I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15482

Migration and Firm-Level Productivity

Richard Fabling
David C Maré
Philip Stevens

AUGUST 2022

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15482

Migration and Firm-Level Productivity

Richard Fabling
New Zealand Productivity Commission

David C Maré
Motu Research and IZA

Philip Stevens
New Zealand Productivity Commission

AUGUST 2022

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Migration and Firm-Level Productivity

We use linked employer-employee microdata for New Zealand to examine the relationship between firm-level productivity, wages and workforce composition. Jointly estimating production functions and firm- level wage bill equations, we compare migrant workers with NZ-born workers, through the lens of a derived "productivity-wage gap" that captures the difference in relative contribution to output and the wage bill. Whether we look at all industries using a common production function, or separately estimate results for the five largest sectors, we find that skilled and long-term migrants make contributions to output that exceed moderately-skilled NZ-born workers, with that higher contribution likely being due to a mix of skill differences and/or effort which is largely reflected in higher wages. Conversely, migrants that are not on skilled visas are associated with lower output and lower wages than moderately-skilled NZ-born, also consistent with a skills/effort narrative. The share of employment for long-term migrants has grown over time (from 2005 to 2019) and we show that their relative contribution to output appears to be increasing over the same period. Finally, we present tentative evidence that high-skilled NZ-born workers make a stronger contribution to output when they work in firms with higher migrant shares, which is suggestive of complementarities between the two groups or, at least, positive mutual sorting of these groups into higher productivity firms.

JEL Classification: D24, J15, J31

Keywords: migrant labour, firm productivity, worker sorting, wage determinants, quality-adjusted labour input

Corresponding author:
Richard Fabling
New Zealand Productivity Commission
PO Box 8036
Wellington 6143
New Zealand

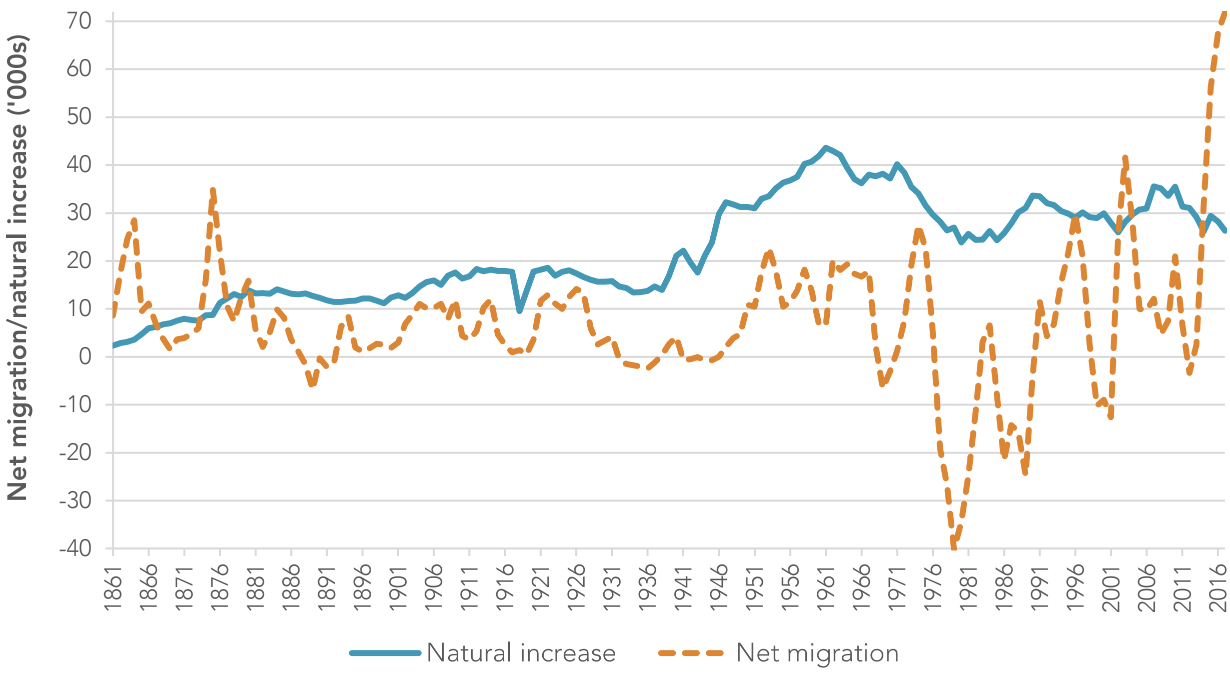
E-mail: richard.fabling@productivity.govt.nz

1 Introduction

Migration is an important element in the functioning of the world economy, creating gains when workers move to where they can have the greatest impact, and from firms employing the best-matched workers they can (Nickell, 2009). These gains will be positive for the world economy as a whole since moving labour from low-productivity to high-productivity countries improves allocative efficiency (Hanson, 2009). The impacts may not, however, be universally positive, likely causing a redistribution of income between source and destination countries and, potentially, changing the distribution of income within each country.

There are a number of reasons why migration can be welfare-enhancing for both the migrant and the country to which they are moving. Immigrant workers can fill gaps where skills are in short supply and bring with them ideas – knowledge of foreign markets, of new ways to do things and new things to do. These benefits may be particularly important for a small, geographically isolated nation like New Zealand. Migrants have also overcome financial and social costs and taken risks to make the move, and so can be expected to be motivated to succeed. There are, however, potential negative effects of immigration that could offset any benefits. Perhaps immigrant workers put downward pressure on the salaries of domestic workers, or struggle to be productive because of language barriers, or differences in societal or cultural norms.

Figure 1 Net migration and natural increase in New Zealand population



Source: (Data1850, 2019; Productivity Commission, 2021)

The large-scale immigration that followed the signing of the Treaty of Waitangi | Te Tiriti o Waitangi transformed New Zealand. As recently as the 1970s, immigration policy settings meant that migrants were overwhelmingly British and European. Policy changes in the 1980s and 1990s led to dramatic changes in the diversity of New Zealand's migrant intake (Productivity Commission, 2021). New Zealand has seen a net inflow of people in four out of every five years during the last century-and-a-half (Figure 1). Migration flows have become larger, and net migration has become more volatile in the last 50 years or so, compared to the preceding 75 years of relative stability.

In this paper, we investigate the link between migrants and productivity in New Zealand. We use information on flows of migrants into and out of New Zealand, visas, earnings and jobs, to see how productivity differs not only between migrants and non-migrants, but also whether migrants from our nearest neighbour – geographically and culturally – Australia, differ from New Zealanders, or from migrants from the rest of the world. We also compare the relative productivity and wages of migrants on different visa types and compare recent and longer-term migrants.

In the following section, we provide some background on the theory and evidence around the relationship between migration and productivity. We describe our empirical model and estimation methodology in section 3 and then, in section 4, describe the data we estimate models on. Sections 5 and 6, respectively, discuss results and conclusions.

2 Migration and productivity

The effect of migration is one the most investigated areas of labour economics, with much of the focus in the field being on the impact of migrant labour on native workers' wages and employment. The results of this analysis are generally consistent, implying the overall wage-reducing effect of migration is somewhere between minor and non-existent (Edo, 2019; Edo et al., 2020; Longhi et al., 2005, 2010; Nickell, 2009; and Maré & Stillman, 2009, for New Zealand-specific findings), though there is evidence of distributional impacts, ie, that there may be winners and losers (eg, Dustmann et al., 2013).

Estimated neutral effects in these studies result from the net outcome of myriad economic impacts operating in opposing directions. The most obvious impact is the simple static effect that an increase in the supply of labour leads to a decline in wages, all other things equal (Borjas, 2003, 2013). However, all other things are seldom equal, not least because migrants demand food and clothing, housing and other amenities. These products and services must be produced, often domestically, increasing the demand for labour.[2] The idea that immigration increases only labour supply, not labour demand,[3] does not appear to be supported by evidence. This is true not only in the long-run, when other factors (such as capital) can adjust, but also in the short-run (Campo et al., 2018; Card, 2012; Edo, 2019; Edo et al., 2020; Longhi et al., 2005, 2010). Indeed, evidence from a particular episode on the Czech-German border appears to confirm this. Dustmann et al. (2017) study Czech workers who commuted across the border to Germany but were prevented from permanently migrating to Germany. Because Czech workers returned home across the border to spend their earnings there was no impact on the demand for labour in the German border municipalities. The impact of this particular policy, therefore, was to temporarily reduce the growth of local native employment in Germany and to produce a moderate decline in the wages of native workers in Germany. In most other situations, this is not likely to be the case (eg, remittances may reduce the demand effect on the local economy, but only if remittances reduce consumption rather than savings).

There are many other avenues for impacts on the economy and wellbeing of the country including innovation, productivity, trade, and output (Campo et al., 2018; Jaumotte et al., 2016). In this paper we focus on the contribution that migrants make to the productivity of New Zealand firms.

2.1 Mechanisms linking migration and productivity

There are multiple mechanisms through which immigrant workers may affect productivity in the destination country. Because of this, the overall impact of migration on productivity is ambiguous and will depend on the balance of factors both directly and indirectly affecting workers and firms, as well as the direct effect of migration on the composition of worker and firm characteristics.

First, the capital stock is not fixed and it will shift in response to changes in the level and composition of labour supply (Lewis & Peri, 2015; Nickell, 2009; Ottaviano & Peri, 2012). Net immigration increases the total labour supply, increasing the return to capital. This in turn leads to an increase in capital investment, and hence productivity and labour demand (Friedberg & Hunt, 1995). This impact will be even higher if migrant workers are complementary with capital, and lower if they are substitutes.

[2] If the supply of products demanded by migrants is inelastic – like housing – the effect may be predominantly to raise prices.

[3] An extreme example of this – that there is a fixed amount of work – has been described as the "lump of labour fallacy", after Schloss (1891). Borjas (2003, 2013) does not go quite this far, arguing that the (short-run) labour demand curve is downward-sloping, rather than completely inelastic.

The second mechanism linking migration and productivity is the direct effect of changing the composition of the labour force (Campo et al., 2018; Nickell, 2009). If immigrant workers are more (less) productive than domestic workers, this difference in ability will raise (lower) the average productivity of the workforce. Immigrant workers may have lower productivity if they do not understand local language, culture or norms. New Zealand is part of a group of English-speaking nations with a high proportion of high-skilled migrants (compared to, eg, European and Nordic countries, Jaumotte et al., 2016), which suggests *prima facie,* that migrants are likely to have a positive impact on average worker productivity.

At the national level, there is also a broader composition effect. Immigration can raise the average productivity of the whole economy because migrants are typically more likely to be of working age than the native-born population (Jaumotte et al., 2016). Further, working age immigrants increase the tax base and reduce per capita medical and retirement costs, at least in the short- to medium-term.

There are also a range of potential within-firm complementarities to consider. Migrants may be complementary with – or substitutes for – other factors of production. Beyond the macroeconomic effect described above, immigration may increase the demand for complementary capital (both physical and intangible). However, an increase in unskilled migrants may disincentivise investment in labour-replacing capital (eg, reduce uptake of automation). Generally, we might expect capital and high-skilled labour to be complements, and capital and low-skilled labour to be substitutes.[4] In this case, immigration of labour at different skill levels may cause firms to invest and/or disinvest in capital of different types (Edo, 2019; Lewis, 2011, 2013; Longhi et al., 2010). The long-run impact of immigration will not be on the average wage alone, therefore, but on the composition of employment and the technologies adopted by firms.

Even at given skill levels, there are specificities to the skills that immigrants have that will affect their impact on the economy. Migrants have access to different ways of working, and knowledge of foreign markets. For example, high-skilled migrants appear to increase patenting and innovation in the US because they are more concentrated in science, technology, engineering and mathematics (STEM) fields than US-born workers (Hunt & Gauthier-Loiselle, 2010; Kerr & Lincoln, 2010), and to be important for international networks of innovation (Kerr & Kerr, 2019). Migrant knowledge and skills may, in turn, be adopted by local workers and firms (ie, there may be positive knowledge spillovers).

