Dependent variable: 1 if the individual is mismatched, 0 otherwise			
Single	0.00224	0.000274	0.0315*
	(0.157)	(0.0178)	(0.0175)
Female	-0.210	-0.0257	0.0113
	(0.134)	(0.0180)	(0.0144)
Foreign-born	-0.568***	-0.0695***	0.0898***
	(0.156)	(0.0163)	(0.0133)
Age 25-34	-0.318	-0.0389	0.0568**
	(0.204)	(0.0256)	(0.0283)
Age 35-44	-0.323	-0.0395	0.0710**
	(0.204)	(0.0282)	(0.0312)
Age 45-54	-0.872***	-0.107***	0.0852***
	(0.246)	(0.0327)	(0.0326)
Age 55-65	-1.156***	-0.141***	0.119***
	(0.279)	(0.0415)	(0.0338)
Upper secondary education	1.116***	0.137***	-0.0597***
	(0.246)	(0.0310)	(0.0218)
Post-secondary, non-tertiary	1.346***	0.165***	-0.0811***
education	(0.283)	(0.0366)	(0.0261)
Tertiary education	1.148***	0.140***	-0.0985***
	(0.244)	(0.0306)	(0.0232)
Firm size: 11-50	-0.128	-0.0156	-0.0540***
	(0.168)	(0.0216)	(0.0184)
Firm size: 51-250	0.0150	0.00183	-0.0651***
	(0.178)	(0.0211)	(0.0170)
Firm size: 251-999	0.300	0.0367	-0.0807***
	(0.229)	(0.0272)	(0.0278)
Firm size: >1000	-0.0689	-0.00843	-0.127***
	(0.304)	(0.0403)	(0.0454)
Fixed contract	-0.669**	-0.0818**	0.0360
	(0.267)	(0.0333)	(0.0284)
Temp agency/No contract/Apprenticeship	0.243	0.0298	-0.0712
	(0.296)	(0.0405)	(0.0596)
Part-time worker	0.466***	0.0570***	-0.0499**
	(0.165)	(0.0204)	(0.0238)
Public sector/NGO	-0.244	-0.0298	-0.0218
	(0.163)	(0.0185)	(0.0170)
Number of observations	2405	2405	2405

Notes: Estimates from logit regressions. Values are marginal effects. The coefficients correspond to the impact of a change in the explanatory variable on the probability of mismatch at the mean of the independent variables. Regressions include as controls age, marital and migrant status, gender, level of education, firm size, contract type, a dummy for working full-time and working in the private sector. Robust standard errors in parentheses. *** denotes statistical significance at the 1% level, ** significance at the 5% level, * significance at the 10% level.

Source: OECD calculations based on the *Survey of Adult Skills* (2015).

Column 3 of Table 1 suggests that as firm size increases, workers are less likely to be under-skilled. These results are consistent with the analysis in Adalet McGowan and Andrews (2015a) that shows that larger firms are better managed and that better managerial quality can account for the association between under-skilling and firm productivity. On average across OECD countries, there is no significant relationship between mismatch and whether a worker is on a permanent or a temporary contract, which is in line with the literature (Table A2). However, in New Zealand, workers on fixed-term contracts relative to indefinite contracts are less likely to be mismatched, which is driven by the lower probability of over-skilling (Table 1, Columns 1 and 2). Part-time workers are more likely to be mismatched (Column 1), which is driven by a higher rate of over-skilling among these workers. Occupational choices in part-time work could be more limited, raising the probability of over-skilling and a switch from full-time to part-time employment could entail occupational downgrading (Sparreboom, 2014; Connolly and Gregory, 2008).

3.3 The effect of policy-related factors on skill mismatch

Table 2 reports the baseline results of the pooled regressions that explore the effects of different policy-related factors on skill mismatch obtained from the estimation of Equation (2). The different specifications control for a similar set of individual and job characteristics as above, but the estimated coefficients are not reported for the sake of brevity. To the extent that skills mismatch is related to productivity through both within-firm and between-firm factors (see Adalet McGowan and Andrews, 2015a), it is important to consider policies and factors that impose frictions on the efficient reallocation of labour, restrict the entry of more productive firms and prevent the exit of less productive firms as potential determinants of skills mismatch. While education policies clearly matter, these links between mismatch and productivity through the reallocation channel suggest that a wider range of policies could affect mismatch.

Well-designed framework policies are associated with lower skills mismatch (Panel A of Table 2). Stringent labour market regulations, both for permanent and temporary employees, are associated with higher mismatch, as they reduce labour market flexibility and the ability of firms to adapt to shocks or changing skills needs (Columns 1 and 2 in Table 2, Panel A).

Policies that decrease barriers to firm entry and increase general competition (e.g. pro-competitive product market regulations) might improve the allocation of skills through several channels. First, by preventing the creation of rents and improving market selection (Pica and Rodriguez, 2005), such policies will allow high skilled workers to be employed in high productivity firms. Second, they can lead to greater market discipline, improving managerial quality and reducing mismatch. This would in turn make it easier to adopt new technologies. Policy and institutional settings with low barriers to firm entry and strong competitive pressures more generally, such as lower product market regulations (PMRs), are associated with a lower probability of skills mismatch (Column 3 in Table 2, Panel A).

By raising exit costs and thus preventing the winding down of low-productivity firms, strict bankruptcy legislation can result in labour, particularly high-skilled workers, being trapped in inefficient firms and jobs that are not sufficiently challenging. This would in turn restrict the ability of high-productivity firms to innovate and grow given a fixed pool of high-skilled workers[6]. Panel A of Table 2 shows that policies that make it easier for firms to exit such as lower costs of closing a business are also associated with a lower probability of mismatch (Column 4)[7].

6. Acemoglu et al. (2013) shows that policy intervention such as R&D tax subsidies are only truly effective if policymakers 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.

7. See Figure A1 for cross-country differences in the cost of closing a business.

Another potential barrier to labour mobility and the efficient allocation of skills in an economy is low rates of residential mobility. Permanent shocks requiring a reallocation of production factors, such as sector and structural changes related to globalisation or technological progress could lead to differences in regional supply and demand (Janiak and Wasmer, 2008). This would, in turn, require high geographical mobility to broaden job search to new areas and increase the probability of finding a suitable job (Büchel and Van Ham, 2003; Hensen et al., 2009).

Table 2. The effect of policy-related factors on skill mismatch

Marginal effects

	(1)	(2)	(3)	(4)	(5)
Dependent variable: 1 if the individual is mismatched, 0 otherwise					
Panel A: **Framework policies**	Employment protection legislation for permanent workers	Employment protection legislation for temporary workers	Product market regulation	Cost of closing a business	
Policy-related factors	0.043**	0.021**	0.042**	0.006**	
	(0.008)	(0.003)	(0.010)	(0.001)	
Number of observations	76183	76183	74224	76183	
pseudo-R2	0.012	0.012	0.01	0.013	
Panel B: **Housing policies**	Transaction costs	Rent control	Tenant-landlord regulations	Cost of obtaining a building permit	Responsiveness of housing supply
Policy-related factors	0.007***	0.017**	0.021**	0.001**	-0.051**
	(0.001)	(0.003)	(0.003)	(0.000)	(0.010)
Number of observations	66863	66529	69002	76183	58390
pseudo-R2	0.011	0.011	0.012	0.009	0.014
Panel C: **Other policies**	Coverage rate of collective bargaining agreements	Participation in lifelong learning (PIAAC data)	Managerial quality		
Policy-related factors	0.001**	-0.002**	-0.002**		
	(0.000)	(0.000)	(0.000)		
Number of observations	71819	76183	76183		
pseudo-R2	0.011	0.012	0.015		

Notes: See Table A1 for detailed explanations of the policy variables. Estimates from logit regressions. Values are marginal effects. The coefficients correspond to the impact of a change in the explanatory variable on the probability of mismatch at the mean of the independent variables. Each column in each panel includes one policy-related variable at a time. Regressions include as controls: age, marital and migrant status, gender, level of education, firm size, contract type, a dummy for working full-time and working in the private sector. Robust standard errors in parentheses. ** denotes statistical significance at the 1% level, * significance at the 5% level.

Source: OECD calculations based on the *Survey of Adult Skills* (2012 and 2015).

Housing market policies vary significantly across countries (Figures A2-A4), and in turn shape residential mobility, which is positively correlated with worker reallocation rates (Caldera Sánchez and Andrews, 2011; Figure A5) and the efficiency of job matching (Henley, 1998). Panel B of Table 2 shows that policies that restrict mobility in housing markets might amplify skills mismatch by limiting labour mobility. By creating lock-in effects, transaction costs affecting the buying and selling of dwellings – e.g. transfer taxes (stamp duties, acquisition taxes), registration fees, notarial or other fees – can reduce residential mobility and increase mismatch (Column 1). Strict rent controls and rules governing tenant-landlord relations favouring tenants are associated with higher skills mismatch. A low price responsiveness of housing supply can reduce labour mobility by affecting the average availability of housing. The responsiveness of housing supply depends on geographical and urban characteristics as well as regulations on the use of land, which influence the allocation of land and housing to different uses. Specifically, the elasticity of housing supply is lower in countries where it takes longer to acquire a building permit, underscoring the importance of efficient land-use regulation and administration (Andrews et al., 2011).

Skills gaps are one of the key determinants of training investment made by firms and workers (McGuinness and Ortis, 2014). Given the changing face of the labour market, both workers who are just entering the labour force and those that are already in the workforce have to be willing to learn new skills. Adult learning and training are important to address such new skill requirements driven by technological change as well as skills loss over time. There is some evidence that work-related training can decrease the gap between skills acquired during formal education and those required on the job (Arulampalam et al., 2004) and reduce mismatch (van Smoorenburg and van der Velden, 2000). Table 2, Panel C shows that higher participation in lifelong learning is associated with lower skills mismatch, reinforcing the importance of skills gained beyond formal qualifications through both on the job-training and opportunities for lifelong education and training as important instruments to reduce skills mismatch. There is evidence that under-skilled workers benefit from employer-provided training, especially those of young workers (Messinis and Olekalns, 2007). However, high-skilled workers are more likely to participate in adult education and training, potentially highlighting the role for policies to increase the participation of low-skilled workers in adult learning (OECD, 2013).