The availability of skilled migrants may reduce the incentive for firms to train their workforce (reflecting the "make or buy" choice, eg, Campo et al., 2018; Timmins et al., 2012). However, skilled migration may also increase the incentive for firms to train native workers for complementary roles, emphasising those workers' comparative advantages. Local workers may be spurred to upskill themselves to leverage off or build a comparative advantage. For example, the comparative advantage of native workers in terms of language and local knowledge can lead to manual workers moving to better paid jobs that have more need for these skills, rather than those workers entering into direct competition with migrants (Peri & Sparber, 2009). Furthermore, training may be directly complementary with migrant workers, and may help overcome any lack of language or cultural competence.

Within-sector complementarities might exist, whereby firms increase in size with the hiring of migrant labour, creating economies of scale, clustering effects, and/or increased competition (Campo et al., 2018). For example, thicker and more diverse labour markets increase the quality of worker-firm (job) matches (Andersson et al., 2007; Delacroix, 2003; Glaeser & Maré, 2001; McLaren, 2003) meaning that workers are less likely to work in roles that are poor matches for their skills and firms are less likely to employ staff with inadequate skills. Any such effect will be moderated by the impact of the migrant workers' lower local knowledge, which will tend to lower match efficiency. Thickness of the labour market can also create a greater diversity of skills, which can create its own benefits (Alesina et al., 2016).

[4] This is not always the case, eg, when skilled craftspeople are replaced with capital and unskilled labour to operate it (eg, mass manufacture of furniture).

2.2 Evidence of a relationship between migration and productivity

Whole economy

Nickell (2010) notes that migration will raise the long-run level of potential output, but that the size of this boost will depend on several factors related to the nature of immigration. In particular, if migrants are more skilled, on average, than natives and there is capital-skill complementarity, then in the long-run both the capital/labour ratio and productivity will be higher. Nickell refers to international evidence cited in OECD (2007) that "suggests immigration can serve to make the labour market as a whole more fluid and wages less sensitive to demand fluctuations." He notes that the short-run effects of immigration on the economy depend on the relative influences of immigration on aggregate supply and demand.

In their study of 188 (mainly) developing countries, Ortega & Peri (2014) provide evidence of a positive effect of openness to immigration on long-run per capita income. They find that the effect of immigration depends less on a country's openness to trade than on its existing workforce, particularly that countries with a highly educated domestic labour force benefit more from immigration. Ortega & Peri draw parallels with research findings that countries endowed with higher human capital are better at absorbing knowledge created abroad, concluding that their results are consistent with immigrants being transmitters of new knowledge and ideas. It may also be the case that the type of migrant differs across recipient countries – ie, that more-highly skilled people choose to migrate to countries where average skills are already relatively high.

Ortega & Peri (2014)'s findings provide "suggestive evidence that one of the channels through which immigration increases labor productivity in the long-run may be by contributing to higher rates of innovation per capita" (p. 248). They note that this evidence doesn't "necessarily imply that the immigrants themselves produce the whole increase in innovation. Combining different and complementary ideas can also make natives more innovative" (p. 248). The diversity of skill types associated with migration has been found to be positively associated with economic output at a macroeconomic level, with the effects being higher for immigrants from richer and culturally proximate countries (Alesina et al., 2016). Cultural proximity may aid the transmission of knowledge between migrant and domestic workers.

Boubtane et al. (2016) take a structural macroeconomic approach, modelling the impact of immigration through the estimation of an augmented Solow-Swan model. They look at economic growth using a dynamic panel data GMM method for 22 OECD countries over 1986–2006. Because of the structure of their model, the impact of migration is felt through its impact on the average level of human capital and a physical capital dilution effect. Boubtane et al. find evidence of both these effects (positive and negative on output, respectively, as theory would suggest), and their simulations indicate that the positive effect dominates the negative effect in almost all countries. In the two countries where the negative impact dominates – Greece and the United States – the net negative effect is small and "represents only one-tenth of the negative impact of a comparable increase in the natural population growth rate" (Boubtane et al., 2016, p. 354).

Boubtane et al.'s results suggest that both the impact of migrants' human capital and a permanent increase in migration flows have a positive effect on GDP per worker, and that the growth impact of immigration is economically significant even in countries that have non-selective migration policies. Specifically, their results suggest that a short-run 50% increase in the net migration rate of the foreign-born would increase GDP per worker by 0.3% per year. In the long-run this effect is, on average, 2% per year, leading Boubtane et al. to conclude that the migration growth effect is "high for all countries except Finland and Germany" (p. 354).

Regions and industries

Peri (2012) uses aggregated annual US state-level data to estimate state-level production functions that allow for substitutability between low- and high-skilled workers. They address the endogeneity of immigrant settlement location by employing a shift-share instrumental variable (IV) approach based on Card (2001), and by exploiting the tendency of migrants to enter the US via three primary routes (Los Angeles, New York, and the US-Mexico border). Peri finds that state-level total factor productivity (TFP) is increased by growth in the migrant share. Their choice of production function – coupled with an assumption that wages reflect marginal productivity – allows them to explore the channels through which productivity increases, finding that immigration favours production technologies that are less capital-intensive and less skills-intensive. Peri also concludes that the capital-labour ratio remains stable when immigration increases, but that the capital-output ratio falls as a consequence of the productivity effect on state-level output. He concludes that the increased availability of low-skilled migrants appears to push firms towards technologies that favour the use of unskilled workers, and encourages immigrants to specialise in manual-intensive tasks and native workers to specialise in communication-intensive tasks.

Campo et al. (2018) look at the relationship between migration and productivity in UK labour markets. They model the one-year change in productivity (and training) as a function of the change in the migrant share of the employed population at the labour market level (Local Authorities or travel-to-work areas). They do not control for other variables, like investment, stating that their focus is on the relationship between migration and productivity, and they are indifferent as to whether this is a direct or indirect relationship. Campo et al.'s first-difference approach accounts for the endogeneity of migrant settlement decisions – ie, that high productivity regions attract more immigrants – if these effects are constant over time. They also address endogeneity following Card (2001) and as implemented by Bianchi et al. (2012).

Campo et al.'s results suggest that immigration has a positive and significant impact on productivity at the labour market level. This result is driven by immigrants with higher levels of education or working in higher-skilled occupations. They interpret the fact that their OLS estimates do not find such results, but that their instrumental variables approach does, as implying that the positive impact of immigration is concentrated in areas with slower productivity growth, and hence helps those regions catch up to the productivity frontier.

Firms

Jacobs et al. (2022) look at migration and firm-level productivity focussing on the issue of over-education, where a worker accepts a job with lower skill requirements than the worker has. Jacobs et al. (2022) jointly estimate wage and productivity equations using Belgian matched employer-employee data, supplemented with measures of over-education, to see if the productivity and wage premia obtained by immigrants and natives are similar. They find that the over-education wage premium is higher for natives than for immigrants. However, since the differential in productivity gains associated with over-education between natives and immigrants outweighs the corresponding wage premium differential, they conclude that over-educated native workers are actually underpaid more than their over-educated immigrant counterparts. Over- and under-education as they define them are both common affecting 20% and 27% of workers respectively. Interestingly, in their sample, over-education (under-education) is more (less) common in native workers than migrants, which may reflect the fact that 42% of Belgian immigrants in the sample are from developing countries.

Aslund et al. (2021) use Swedish linked employer-employee data to demonstrate a strong pattern of migrant sorting based on firm productivity, where firms are assigned to productivity deciles based on average (detrended) labour productivity. In particular, they find that immigrants constitute 20-25% of employment in the four lowest productivity deciles, and 10% of employment in the top productivity decile. Differences in firm-level productivity account for a substantial share of wage differences between migrants and natives, since the average wage is increasing in measured (labour) productivity.

On a similar theme, Dostie et al. (2020) use linked employer-employee data for Canada to demonstrate assortative matching of high-skilled (bachelor degree and above) workers – both natives and migrants –

into high wage premium firms. They do this using a two-way log wage fixed effect model (similar to the model we use to estimate New Zealand worker skill) and estimate the model separately for natives and (resident) immigrants. Calibrating their two sets of estimates using a theoretical rent-sharing model and firm-level value-added data, they show that the sorting of workers into high wage premium (high productivity) firms accounts for a substantial proportion of the wage gap between migrants and natives. In contrast, the native-migrant wage gap is not driven by a tendency for firms to have higher premia for natives than they do for migrants. Looking at a cohort of recent migrants they show that skilled migrants from "non-traditional" source countries experience a weaker sorting effect, but that these workers move up the job ladder (ie, move to higher paying firms) over the following five years, which Dostie et al. attribute to employers learning about the quality of the degrees that these migrants hold.

Maré & Fabling (2013) examine the relationship between local workforce composition and the (multifactor) productivity of New Zealand firms. They consider three local area population characteristics, the proportion: foreign-born; highly qualified; and newly arrived in the area. High productivity firms are disproportionately located in areas with a high proportion of immigrants, skilled workers, and new arrivals. However, the positive bivariate relationship between migration and productivity disappears when the other two local area variables are included. Maré & Fabling's results are robust to using IV and first-difference estimators, leading them to conclude that there is evidence of local labour market agglomeration effects – particularly that firms benefit from productive spillovers when they operate in areas with high-skilled workers. They also estimate specifications that separate local area population shares into high-skilled and low-skilled migrants, and migrants that are new to the area and those that have been there for five years or more. Their results highlight the importance of allowing for heterogeneity in the workforce. In particular, they find that high-skilled migrants who are new to the area are associated with higher productivity, with a 10% increase in degree-qualified migrants entering an area associated with 1.2% higher productivity. International studies using similar IV estimator approaches – and focussing on (largely) skilled migration into advanced economies – also find causal relationships between the local labour market migrant share and firm-level productivity for a subset of studied industries (manufacturing firms in France, Mitaritonna et al., 2017; service firms in the UK, Ottaviano et al., 2018; and skill-intensive firms in Switzerland, Beerli et al., 2021).

The transmission of knowledge and, hence, innovation might generate a positive migrant-productivity relationship. McLeod et al. (2014) look at the impact of the proportion of long-term and recent migrants on a range of innovation outcomes in New Zealand firms. They find that firms with a higher share of high-skilled recent migrants are more likely to introduce new marketing methods, new products, and products that are new to New Zealand. As with Maré & Fabling (2013), the estimated relationships between firm innovation outcomes and migrant shares weaken when other (firm and worker) characteristics are taken into account.

3 Empirical model

3.1 Basic production model

Our empirical model starts from a general production function of the form:

$$Y = Af(M, K, \tilde{L}) \tag{1}$$

where Y is gross output, A captures factors that influence multifactor productivity, M is intermediate consumption, K is capital services and $\tilde{L}$ is effective labour input. The main contribution of this paper is in how we model effective labour as a weighted combination of NZ-born (native) and migrant labour shares. Weights on each labour type are estimated simultaneously with other production function parameters. To aid understanding of the estimated effective labour input weights, we additionally estimate a firm-level wage bill (W) equation that replicates the exact functional form of the productivity equation (as is done in previous work looking at productivity-wage differentials across heterogenous labour types, such as Hellerstein et al. (1999), Hellerstein & Neumark (1995, 1999, 2007, 2008) and, for New Zealand, Sin et al. (2020). The comparison of production function and firm-level wage bill equation weights on each type of labour helps address the fact that we do not directly measure worker hours or ability, since we expect variation in effort and ability across workers to be identified by higher weights in both the production function and wage bill equation.