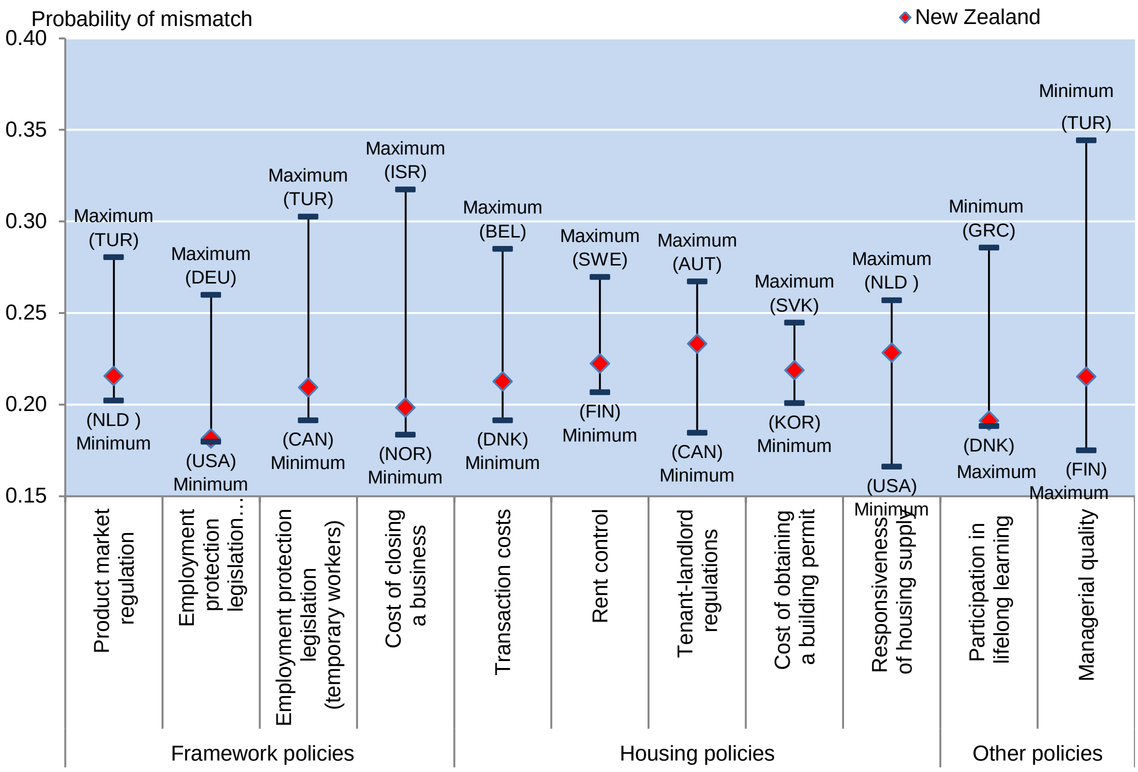
Higher managerial quality improves within-firm and aggregate productivity (Bloom et al., 2012) largely through the application of modern HR practices (e.g. monitoring) and organisational restructuring, which promote more efficient technological adoption, but there are large cross-country differences in terms of managerial quality (Figure A6). Better managed firms may also be less susceptible to mismatch. Using industry-level data, Adalet McGowan and Andrews (2015a) shows that higher managerial quality is associated with lower rates of under-skilling and higher within-firm productivity, and that differences in managerial quality can account for the negative association between under-skilling and within-firm productivity. Micro-data analysis also shows that higher managerial quality is associated with lower skills mismatch (Table 2, Panel C). Policies that promote competition in product markets are a key determinant of managerial quality to the extent that they impose greater market discipline, which truncates the left tail of poorly managed – and unproductive – firms (Bloom et al., 2014).

3.4 The economic significance of policy-related factors for skills mismatch

To understand the economic significance of the effect of policy-related factors on skills mismatch and the reductions in mismatch that could be associated with policy reform, Figure 3 shows how different policy scenarios influence mismatch based on the estimates in Table 2. The dot is the probability to have mismatch evaluated at the value of the policy for New Zealand and individual characteristics. The distance between the Min/Max of the relevant policy indicator and the value for New Zealand is the change in the probability of skills mismatch associated with the respective policy change.

In international perspective, New Zealand ranks well in many of the policies that have been found to be associated with skill mismatch. For example, in terms of EPL and participation in lifelong learning, New Zealand is at best practice. Looking at other policies suggests that there is some room to improve the allocation of skills with further improvements to policy settings. For example, making rules governing tenant-landlord relations more landlord-friendly (by easing them to the best practice in Canada) would be associated with a 4.8 percentage point decrease in mismatch.

Figure 3. The probability of skills mismatch and policies

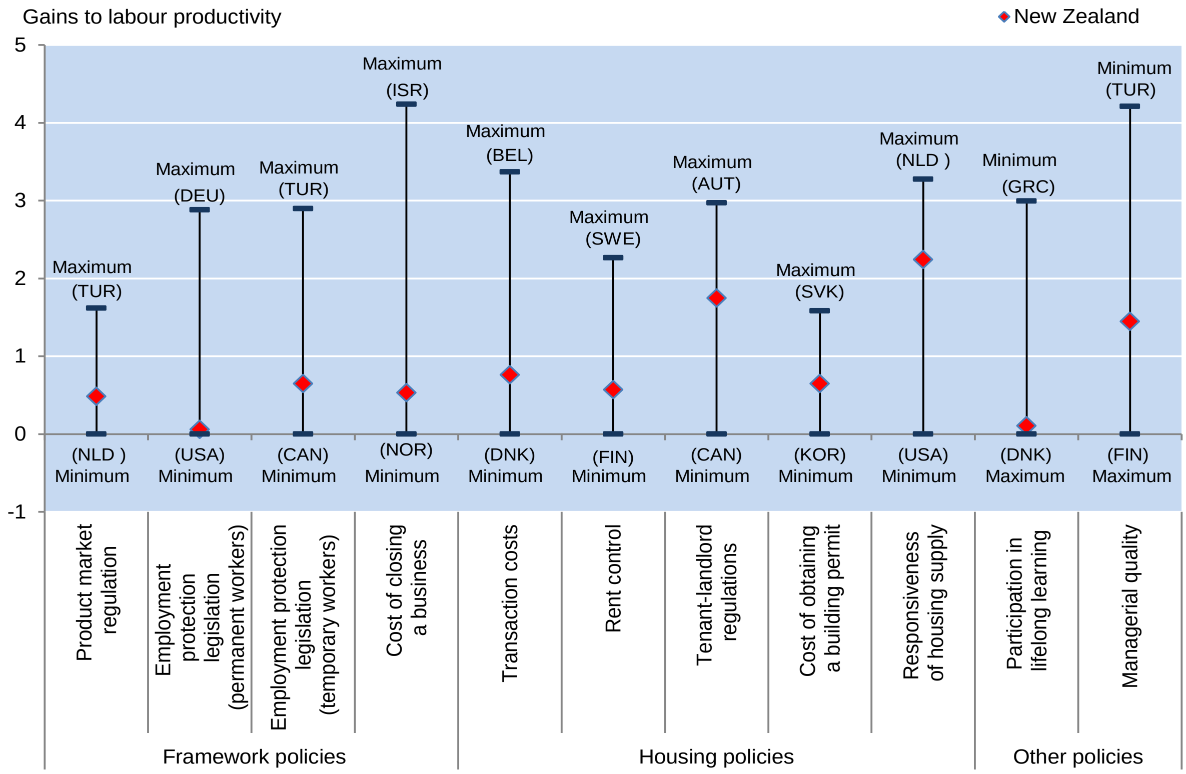


Notes: The dot is the probability to have mismatch evaluated at the level of the policy in New Zealand and individual characteristics, which include age, marital and migrant status, gender, level of education, firm size, contract type, a dummy for working full-time and working in the private sector. The distance between the Min/Max and the dot is the change in the probability of skill mismatch associated with the respective policy change.

Source: OECD calculations based on the Survey of Adult Skills (2012 and 2015).

Finally, Figure 4 reports the potential gains for labour productivity from policy reforms that reduce skills mismatch, although these estimates should be treated with some caution. For example, while managerial quality in New Zealand is high in international perspective, reaching the highest levels of managerial quality in Finland would be associated with a 1.4 percentage point gain in labour productivity. It should be noted that the effects presented in Figure 4 cannot be cumulated as they reflect bivariate correlations rather than causal links.

Figure 4. Estimated gains to labour productivity from policy reforms that reduce skills mismatch



Notes: Estimates are based on logit regressions of probability of mismatch controlling for age, marital and migrant status, gender, level of education, firm size, contract type, a dummy for working full-time and working in the private sector and OLS regressions of labour productivity on skills mismatch.

Source: OECD calculations based on the *Survey of Adult Skills* (2012 and 2015).

4. Conclusion

This paper extends earlier OECD work exploring the link between skill mismatch, productivity and policies to include the countries in the second wave of OECD Survey of Adult Skills, with a special focus on New Zealand. We find that the percentage of workers who are mismatched in terms of skills, at 28% in New Zealand, is slightly over the OECD average of 25%. The share of over-skilling is at the OECD average of 18%, while the share of under-skilling at around 10% is above the OECD average of 7%. The results suggest that improving the allocation of skills to OECD best practice could be associated with an increase in productivity of around 7% in New Zealand.

The main results suggest that differences in skills mismatch across countries are associated with differences in the policy environment. After controlling for individual and job characteristics, skills mismatch is lower in countries with well-designed framework conditions that promote efficient reallocation, while housing policies that do not impede residential mobility also loom large. Lower mismatch is also associated with greater flexibility in wage negotiations and higher participation in lifelong learning as well as better managerial quality. While New Zealand performs well in many of the policies found to be associated with skills mismatch, there is scope to improve the allocation of skills by moving policies to the OECD best practice.