Our estimating equation for (1) takes the transcendental logarithm (translog) form, which is a general production function that is a second-order approximation to a range of alternative functions (Berndt & Christensen, 1973; Christensen et al., 1973; Griliches & Ringstad, 1971). For output, we estimate:

$$\begin{aligned} y_{it} = \beta_0 + \beta_m m_{it} + \beta_k k_{it} + \beta_l \tilde{l}_{it} + \beta_{mm} m_{it}.m_{it} + \beta_{mk} m_{it}.k_{it} + \beta_{ml} m_{it}.\tilde{l}_{it} \\ + \beta_{kk} k_{it}.k_{it} + \beta_{kl} k_{it}.\tilde{l}_{it} + \beta_{ll} \tilde{l}_{it}.\tilde{l}_{it} + \beta_Z Z_{it} + \epsilon_{it} \end{aligned} \tag{2}$$

for firm i in year t where lower-case variables denote logged values of output and inputs, Z_{it} is a set of industry and year controls (intercept dummies and time trends in pooled industry regressions, or industry-year dummies for industry-specific regressions) and ϵ_{it} is an error term. The associated firm-level wage bill equation (with error term η_{it}) is:

$$\begin{aligned} w_{it} = \gamma_0 + \gamma_m m_{it} + \gamma_k k_{it} + \gamma_l \tilde{l}_{it} + \gamma_{mm} m_{it}.m_{it} + \gamma_{mk} m_{it}.k_{it} + \gamma_{ml} m_{it}.\tilde{l}_{it} \\ + \gamma_{kk} k_{it}.k_{it} + \gamma_{kl} k_{it}.\tilde{l}_{it} + \gamma_{ll} \tilde{l}_{it}.\tilde{l}_{it} + \gamma_Z Z_{it} + \eta_{it}. \end{aligned} \tag{3}$$

3.2 Labour input

Reflecting the diversity of the New Zealand labour market and the richness (and limitations) of the available microdata, we estimate production functions utilising permutations of the following labour types (described in detail in section 4):

Box 1 **Labour types**

1. NZ-born (native) (L_{NZ})
   - 1a. Low-skilled NZ-born $(L_{NZ,Lo})$
   - 1b. Moderately-skilled NZ-born $(L_{NZ,Mod})$
   - 1c. High-skilled NZ-born $(L_{NZ,Hi})$
2. Migrants (foreign-born): (L_{Mig})
   - 2a. Australian (L_{Oz})
   - 2b. Long-term migrant: (5+ years) (L_{LT})
   - 2c. Recent migrant: (<5 years) (L_{RM})
     - Skilled resident (L_{SR})
     - Skilled non-resident (primarily work visas) (L_{SNR})
     - Other resident (L_{OR})
     - Other non-resident (L_{ONR})

Since we estimate production functions with up to eight of these labour types, it is impractical to include each type as a completely independent input into the production function. The number of translog parameters to estimate rises non-linearly with the number of inputs, affecting both feasibility of estimation – particularly if labour inputs are highly correlated – and feasibility of interpretation (ie, an overwhelming number of parameters to interpret). Additionally, with separate labour inputs, the estimation sample is restricted to firms that have all labour types, which is likely to cause selection bias in the estimated coefficients. Instead, we include a single effective labour input $(\tilde{L})$ which is a full-time equivalent labour share $(S_j = L_j/L)$ weighted average of each of the j labour types. For the production function and firm-level wage bill equation, respectively, $\tilde{L}$ takes the following form:

$$\tilde{L} = L\left(S_0 + \sum_{j>0}[(1+\phi_j).S_j]\right) \tag{4}$$

$$\tilde{L} = L\left(S_0 + \sum_{j>0}[(1+\psi_j).S_j]\right) \tag{5}$$

where, eg, $(1+\phi_j)$ is the estimated weight on each labour type in the production function, relative to a chosen base worker type $(j = 0)$ with weight of one. The specification of the estimated weights as one plus a group-specific parameter means that finding that an effective labour input parameter is insignificantly different from zero implies that we cannot reject the hypothesis that the associated labour group has the same weight as the base group. In some specifications, the base labour type is NZ-born workers, and in others it is moderately-skilled NZ-born workers. With this specification of effective labour input, any difference between the base group contribution to productivity and firm-level wages is incorporated into the estimated coefficient on effective labour in the respective equation (since, in effect, we set $\phi_0 = \psi_0 \equiv 0$). This normalisation affects the interpretation of differences between productivity and wage coefficients for the remaining j labour groups (discussed in section 5).

3.3 Estimation

The model (2)-(5) is jointly estimated using non-linear seemingly unrelated regression (Zellner, 1962, 1963). However, because multiple observations of the same firm do not provide completely independent information, standard errors will tend to be too small, risking over-rejection of true null hypotheses. To correct for this issue, we estimate standard errors clustered on firm using the Huber-White sandwich estimator (Huber, 1967; White, 1980, 1982).

In order to investigate whether the relative contribution of migrant labour to productivity has evolved over time, we also estimate the model for three independent five-year periods (2005-2009; 2010-2014; 2015-2019). The production technology facing firms is likely to differ across industries. Therefore, in addition to estimating pooled production functions with industry controls, we estimate regressions for a subset of the largest industry sectors.

4 Data and summary statistics

Our analysis is based on two collections of administrative and survey data: the Integrated Data Infrastructure (IDI) and the Longitudinal Business Database (LBD).[5] The method that creates the labour and productivity data we use is described in detail in Fabling (2011) and Fabling & Maré (2015a, 2015b, 2019). Both labour and productivity data are largely based on firm-level tax filing and jointly cover the 2001 to 2019 financial years. For measurement and conceptual reasons, the productivity dataset is restricted to the private-for-profit sector and excludes industries where Stats NZ deems output too hard to measure accurately. Individual jobs are observed monthly and include an approximate FTE measure, which we aggregate together with working proprietor (WP) labour to calculate total labour input at each firm in a year.

As outlined in the previous section (Box 1), the estimated production functions and firm-level wage bill equations allow for differences between workers based on individual characteristics. To implement this disaggregated effective labour input approach, we start by identifying whether each worker is NZ-born. For the non-NZ-born (migrant) sub-population, we then establish whether they are Australian-born – having the right to live and work in New Zealand without a visa – or non-Australian born. For non-

[5] We use data from the 20201020 IDI which, at the initial time of writing, was the most recent IDI instance that had related productivity tables in the LBD.

Australian-born migrants, we determine whether they are a recent migrant – arrived in New Zealand to live within the last five years – or a long-term migrant. Recent migrants are then grouped based on whether they have a resident or non-resident visa, and whether that visa is classified as skilled or not.

We also consider specifications where the NZ-born labour input is divided into three groups, determined by a measure of the market value of the individual workers' skills. This classification comes from an estimated two-way fixed effect model that decomposes log real wages into five components related to: year; worker observables (quartic in age by sex); worker fixed effect; firm fixed effect and a residual year-specific job match component (as in Maré et al., 2017b, who follow the method of Abowd et al., 1999). The firm fixed effect is the wage premium paid by a firm to all employees regardless of ability, while the worker fixed effect is a portable wage premium received by a worker wherever they work. In our analysis, we treat the sum of worker fixed effect and worker observables as a proxy measure of skill, classifying NZ-born workers as high-skill (low-skill) if their measured skill is in the top (bottom) year-sex-specific quartile. Thus, in any year a quarter of NZ-born male and female FTE is high-skill, a quarter is low-skill, and the remaining half is moderately-skilled. A worker can change skill groups due to ageing and the movement of skill group boundaries over time. This classification allows us to compare migrant productivity to NZ-born workers of different labour market earnings ability, without having to rely on, eg, incomplete data on qualifications.

To allocate workers to the appropriate migrant labour type we require additional data linked to individual workers in the IDI, specifically Ministry of Business, Innovation and Employment (MBIE) visa decisions and border movements data; Department of Internal Affairs (DIA) birth records; and unimputed Census (2013 and 2018) responses.

DIA birth records are used to identify NZ-born individuals, with supplemental use of Census responses to account for non-linking of birth records to other data in the IDI, primarily for married women (see Appendix A). To distinguish Australian-born from other migrants, we first use Census country of birth and then, in the absence of that, we use border movements data.[6] The latter is only approximately correct, since the border movements data include passport nationality, rather than birth country. We match Census and border movements data to determine appropriate rules for identifying Australian-born migrants, ultimately assuming that a migrant is Australian-born if they are observed crossing the border on an Australian passport, but never on another foreign (non-NZ) passport.[7] Across all years of labour data, country/region of birth is derived from DIA birth records for 65% (70%) of total female (male) FTE employment, while Census responses are used for 30% (23%). MBIE data, which results in approximate identification of country of birth, are used only in conjunction with 5% (6%) of total FTE employment of women (men).

Not all workers are covered by these data, meaning that country of birth is missing for individuals who are not identified as NZ-born in DIA birth records, have no useable Census response, and who never arrive or leave New Zealand at any time after mid-1997 (the first year of MBIE border data). Less than one% of aggregate FTE employment has missing country/region of birth and, in the subsequent firm-level analysis, we impute missing characteristics with the mean of observed co-worker characteristics, after dropping firm-level observations where workers with observables constitute less than three quarters of firm-level total labour input.

To identify whether a non-Australian-born migrant is recent or long-term, we use Census responses and border movements data. Because the border movement and visa data are left-censored (they start in July 1997), we restrict our firm-level analysis to the 2005 financial year onwards to limit the potential for misclassifying individuals' arrival date due to missing migration data. Then, where there is a useable Census arrival date response, we take that response as given.[8] In the absence of a Census response, we assume arrival in New Zealand is in July 1997 for workers who are first observed in the movements data

[6] For individuals with conflicting responses across the two censuses, we prioritise responses with both country and arrival month (for non-NZ-born) over partial responses, and then prioritise the 2013 Census response over the 2018 Census response.

[7] Unreported testing suggests that using visa data in conjunction with movements data does not improve the accuracy of birth country identification.

[8] Where Census year of arrival is reported but month of arrival is missing, we assume the month is January (since month is an optional "if known" field).

as departing New Zealand, or who are never in the movements data. The logic for the latter group is that, since these individuals are employees of New Zealand firms, they are highly likely to be in New Zealand and, therefore, must have arrived in New Zealand prior to July 1997. We assume that this (censored) arrival is for the purpose of living in New Zealand. For remaining individuals, we approximate arrival to live in New Zealand, rather than arrival on a temporary basis, by looking for the first arrival associated with a stay of at least 120 days. Census responses account for 82% of total FTE, with 4% of arrival dates being left-censored and assumed to be July 1997, and a further 13% determined by the first stay of 120 days or more.[9] Testing our method for administrative-based responses against Census actual responses, we estimate that 98.5% of total FTE is associated with an arrival month that is within a year of actual arrival.

Finally, visa decision data are used to identify residence versus other visas for recent arrivals, as well as whether the visa is classified as skills-related or not. The decisions data are first restricted to visa approvals and then assigned to one of 30 visa sub-streams, following the methodology used by MBIE, in their statistical reporting (MBIE, 2020, and associated SAS code). The main purpose of this recoding – which depends on application criteria, application stream, and whether an individual is the primary or secondary applicant – is to consistently combine similar visas over time into meaningful groupings that abstract from policy changes to the various visa programmes.

To convert the point-in-time decisions data to spells data, we make use of reported visa expiry dates, eliminating gaps between the end of one visa and the start of another if that gap is at most 30 days (by extending the duration of the earlier visa). Where visa end dates are missing, we assume the visa duration is the 90th percentile of observed visa durations for that particular visa sub-stream. We use the 15th of each employment month as the reference date for determining the current visa sub-stream and, where the visa spells data has a gap – ie, where we observe employment in the absence of an active visa – we impute the sub-stream using the prior visa or, in the rare cases where a prior visa is absent, the subsequent visa. For individuals where we observe no visa data, we rely on arrival visa in the border movements data (classifying migrants to generic "other" categories due to lack of fine detail in the movements data). Overall, 95% of recent migrant FTE is classified to a visa sub-stream based on a current active visa in the visa decisions data, 3% is imputed (primarily from a prior visa), and 2% is based on arrivals data.

4.1 Migrant employment patterns

Table 1 reports the aggregate FTE share for each MBIE visa sub-stream, and the classification of those sub-streams to the four recent migrant groups of interest. The skilled residents group includes entrepreneur and investor categories, and accounts for 28% of recent migrant FTE.[10] Skilled non-residents account for 19% of recent migrant FTE, mainly workers on essential skills visas. Other residents and other non-residents account for 16% and 37% of total recent migrant FTE.