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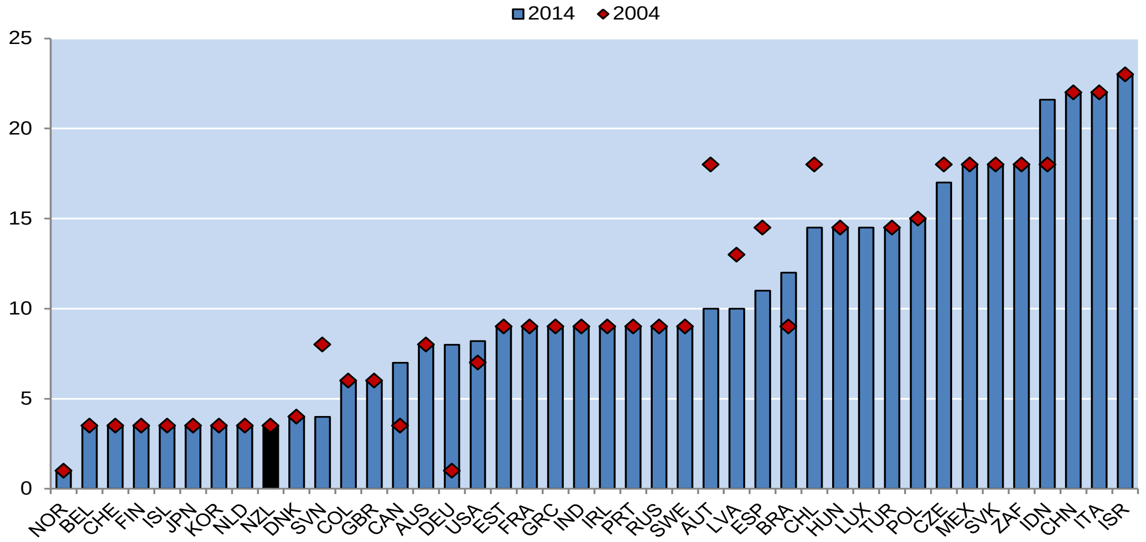
APPENDIX A: SELECTED POLICY INDICATORS

Figure A1. Cost of closing a business

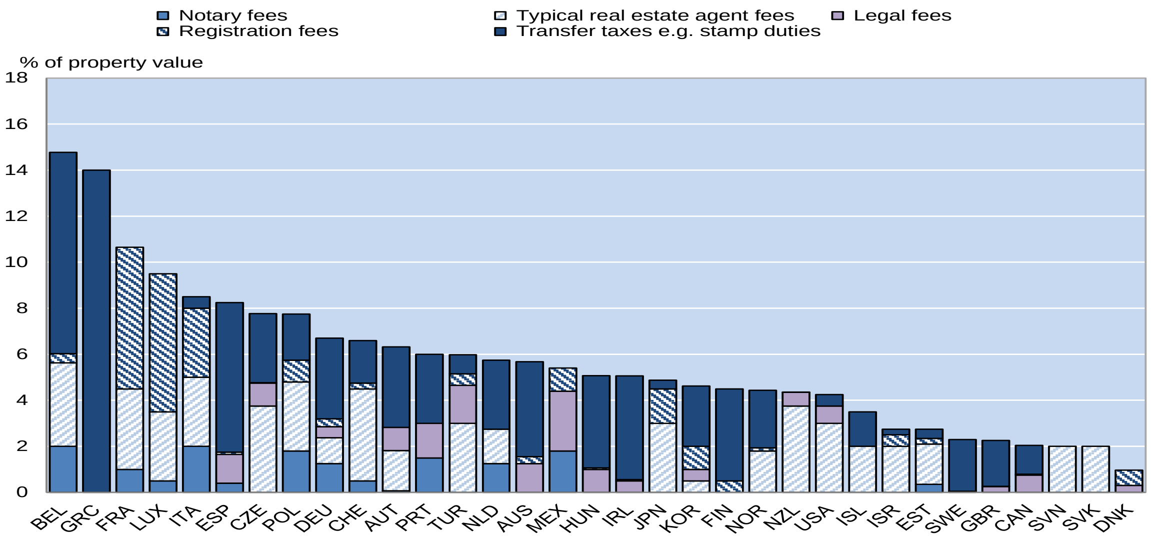
The average cost of bankruptcy proceedings as a percentage of the estate's value



Notes: The cost is calculated on the basis of questionnaire responses and includes court fees and government levies; fees of insolvency administrators, auctioneers, assessors and lawyers; and all other fees and costs. Data refer to 2005 for Iceland. 2004 data refer to São Paulo for Brazil, Shanghai for China, Mumbai for India, Jakarta for Indonesia, Mexico City for Mexico, New York for the United States, Tokyo for Japan and Moscow City for Russia.

Source: World Bank Doing Business Database.