[9] The remaining 0.7% of arrival dates are determined by looking for stays of decreasing duration in 30-day increments, or by taking the first arrival on a non-visitor visa, or the first arrival date.

[10] Primary and secondary applicant distinctions are not used to distinguish labour types.

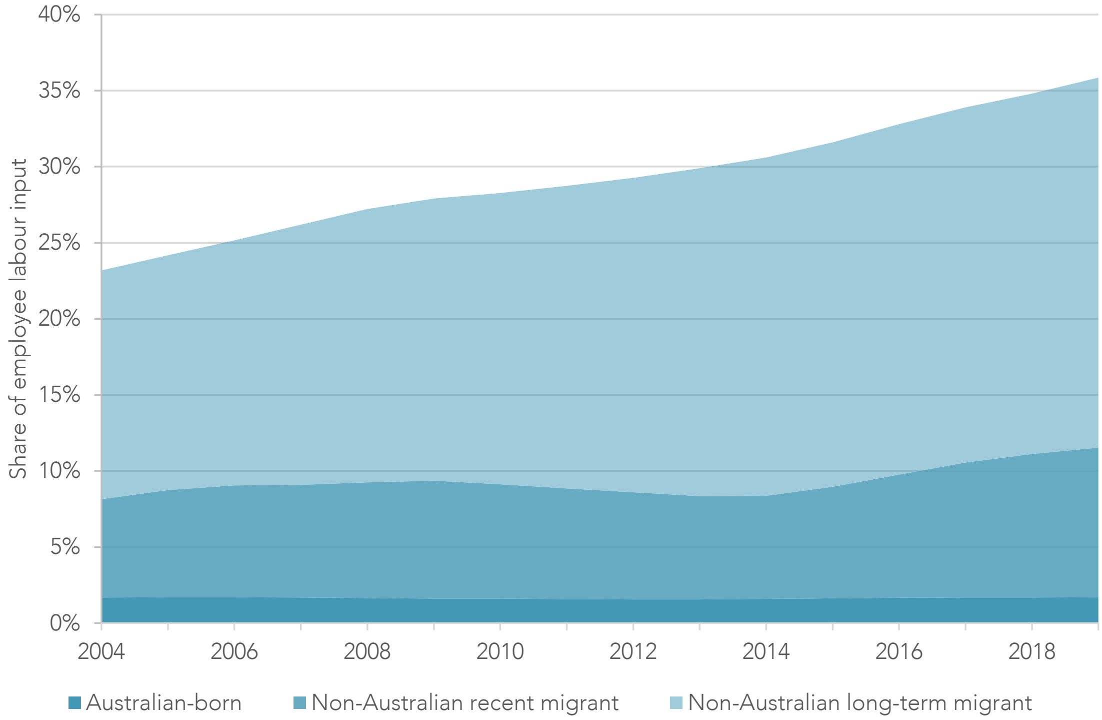
Table 1 FTE-weighted contribution of MBIE visa sub-streams to recent migrant types

Visa sub-stream	FTE share	Visa sub-stream	FTE share
Skilled resident (SR)		Skilled non-resident (SNR)	
Res – Skilled (Primary)	17.75%	Work – Essential Skills	15.64%
Res – Skilled (Secondary)	9.68%	Work to Residence	3.74%
Res – Entrepreneur (Primary)	0.04%	**Total**	**19.38%**
Res – Entrepreneur (Secondary)	0.09%		
Res – Investor (Primary)	0.03%		
Res – Investor (Secondary)	0.07%		
Long-Term Business Visa – Investor (Primary)	0.07%		
Long-Term Business Visa – Investor (Secondary)	0.00%		
Total	**27.73%**		
Other resident (OR)		Other non-resident (ONR)	
Res – Other Capped	1.32%	Student – Fee Paying	5.02%
Res – Other Business/Skilled (Deferrals)	0.04%	Student – Other	0.23%
Res – Other International/Humanitarian	0.41%	Study to work	6.93%
Res – Pacific (Primary)	1.09%	Visitor	1.04%
Res – Pacific (Secondary)	0.56%	Work – Family	8.83%
Res – Parent	0.94%	Work – Other	3.66%
Res – Partnership	8.00%	Work – Recognised Seasonal Employer	1.63%
Res – Refugee	0.34%	Work – Working Holiday Scheme	9.23%
Res – Other Uncapped	0.95%	All other temporary visas	0.10%
Res – Unknown	2.56%		
Total	**16.22%**	**Total**	**36.66%**

Notes: Shares are of recent migrants pooled over the period 2004-2019 (calendar years) and are based on total FTE employment from the Fabling-Maré labour tables for all employees with observed characteristics (country/region of birth, age and sex).

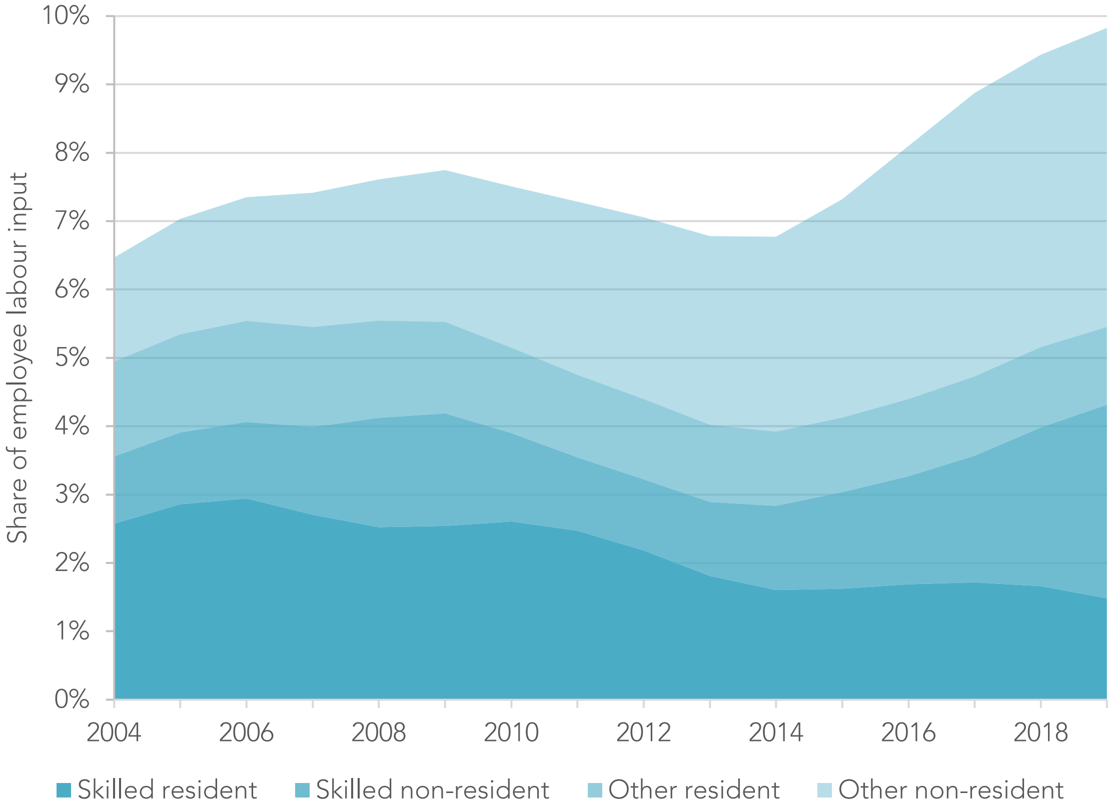
Figure 2 and Figure 3 bring together these classifications, showing how the aggregate contribution of migrants to total FTE employee labour input varies by calendar year. Long-term (5yr+) non-Australian migrants are the largest contributor to total employee labour input, and this contribution grows steadily over time – initially accounting for 15% of FTE in 2004 and rising to over 24% of FTE in 2019. The recent (<5yr) non-Australian migrant share of total FTE also grows over this period, rising from 6.5% of the total in 2004 to 9.8% in 2019. Figure 3 shows that the growth of recent migrant labour share is driven by growth in the non-resident migrant categories offset by decreases in the contribution of recent residents. In particular, the proportion of total FTE in both skilled and other non-resident migrants almost triples from a low base, rising from 1% in 2004 to 2.8% in 2019 for skilled non-residents, and from 1.5% to 4.4% for non-skilled.

Figure 2 Share of total employee FTE by recency of migration



Notes: Shares are for each calendar year and are based on total FTE employment from the Fabling-Maré labour tables for all employees with observed characteristics (country/region of birth, age and sex). Employees with missing characteristics account for 1.1% of total FTE. Migrant categories are defined in Box 1 and Table 1.

Figure 3 Share of total employee FTE for recent migrants by visa category



Notes: See Figure 2 notes.

In Table 2 we link migrants employed in 2013 to their Census responses in that year and report the proportion of 2013 FTE by birth country, restricted to the top 20 contributing countries. For each country, we then also report the share of long-term and recent migrants by visa group (four right-most columns). For example, migrants from the United Kingdom account for almost 28% of total migrant FTE in 2013 and are predominantly long-term migrants (87% of UK FTE) or skilled residents (7% of UK FTE). In contrast, for example, Filipino-born migrants are more likely to be recent migrants with a relatively large proportion of individuals on skilled non-resident visas.

Table 2 Non-Australian migrant birth country in 2013

Birth country	Share of migrant FTE	Visa group share of country FTE				
		Long-term	Skilled resident	Skilled non-resident	Other resident	Other non-resident
United Kingdom	27.7%	86.6%	7.3%	2.1%	2.5%	1.5%
India	8.2%	71.3%	11.3%	2.6%	3.9%	11.0%
South Africa	7.6%	79.4%	13.7%	3.1%	2.1%	1.7%
Fiji	7.1%	81.9%	6.0%	3.3%	5.4%	3.5%
China, People's Republic of	6.3%	85.4%	3.8%	1.7%	3.1%	6.0%
Samoa	6.1%	92.3%	0.1%	0.3%	5.9%	1.5%
Philippines	5.3%	69.8%	15.4%	7.0%	3.2%	4.6%
Tonga	2.6%	91.3%	0.4%	0.6%	4.6%	3.1%
United States of America	1.9%	80.5%	6.4%	3.2%	5.6%	4.3%
Malaysia	1.9%	89.0%	5.1%	1.9%	1.7%	2.2%
Netherlands	1.6%	93.0%	3.5%	1.2%	1.5%	0.9%
Cook Islands	1.5%	97.1%	0.0%	0.0%	2.9%	0.0%
Korea, Republic of	1.4%	86.6%	3.3%	4.0%	1.3%	4.9%
Germany	1.3%	78.8%	8.6%	4.5%	3.7%	4.5%
Zimbabwe	1.2%	79.3%	11.4%	3.9%	3.6%	1.7%
Sri Lanka	1.2%	81.8%	8.0%	3.2%	2.5%	4.5%
Canada	1.1%	84.8%	3.6%	3.1%	4.7%	3.8%
Ireland	1.0%	68.4%	8.2%	10.1%	5.3%	8.1%
Japan	0.8%	80.8%	3.4%	6.7%	3.3%	5.8%
Taiwan	0.7%	95.6%	1.0%	0.5%	1.5%	1.4%
Other (non-top 20)	13.5%	83.4%	4.6%	3.1%	4.4%	4.4%

Notes: Shares are based on total FTE employment in 2013 from the Fabling-Maré labour tables for non-Australian migrant employees with observed characteristics and who have a useable 2013 Census country of birth response. Migrant categories are defined in Box 1 and Table 1.

While the data used to produce the employment statistics in Figure 2 and Figure 3 cover the entire economy, production function estimates are restricted to firms that have the necessary data on real gross output and inputs (intermediate consumption and capital services). In addition to these data constraints, we also restrict the sample to remove firms with less than ten FTE of employee labour input. In small firms, the observed labour allocation across worker types may not be representative of the firms' desired skill mix, but rather result from the binary (full-time) nature of most jobs. Restricting the sample based on firm size also removes observations where we expect measurement error to be more problematic (Fabling & Sanderson, 2014). To that end, we also remove firms in their first and last year of operation, where measured productivity may not be particularly representative of true productivity. Finally, we exclude firms where the total FTE with the necessary worker characteristics (age, sex, country of birth) accounts for less than 75% of total L, which mainly removes a small number of firms that have a large number of working proprietors (WPs). As noted earlier, with substantial coverage of employee characteristics at the firm level, we then impute unobserved worker characteristics (and WPs) from the mean of observed co-worker characteristics.

Overall, the productivity sample includes 49% of total private sector labour input (excluding hard-to-measure industries). Coverage varies substantially by industry, since some industries – particularly in the agricultural sector – are dominated by small firms, many of which are WP-only firms (Table B.1). In the estimation dataset, WPs account for 1.3% of total labour input, and the loss of WP-only firms is a major factor in the reduced coverage of total L in the estimation sample. In terms of coverage of employees, the final estimation sample covers 62% of FTE employment, despite the fact that we only include around 4% of active firm-year observations, reflecting the fact that a large proportion of jobs are concentrated in large employers, and that large employers have relatively high coverage in the productivity dataset. The remainder of the paper is based on this reduced sample of larger incumbent firms with observed productivity and labour group characteristics.

We make use of two other components of the labour and productivity dataset in the estimation that follows. We control for industry using the 39 "production function" industries included in the productivity dataset, which are predominantly aligned to New Zealand Standard Industrial Output Categories (NZSIOC) level 3 with some industries pooled at level 2 due to sample size (Table B.1 lists the industry groupings, together with their industry identifier).[11] The firm-level wage bill comes from monthly employee gross earnings, aggregated from the labour dataset. Gross earnings are deflated to 2019 dollars and scaled up to include WP labour compensation by assuming WPs earn the average (per FTE) worker wage rate at the firm.

Table 3 Firm-level summary statistics

	Mean	25th	50th	75th
Production and firm-level wages				
ln(gross output), y	15.37	14.52	15.14	15.97
ln(intermediate consumption), m	14.38	13.40	14.23	15.21
ln(capital), k	12.81	11.94	12.64	13.56
ln(total gross earnings), w	14.23	13.53	13.97	14.67
ln(labour), l, unadjusted for composition	3.27	2.63	2.99	3.63
Employment shares				
Labour characteristics coverage	95.4%	92.3%	97.8%	100%
NZ-born, S_{NZ}	71.2%	59.6%	76.8%	88.6%
Australian-born, S_{Oz}	1.6%	0.0%	0.0%	2.3%
Non-Australian-born migrant	27.1%	9.8%	21.2%	38.4%
Long-term (5+ years), S_{LT}	18.2%	6.8%	14.5%	26.0%
Recent (<5 years), S_{RM}	8.9%	0.0%	4.1%	11.1%
Skilled resident, S_{SR}	2.0%	0.0%	0.0%	2.6%
Skilled non-resident, S_{SNR}	1.8%	0.0%	0.0%	1.1%
Other resident, S_{OR}	1.4%	0.0%	0.0%	1.4%
Other non-resident, S_{ONR}	3.7%	0.0%	0.1%	3.1%

Notes: Statistics are for the productivity estimation sample, which covers the 2005-2019 financial years for firms with: measured non-zero productivity components; 10+ FTE employees; incumbent (non-entrant/exiter) status; and firm FTE with observed characteristics at least 75% of total L. Migrant categories are defined in Box 1 and Table 1.

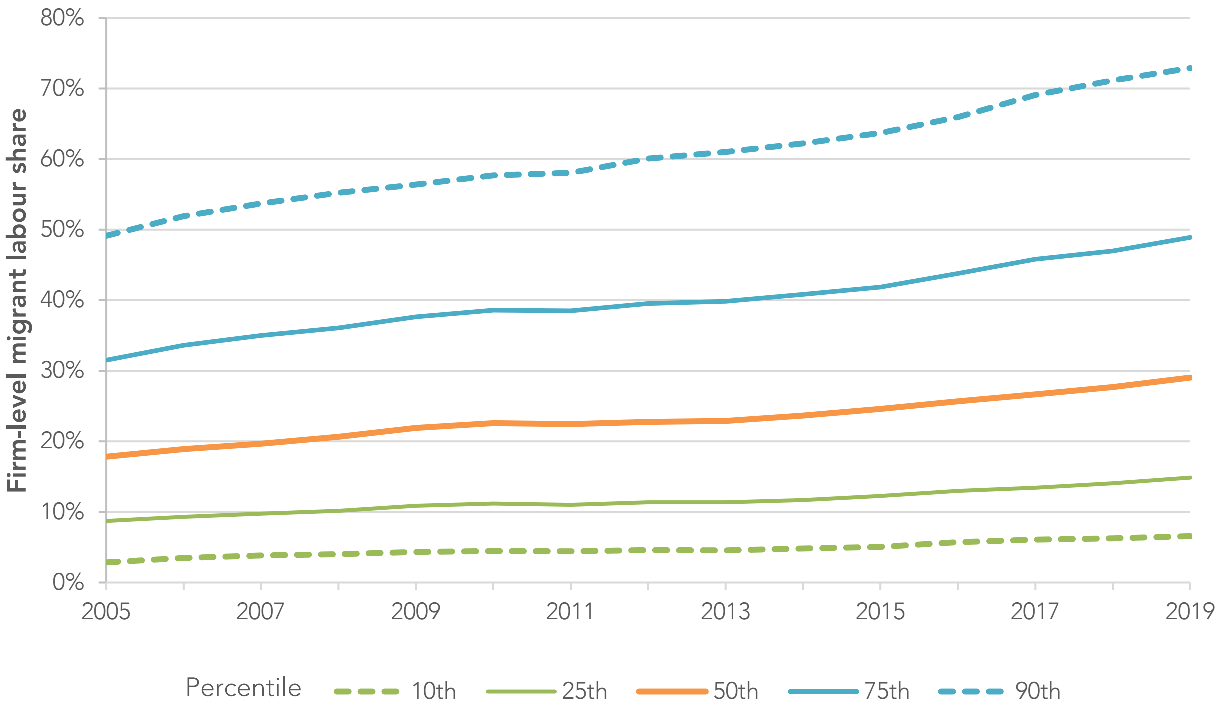
Table 3 reports productivity components, wage bill and labour share summary statistics – mean, median and 25th/75th percentiles – for the 174,687 firm-year observations in the productivity sample. The labour characteristics coverage variable shows the firm-level percentage of total labour input for which we directly observe individual characteristics. While only around 1% of employee FTE is missing these characteristics, the missing share reported here is higher due to the presence of working proprietors. Overall, the employment shares we use apply to at least 92% of total labour input for three quarters of firms and are bounded below by 75% coverage due to population restrictions. Australian-born labour

[11] Industry KK1_ includes all of finance and insurance, except for auxiliary finance and insurance services, which is a separate production function industry (KK13).

input is negligible for most firms, motivating the pooling of Australian-born and long-term migrants in most specifications.

Figure 4 plots how the distribution of the firm-level migrant labour share has evolved over time for the estimation sample. Consistent with the increasing importance of migrants in the New Zealand labour market over time (Figure 2), the entire distribution of the migrant share shifts upward over the 2005 to 2019 financial year period. The median firm-level share of foreign-born rises from 18% to 29%. Over the same 15 years, the proportion of firms with a majority of foreign-born workers rises from around 10% to around 25%.

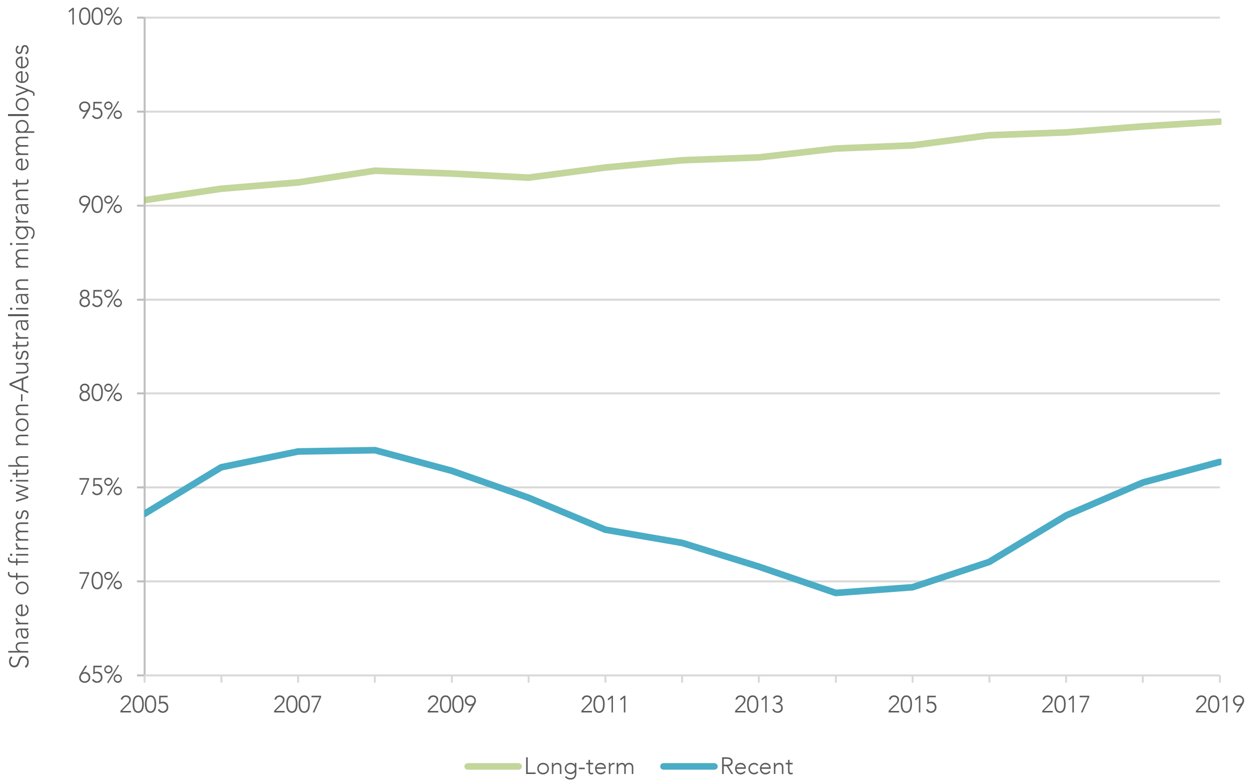
Figure 4 Distribution of migrant labour share in firms over time



Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes).