Figure A2. Transaction costs on buyer by type, 2009

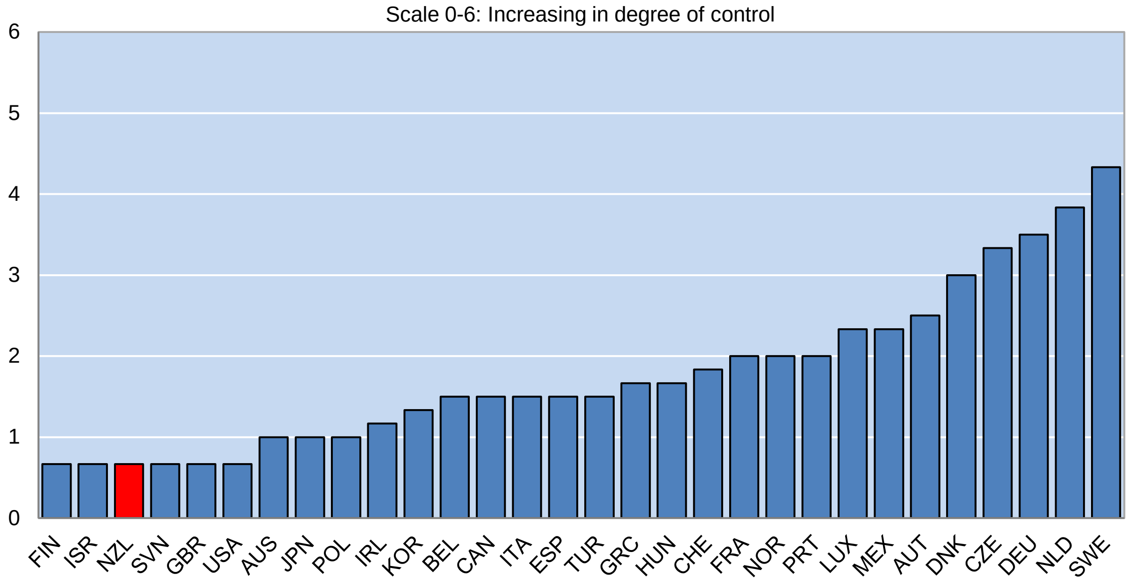


Notes: Transaction costs refer to average costs.

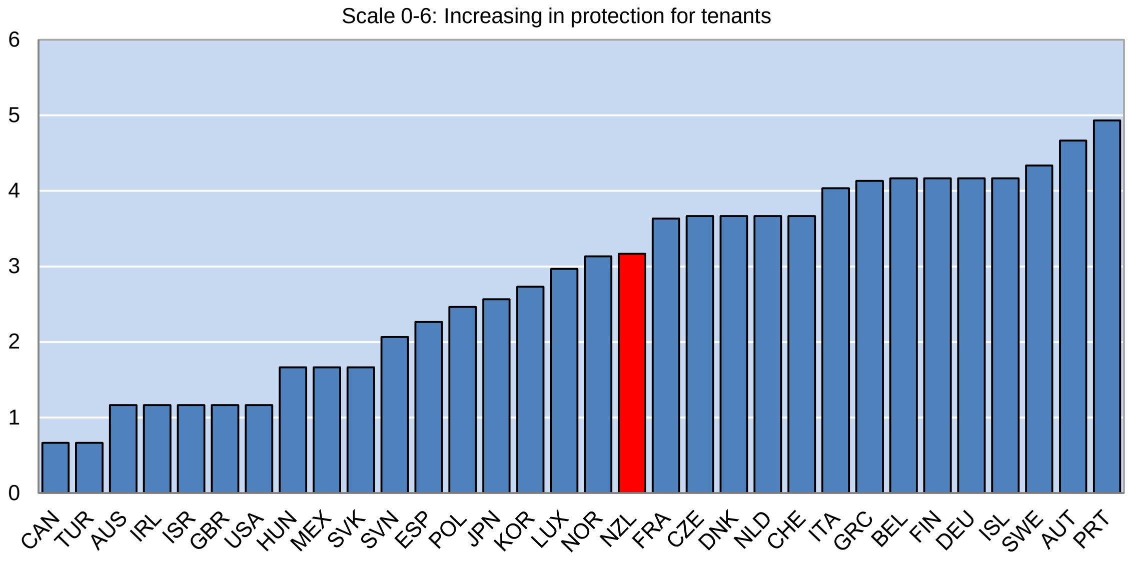
Source: Andrews et al. (2011).