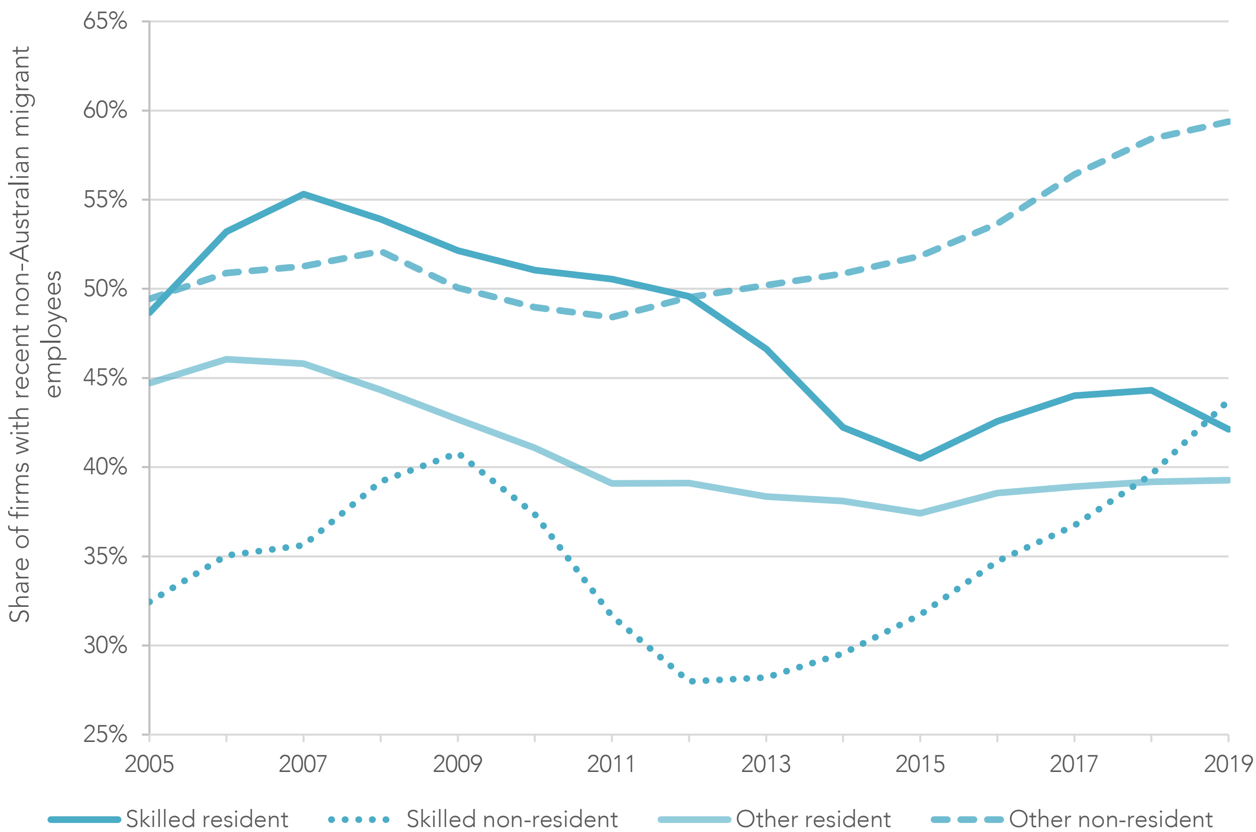
Figure 5 and Figure 6 provide a slightly different perspective on these trends by reporting the percentage of firms that have migrants of each type. Figure 5 shows that the proportion of productivity industry firms with at least one long-term migrant has risen from 90% to almost 95% over the sample period, while the proportion of those firms with recent migrants appears to be cyclical. Figure 6 disaggregates the recent migrants into the four visa groups. While skilled non-residents (dotted line) appear to follow a cyclical pattern – with a declining proportion of firms with this type of worker after the Global Financial Crisis – the apparent cyclicality of the share of firms with recent migrant employment is being driven by the interaction of a trend decline in the contribution of resident migrants (solid lines) and the rapid increase in the prevalence of other non-resident migrants from 2011. Again, the aggregate trends for larger private sector productivity industry firms mimic the whole-economy trends reported in Figure 2 and Figure 3, reflecting the substantial proportion of aggregate employee labour input captured by these firms (62%, Table B.1).

Figure 5 Proportion of firms with non-Australian migrants by year and recency of arrival



Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes).

Figure 6 Proportion of firms with non-Australian recent migrants by year and visa group



Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes).

Table 4 reports the means of key firm-level parameters grouped into quartiles of the proportion of migrant labour input. The first reported statistic is the mean migrant share (S_{Mig}) within the quartile, which varies from 5.5% of labour input for low migrant share firms, to 61.3% for high migrant share firms. The bottom row of the table reports the same summary statistics for all firms pooled, with the overall firm-level average migrant share being 28.8%. On average, low and high migrant share firms differ in minor ways on several dimensions: low migrant share firms are smaller, have higher (log) labour productivity (LP), and a higher capital-labour ratio ($k - l$) than high migrant share firms. Conversely, high migrant share firms have higher average wages ($w - l$) and disproportionately greater concentration of low- and high-skilled NZ-born in their non-migrant labour input.

Table 4 Firm-level summary statistics by quartile of firm migrant share

Migrant share quartile	S_{Mig}	l	Mean LP	$k - l$	$w - l$	Mean share of NZ-born Low skill	High skill
1st (low)	5.5%	3.02	11.45	9.54	10.90	24.3%	16.5%
2nd	17.2%	3.30	11.46	9.55	10.95	24.8%	21.8%
3rd	31.0%	3.44	11.52	9.58	11.03	23.5%	27.2%
4th (high)	61.3%	3.33	11.40	9.48	10.96	26.9%	27.7%
Total	28.8%	3.27	11.46	9.54	10.96	24.6%	22.2%

Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes).

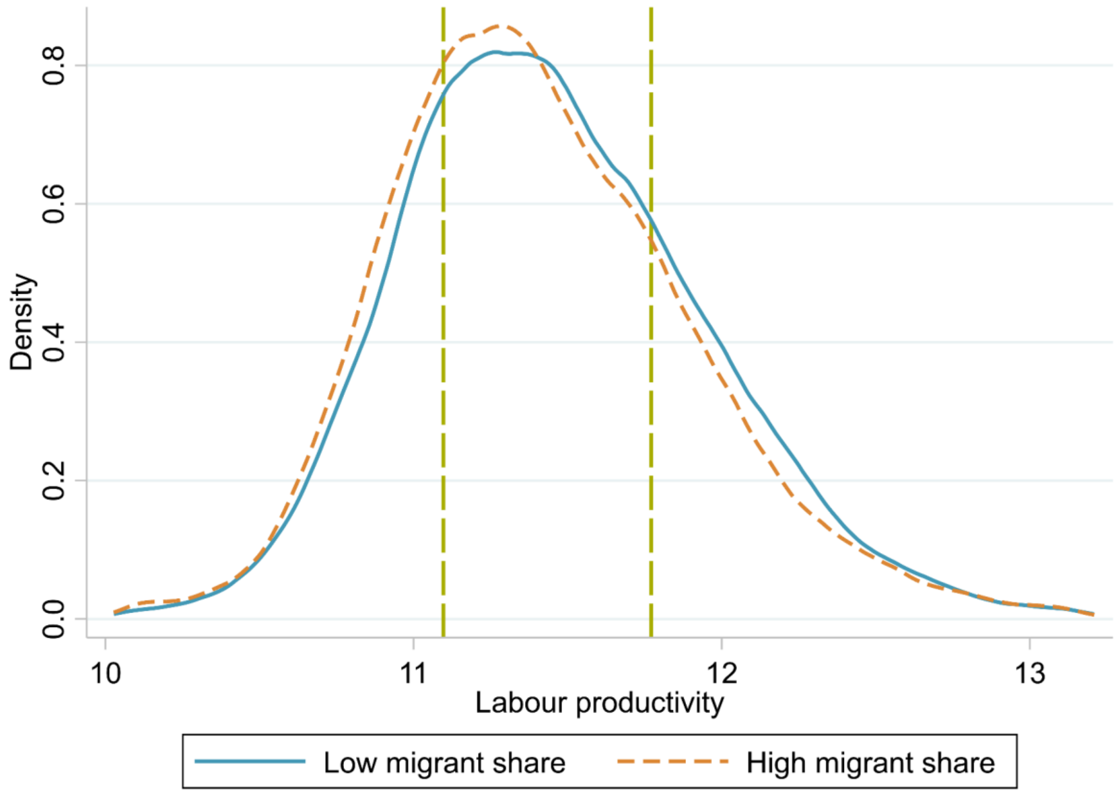
Figure 7 and Figure 8 plot smoothed distributions (kernel densities) of labour productivity and wages for low and high migrant share firms. These two metrics are closely related to the dependent variables in subsequent regressions, except that they directly account for labour input and, in the case of LP, also intermediate consumption. The figures have vertical dashed lines at the 25th and 75th percentile of the overall distribution, so that half of all firm-year observations lie between the two lines.

Figure 7 shows that the mean labour productivity difference between low and high migrant share firms reflects a rightward shift and stretching of the LP distribution for low migrant share firms relative to high migrant share firms. These differences may reflect differences in the productivity of migrants and NZ-born or may reflect sorting of migrants into particular kinds of firms. For example, high migrant share firms may be concentrated in different industries or work with less capital than those firms employing fewer migrants. Both the average migrant share and average labour productivity rise over time, which works against the observed pattern of higher LP in low migrant share firms. Our regression approach models the production technology in a way that can account for these factors, including industry-level trends in both left- and right-hand side variables.

In contrast, the distribution of firm-level average wages per FTE is substantively different across low and high migrant share firms (Figure 8). The wage distribution for firms that employ a high share of migrant workers has a greater mass to the left and to the right than low migrant share firms. That is, the migrant worker wage experience is materially more diverse than is the case for NZ-born workers. The joint estimation of production functions and firm-level wage bill equations helps distinguish whether these differences in firm-level wages are due to relative productivity or reflect some other kind of heterogeneity across workers and firms.

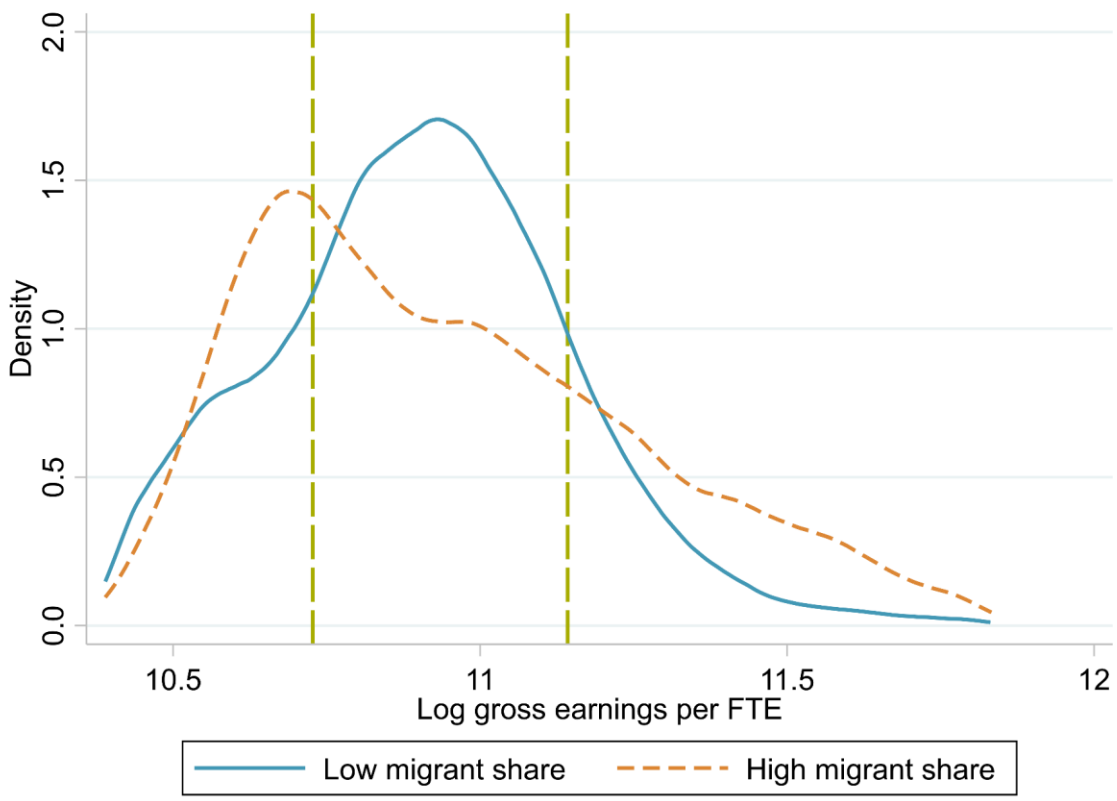
There is substantial heterogeneity in migrant employment across industries, as evidenced by Table 5 which reports employment shares by broad industry (extended to the production function industry level in Table B.2). In particular, the share of long-term migrants – the largest migrant group – varies from below 15% in the primary sector to over 20% in most of the service sector.

Figure 7 Distribution of LP for high and low migrant share firms



Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes). Kernel density plots using default Stata smoothing parameters. Distributions are truncated at 1st and 99th percentile for confidentiality. Low (high) migrant share firms are in the bottom (top) quartile of migrant employment share, S_{Mig}. Vertical dashed lines indicate 25th/75th percentiles of labour productivity.

Figure 8 Distribution of average wage for high and low migrant share firms



Notes: See Figure 7 for notes. Vertical dashed lines indicate 25th and 75th percentile of log gross earnings per FTE.

Table 5 Aggregate employment shares by industry

	Industry (NZSIOC level 1)	Annual average N	L	Industry employment share NZ	Oz	LT	SR	SNR	OR	ONR
AA	Agriculture, forestry & fishing	687	18,240	68.2%	1.1%	13.4%	0.8%	2.1%	2.1%	12.4%
BB	Mining	55	3,613	82.9%	3.1%	9.2%	1.6%	1.6%	0.6%	1.0%
CC	Manufacturing	2,418	151,860	69.7%	1.3%	22.8%	1.9%	1.2%	1.6%	1.5%
DD	Electricity, gas, water & waste	80	11,580	72.5%	1.6%	20.9%	2.4%	0.9%	1.0%	0.7%
EE	Construction	1,478	59,627	77.2%	1.6%	14.2%	2.2%	2.7%	0.8%	1.3%
FF	Wholesale trade	1,180	52,973	71.4%	1.5%	21.2%	2.2%	0.9%	1.3%	1.5%
GH	Retail trade & accommodation	2,492	135,100	67.0%	1.8%	20.1%	2.2%	1.5%	1.9%	5.6%
II	Transport, postal & warehousing	632	57,560	75.5%	1.4%	19.4%	1.2%	0.7%	1.0%	0.8%
JJ	Information media & telecoms	137	21,127	66.8%	1.9%	24.1%	3.5%	1.0%	1.3%	1.4%
KK	Financial & insurance services	191	39,933	67.3%	1.8%	25.8%	2.5%	0.5%	1.2%	1.0%
LL	Rental, hiring & real estate services	109	5,380	69.6%	1.7%	20.7%	1.9%	1.4%	1.6%	3.1%
MN	Professional, scientific, technical, admin & support services	1,697	94,660	63.0%	1.8%	22.5%	3.4%	2.1%	1.9%	5.3%
RS	Arts, recreation & other services	489	15,667	67.5%	2.1%	19.9%	2.4%	2.4%	1.6%	4.0%
	Total (productivity industries)	11,646	667,320	69.3%	1.6%	20.8%	2.2%	1.5%	1.5%	3.1%

Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes).

Figure 9 and Figure 10 show this variability in migrant presence at the production function industry level. Rather than reporting aggregate industry shares of migrant employment (as are shown in Table 5 and Table B.2), these figures show average firm-level migrant shares – ie, the effective labour input components used to estimate industry-specific models. Figure 9 orders industries by the average firm-level skilled resident migrant share, additionally showing the average skilled non-resident share (on the right-hand scale). Bearing in mind that sample coverage for the agricultural sector is low (due to our firm size restrictions), it is clear that this sector makes the least use of skilled resident labour, though dairy cattle farming (AA13) is the industry with the greatest average share of skilled non-resident labour. At the other end of the spectrum, telecoms (JJ12) firms are most likely to use skilled resident labour, followed by professional, scientific and technical services (MN11).

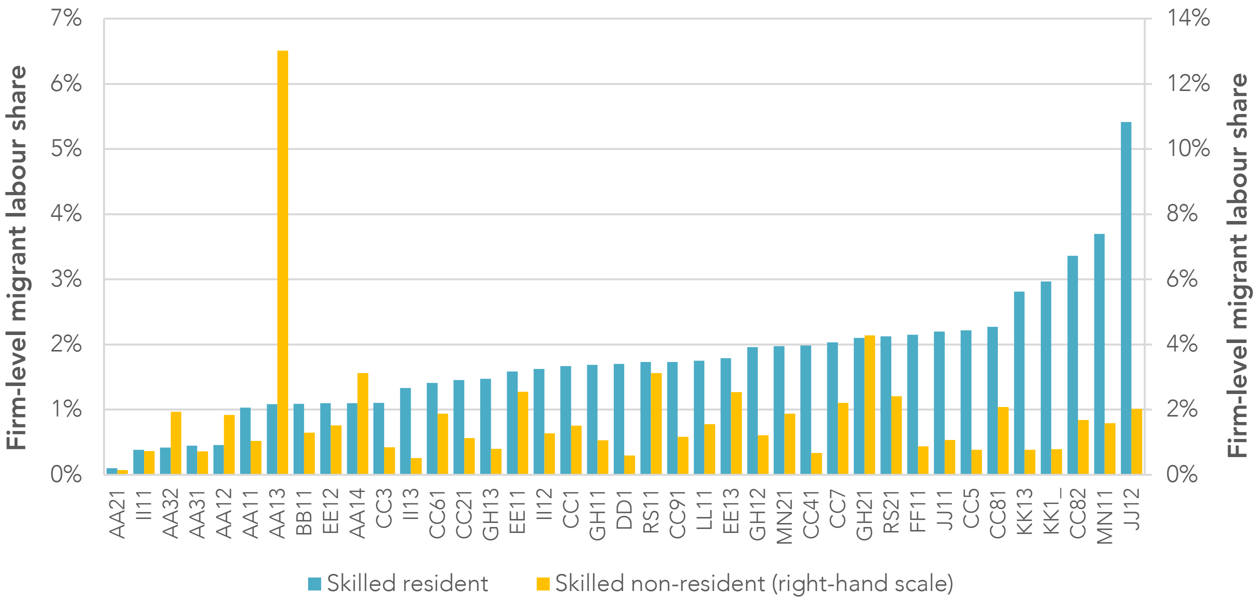
Looking at the remaining two visa groups, Figure 10 shows industries sorted by the average other resident employment share, also reporting the average other non-resident share (on the right-hand scale). Again, the agricultural sector is less likely to intensively employ migrants, with the exception of horticulture and fruit growing (AA11) and agriculture support services (AA32), which are key industries for recognised seasonal employer and working holiday scheme workers (both of which are included in the other non-resident visa grouping). Similarly, accommodation and food services (GH21) industries rely on temporary workers, with other non-resident migrants accounting for around 13% of employment for the average firm in the industry. The significant variation in the use of different worker types across firms and over time supports our estimation strategy and results.

5 Regression results

5.1 Interpretation of coefficients

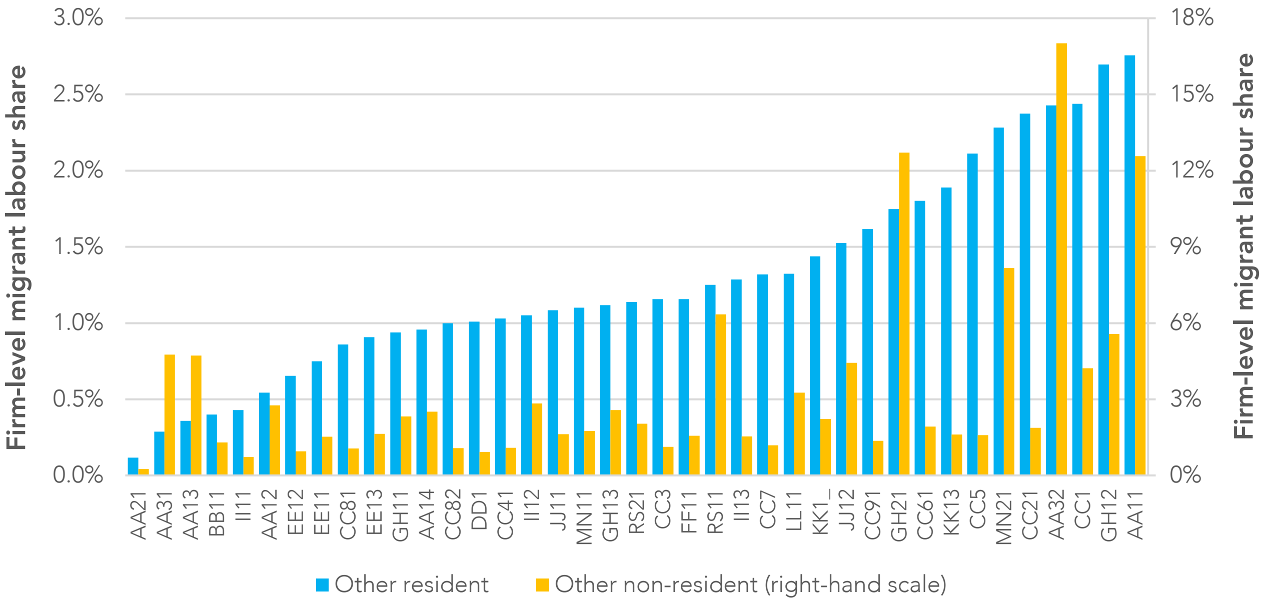
It is important to bear two related things in mind – one conceptual and one data-related – when interpreting the estimation results. First, the effective labour share coefficients are relative to those of the base ($j = 0$) labour type – either all NZ-born workers, or moderately-skilled NZ-born workers. If a ϕ_j coefficient is statistically insignificant, the relationship between that particular labour type and output is found to be insignificantly different from the base labour type, ie, those two labour types make a similar contribution to output (on a per-FTE basis). Similarly, a statistically insignificant ψ_j coefficient indicates that the jth labour type receives a (FTE-adjusted) share of firm-level wages comparable to that of the base labour type.

Figure 9 Average firm-level skilled recent migrants by industry



Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes) and by production function industry (see Table B.1 for industry definitions).

Figure 10 Average firm-level other recent migrants by industry



Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes) and by production function industry (see Table B.1 for industry definitions).

Second, our measure of labour input is only an approximation of true full-time equivalent employment (Fabling & Maré, 2015b), since the IDI does not contain comprehensive hours worked information for employees. Since the available labour input measure averages monthly employment at the firm, it captures some variation in employment (eg, seasonality that affects the extensive margin of employment), but not changes in hours (the intensive margin) for most individuals. This measurement shortcoming in the New Zealand data is most problematic for analyses where labour groups have systematically different average hours, eg, studies examining the gender wage gap (eg, Sin et al., 2020, who systematically test the robustness of their results to mismeasurement of hours). We suspect that average hours might be similar across the labour groups that we use, though some visa conditions – eg, student visas – place restrictions on full-time work. Since the classification of low-skilled NZ-born workers is based on (FTE-adjusted) gross earnings we will inevitably identify some individuals as low-skill when they are, in fact, higher-skilled individuals working part-time.

Overall, therefore, it is important to be aware of measurement issues when interpreting the results. These issues are one of the reasons why we also estimate firm-level wage bill equations. Production function coefficients may differ across labour types because of unobserved differences in hours worked, or differences in skills or effort. When we discuss productivity in what follows, we want to capture the contribution to gross output a particular labour type makes relative to the base worker type, holding hours and ability constant. This interpretation is achieved by focussing on the difference between ϕ_j and ψ_j coefficients – dubbed the "productivity-wage gap" – since the wage coefficient should capture compensation for both hours and ability (relative to the base group). Therefore, the difference between the two coefficients captures the residual productivity difference controlling for hours and ability relative to the reference group gap or, put another way, the pay gap between groups controlling for productivity differences.

5.2 Pooled industries

Table 6 and Table 7 present results from joint estimation of translog production functions and firm-level wage bill equations (2)-(5), respectively. These estimates pool all firms in the sample – ie, assume a common production function across industries – and then include productivity industry-specific linear time trends and intercepts to allow for differing technological progress across industries over time. Since the number of estimated coefficients is large and we are only interested in the labour type weights, we relegate estimated coefficients on inputs (m, k, and $\tilde{l}$) to the appendix (Table B.3), and do not report industry trend or intercept coefficients. Since we focus on the difference between productivity and wage bill equation effective labour input weights, these are reported separately in Table 8 together with stars indicating whether these gaps are significantly different from zero (ie, different from the base group gap).

Each column of Table 6-Table 8 represents an independent model reflecting alternative specifications of the effective labour input terms. In the simplest specification (column 1), there are two labour types – migrant and NZ-born – where the latter are the reference group, ie, the group whose productivity-wage gap is normalised to be zero. In the remaining specifications, NZ-born workers are divided into three skill groups and the reference group is moderately-skilled NZ-born, with low-skilled and high-skilled NZ-born now allowed to have non-zero productivity-wage gaps.