Figure A3. Pro-tenant regulations, 2009

A: Rent control in the private rental market, 2009



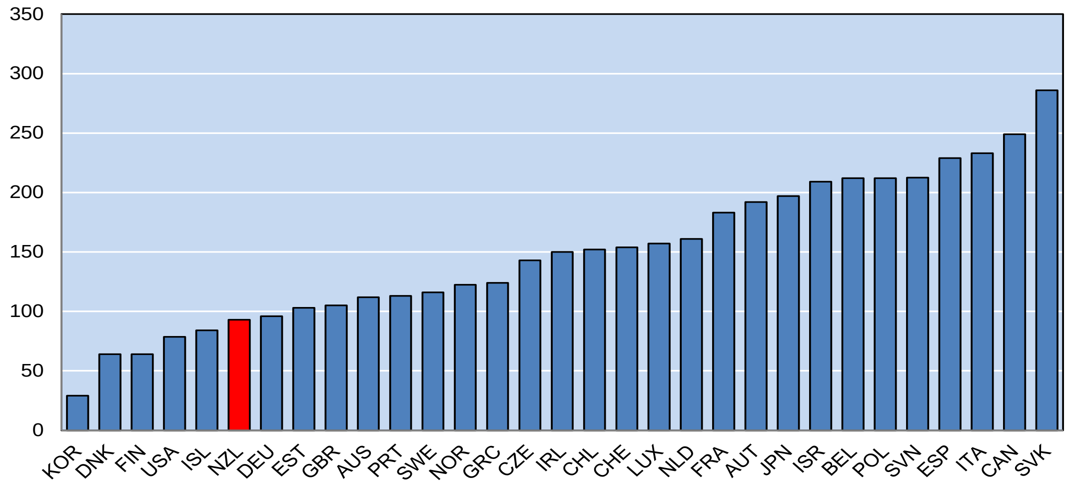
B: Tenant-landlord regulations in private rental market, 2009



Notes: Panel A: This indicator is a composite indicator of the extent of controls of rents, how increases in rents are determined and the permitted cost pass-through onto rents in each country. Panel B: The indicator measures the extent of tenant-landlord regulation within a tenancy. It includes the ease of evicting a tenant, degree of tenure security and deposit requirements.

Source: Andrews et al. (2011).

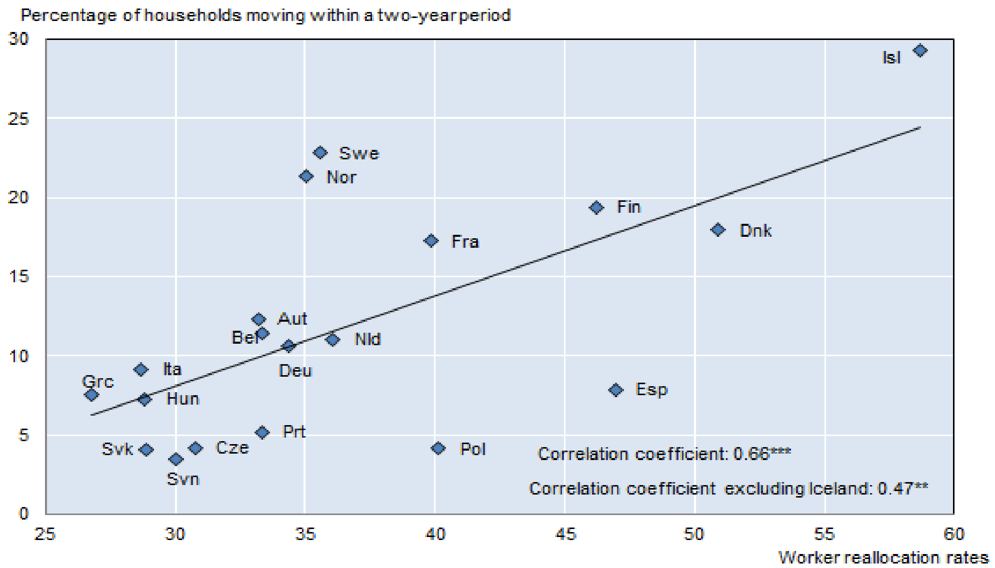
Figure A4. Number of days to obtain a building permit, 2014



Notes: The number of days to obtain a building permit measured as the median duration that local experts indicate is necessary to complete a procedure in practice.

Source: World Bank Doing Business (2014).

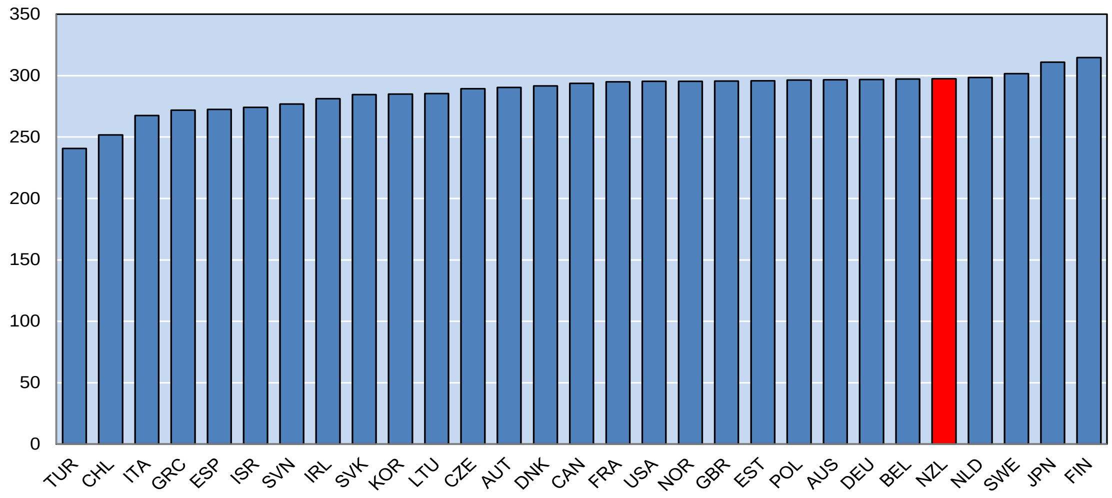
Figure A5. Residential mobility and worker reallocation rates



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.

Figure A6. Average proficiency score of managers in literacy; total economy



Notes: Average proficiency scores refer to the unweighted average of the proficiency scores of managers in each country across all industries.

Source: OECD calculations based on the *Survey of Adult Skills* (2012 and 2015).

Box A1. 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. 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.[1]

There are two main issues that need to be taken into consideration when these data are used.[2] 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.

1. 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.
2. For more details, see OECD (2013), *Technical Report of the Survey of Adult Skills* (PIAAC), Paris.

Table A1. Data sources for policy-related variables

Product market regulation	Overall PMR index from OECD, Product Market Regulation Database, 2008
EPL (permanent)	OECD, Employment Protection Legislation Database, indicator for the protection of permanent w orkers against individual and collective dismissals, 2013
EPL (temporary)	OECD, Employment Protection Legislation Database, indicator for the regulation on temporary forms of employment, 2013
Cost of closing a business	World Bank, Doing Business Database, 2014
Transaction Costs	Andrew s et al. (2011), data refer to 2009
Rent control	Andrew s et al. (2011), data refer to 2009
Tenant-landlord regulations	Andrew s et al. (2011), data refer to 2009
Cost of obtaining a building permits	World Bank, Doing Business Database, 2014
Responsiveness of housing supply	Andrew s et al. (2011), data refer to 2009
Participation in lifelong learning	Calculations based on PIAAC, 2011-12
Managerial quality	Calculations based on PIAAC, 2011-12

Notes: Transaction costs include a number of fees such as transfer taxes (e.g. stamp duties), registration fees incurred when registering the property in the land registry, notarial or other legal fees and typical real estate agency fees. Rent control is a composite indicator of the extent of controls of rents, how increases in rents are determined and the permitted cost pass-through onto rents in each country. The tenant-landlord regulation indicator measures the ease of evicting a tenant, degree of tenure security and deposit requirements. The responsiveness of the housing supply is based on the estimates of the long-run elasticity of new housing supply, where new supply is measured by residential investment.

Table A2. The effect of individual characteristics on skills mismatch: pooled cross-country regressions

Marginal effects

	(1)	(2)	(3)
	Skill mismatch	Over-skilled	Under-skilled
Dependent variable: 1 if the individual is mismatched, 0 otherwise			
Single	0.002	-0.009	0.008
	(0.008)	(0.007)	(0.005)
Female	-0.051**	-0.057**	0.005
	(0.006)	(0.006)	(0.004)
Foreign-born	0.022	-0.095**	0.070**
	(0.011)	(0.010)	(0.006)
Age 25-34	-0.004	-0.017	0.009
	(0.012)	(0.010)	(0.009)
Age 35-44	-0.031*	-0.047**	0.017*
	(0.012)	(0.010)	(0.008)
Age 45-54	-0.058**	-0.095**	0.038**
	(0.012)	(0.010)	(0.008)
Age 55-65	-0.044**	-0.147**	0.071**
	(0.015)	(0.013)	(0.008)
Upper secondary education	-0.011	0.082**	-0.046**
	(0.011)	(0.010)	(0.005)
Post-secondary, non-tertiary	0.010	0.128**	-0.084**
education	(0.016)	(0.015)	(0.011)
Tertiary education	0.024*	0.138**	-0.075**
	(0.011)	(0.011)	(0.005)
Firm size: 11-50	-0.007	-0.007	0.000
	(0.009)	(0.008)	(0.005)
Firm size: 51-250	0.015	0.018*	-0.005
	(0.001)	(0.008)*	(0.006)
Firm size: 251-999	0.006	0.015	-0.011
	(0.013)	(0.012)	(0.008)
Firm size: >1000	0.032**	0.034**	-0.004
	(0.012)	(0.011)	(0.007)
Fixed contract	-0.017	-0.009	-0.004
	(0.009)	(0.007)	(0.006)
Temp agency/No	0.005	0.021	-0.01
contract/Apprenticeship	(0.021)	(0.019)	(0.010)
Part-time worker	0.027**	0.030**	-0.001
	(0.009)	(0.008)	(0.005)
Public sector/NGO	-0.019*	-0.023**	0.005
	(0.008)	(0.007)	(0.004)
Number of observations	76183	76183	76183
pseudo-R2	0.009	0.047	0.079

Notes: Estimates from logit regressions. Values are marginal effects. The coefficients correspond to the impact of a change in the explanatory variable on the probability of mismatch at the mean of the independent variables. Regressions include as controls age, marital and migrant status, gender, level of education, firm size, contract type, a dummy for working full-time and working in the private sector. Robust standard errors in parentheses. ** denotes statistical significance at the 1% level, * significance at the 5% level.