Column (1) of Table 6 implies that a migrant, on average, is equivalent to 97% of an average NZ-born worker in terms of effective labour input into production (significantly different from equal weights at the 10% level). At the same time the average migrant is equivalent to 107% of an average NZ-born worker in terms of input into the firm-level wage bill equation (Table 7, column 1). Together, these estimates imply that the productivity-wage gap for migrants is 10 percentage points (pp) lower for migrants than it is for NZ-born workers (column 1 of Table 8, significantly different from zero at the 1% significance level) – ie, that migrants are more well paid than native-born, given their apparent relative contribution to output. Put another way, it does not appear that the reason why the migrant contribution to output is lower than the native contribution is due to hours worked or due to average skill differences, since migrants attract a positive wage premium relative to natives. Bear in mind that a negative gap does not imply that a worker group is overpaid, given their productivity. Rather, it indicates that the gap for this labour type is less than the gap for the base type (which has been *normalised* to be zero).

Pooling migrants and NZ-born into single groups disguises significant heterogeneity in outcomes across workers. We uncover some of these differences in specifications (2)-(5). Firstly, in column (2), we disaggregate the NZ-born workforce into three skill groups, with the ($j = 0$) reference group now being moderately-skilled NZ-born. In some sense this decomposition is a robustness test for the method, since the classification of NZ-born workers into skill groups relies on a decomposition of worker-level wages, as described in section 4. Reflecting that classification approach, the firm-level wage bill equation weights on low-skilled and high-skilled NZ-born are markedly different, with low-skilled contributing 164pp less to effective labour input than high-skilled NZ-born (column 2 of Table 7). Comfortingly, this substantial gap is also reflected in the estimated ϕ_{NZ} coefficients in the production function where the difference between low- and high-skilled is 200pp (column 2 of Table 6).

Table 6 Production function estimates – pooled industries

	(1)	(2)	(3)	(4)	(5)
$\phi_{NZ,Lo}$		-0.381***	-0.387***	-0.387***	-0.382***
		[0.027]	[0.027]	[0.027]	[0.027]
$\phi_{NZ,Hi}$		1.621***	1.613***	1.612***	1.607***
		[0.072]	[0.072]	[0.072]	[0.072]
ϕ_{Mig}	-0.030*	0.035*			
	[0.016]	[0.021]			
ϕ_{Oz}			0.218*	*pooled with* ϕ_{LT}	
			[0.128]		
ϕ_{LT}			0.090***	0.093***	0.104***
			[0.028]	[0.028]	[0.028]
ϕ_{RM}			-0.033	-0.035	
			[0.031]	[0.031]	
ϕ_{SR}					0.198**
					[0.085]
ϕ_{SNR}					0.215***
					[0.067]
ϕ_{OR}					-0.316***
					[0.117]
ϕ_{ONR}					-0.123***
					[0.044]
N	174,555	174,555	174,555	174,555	174,555
R^2	0.946	0.950	0.950	0.950	0.950

Notes: Estimated jointly with the firm-level wage bill equation (results reported in Table 7) as a pair of non-linear seemingly unrelated regressions. Estimated coefficients on inputs are reported separately in Table B.3. Long-term migrants include Australian-born in specifications (4) and (5). Robust standard errors (clustered on firm) in brackets. ***;**;* indicates coefficient significantly different from zero at 1;5;10% level respectively. Industries are pooled and each specification includes production-function industry linear time trends and intercepts (excluding the largest industry, MN11).

At least some of the difference in both estimates is likely due to how we measure labour input and the inclusion of some low hours-high wage rate individuals in the low-skill group. The productivity-wage gap comparison (column 2 of Table 8) helps with this issue suggesting that the gap for low-skilled NZ-born is insignificantly different from the moderately-skilled NZ-born. High-skilled NZ-born, on the other hand, appear to receive a smaller wage premium than expected given their productivity relative to the moderately-skilled. Given our focus on migrants and productivity, and the proxy nature of our skills measure, we leave the interpretation of potential difference between NZ-born skill groups to future work. For the remainder of the paper, the estimated weights on NZ-born skill groups can be thought of as benchmark comparisons of migrants against different points in the distribution of NZ-born worker skill.

Table 7 Firm-level wage bill equation estimates – pooled industries

	(1)	(2)	(3)	(4)	(5)
$\psi_{NZ,Lo}$		-0.398***	-0.405***	-0.404***	-0.400***
		[0.007]	[0.007]	[0.007]	[0.007]
$\psi_{NZ,Hi}$		1.241***	1.239***	1.235***	1.225***
		[0.020]	[0.020]	[0.020]	[0.020]
ψ_{Mig}	0.072***	0.071***			
	[0.007]	[0.007]			
ψ_{Oz}			0.480***	*pooled with ϕ_{LT}*	
			[0.040]		
ψ_{LT}			0.114***	0.121***	0.123***
			[0.009]	[0.009]	[0.009]
ψ_{RM}			0.008	0.003	
			[0.009]	[0.009]	
ψ_{SR}					0.700***
					[0.031]
ψ_{SNR}					0.284***
					[0.019]
ψ_{OR}					-0.379***
					[0.024]
ψ_{ONR}					-0.182***
					[0.011]
N	174,555	174,555	174,555	174,555	174,555
R^2	0.956	0.973	0.973	0.973	0.974

Notes: Estimated jointly with the production function (results reported in Table 6) as a pair of non-linear seemingly unrelated regressions. See Table 6 for further notes.

Table 8 Productivity-wage gap ($\phi - \psi$) – pooled industries

	(1)	(2)	(3)	(4)	(5)
Low-skilled NZ-born		0.017	0.017	0.017	0.018
High-skilled NZ-born		0.379***	0.375***	0.378***	0.382***
Migrant	-0.102***	-0.036*			
Australian-born			-0.262**	*pooled with LT*	
Long-term migrant			-0.024	-0.028	-0.019
Recent migrant			-0.041	-0.038	
Skilled resident					-0.502***
Skilled non-resident					-0.069
Other resident					0.063
Other non-resident					0.059

Notes: Estimated productivity wages gaps based on difference between coefficients in Table 6 and Table 7. See Table 6 for further notes.

Care must be taken in comparing the coefficients on the migrant share across specifications (1) and (2), since the baseline comparison group changes. This issue arises only for that particular comparison, since specification (2)-(5) have the same reference group. In the production function, migrants have weights 3pp below the average NZ-born worker, but 3.5pp above a moderately-skilled NZ-born worker. Estimated migrant share coefficients in the wage bill equation are stable, possibly because the wage-based ranking of NZ-born skill groups means that the middle 50% of the skill distribution are similar in characteristics to the average NZ-born worker overall. Focussing on the productivity-wage gap, the average migrant has a 3.6pp smaller gap than the average moderately-skilled NZ-born worker, significantly different from zero at the 10% level. The economically small size of this gap suggests that migrants are, on average, similar to moderately-skilled NZ-born workers.

Column (3) of Table 6 and Table 7 report effective labour coefficients when we disaggregate migrants into three groups: Australian-born, long-term (5+ years), and recent (<5yrs). Comparing columns (2) and (3) suggests that the apparent output and wage advantage of migrants, relative to moderately-skilled natives, is due to long-term and Australian migrants, with recent migrants being indistinguishable from the base group. The larger of these groups – long-term migrants – has comparable coefficients in the production function and wage bill equation suggesting that the productivity advantage over moderately-skilled NZ-born is due to hours or skills that are compensated for in the labour market. In terms of the productivity-wage gaps, then, neither recent nor long-term migrants have gaps significantly different from the base group (column 3 of Table 8). Differences between recent and long-term migrants may relate to the additional New Zealand labour market experience that the latter group has, and/or may be the result of self-selection, whereby those migrants who have the most useful skills or have the best job matches are less likely to leave New Zealand, or the policy-determined selection process that picks which migrants get to stay long-term.

Australian-born migrants have significantly higher weight in both the production function and firm-level wage bill equation than moderately-skilled NZ-born (22pp and 48pp higher, respectively), but considerably below that of high-skilled NZ-born in both cases. Overall, the productivity wage-gap is 26pp lower for Australian-born than it is for the base group. While this distinction between Australian-born migrants and long-term migrants is intriguing, the majority of firms in the sample have no Australian-born workers (Table 3). To aid the identification of parameters in subsequent models we, therefore, absorb Australian-born into the long-term migrant group for the remainder of the analysis. Column (4) shows that this merging of groups has almost no effect on the estimated coefficients for long-term migrants, reflecting the relative group sizes. In what follows we simply describe this group as long-term migrants for ease of exposition.

The final column of Table 6-Table 8 relate to a model where recent migrants are disaggregated into the four visa groups (as in Box 1). Again, this disaggregation reveals substantial heterogeneity in migrant groups, and shows the importance of separating out migrant categories in our estimation. Consistent with expectations, skilled migrant categories have higher estimated weights than other migrant categories in both the production function and the firm-level wage bill equation. The signs of the estimated effective labour coefficients are consistent across the productivity and wage bill equations for all worker types – ie, migrants and NZ-born groups that have higher (lower) apparent productivity are also paid more (less) relative to the base group. Further, the signs on these coefficients are consistent with the idea that some groups – high-skilled NZ-born, skilled migrants, and long-term migrants – on average, have more marketable labour market skills than the remaining groups (and moderately-skilled NZ-born workers).

For all visa groups, except for skilled residents, wage bill equation coefficients are insignificantly different from productivity function coefficients suggesting that the relative productivity of these groups is explained by skill and effort/hours (column 5 of Table 8). Skilled residents have a substantial (-50pp) productivity wage gap compared to the base group, which sits in stark contrast to the positive gap for high-skilled NZ-born, and the insignificantly different from zero gap for skilled non-residents and other visa categories. Potentially, a large negative gap signals that the firm benefits from this worker type in ways that are not reflected in contemporaneous output, eg, through connections gained to international markets or contributions to innovation.

5.3 Time variation in gaps

The overall migrant share and the composition of that share have both changed markedly over the last fifteen years (Figure 2 and Figure 3). In this subsection we test whether these changes affect our estimated productivity-wage gaps. To do this we divide the available time period into three five-year subperiods: 2005-2009 (labelled t=1), 2010-2014 (t=2), and 2015-2019 (t=3). Choosing five-year periods has the key advantage of aligning to the minimum definition of long-term migrant, meaning that membership of the recent migrant group is completely non-overlapping between $t = 1$ and $t = 3$. Comparison of these two periods, therefore, is a clean way of testing for composition-related differences in migrant contributions to firm output, and we focus on the comparison of coefficients across those two periods.

We estimate a translog production function – wage bill equation pair that mimics the eight labour type specification in column (5) of Table 6 and Table 7, modifying the specification of the effective labour input to allow the coefficients on the non-base groups to vary across time periods. This additional functional flexibility is achieved through interaction terms of the group share variable with time period indicator variables. For the production function, the specification of the effective labour input is:

$$\tilde{L} = L\left(S_0 + \sum_j \left[\left(1 + \phi_j + \phi_{j,t=2} \times \delta(t=2) + \phi_{j,t=3} \times \delta(t=3)\right).\mathrm{S_j}\right]\right) \tag{6}$$

where $\delta(.)$ is an indicator function that equals one if the condition holds and zero otherwise. The same functional form is applied to the firm-level wage bill equation. The new parameters $\phi_{j,t=2}$, $\phi_{j,t=3}$, $\psi_{j,t=2}$ and $\psi_{j,t=3}$ capture the change in effective weight for subgroup j relative to 2005-2009 ($t = 1$). A statistical test of whether a sub-period-specific coefficient is different from zero is, therefore, a test of whether we can reject the subgroup weight being unchanged from its $t = 1$ value. To recover the productivity-wage gap for periods other than the base period, we must sum the base period gap with the additional gap implied by the period-specific interaction terms. For example, the 2015-2019 ($t = 3$) gap is given by:

$$(\phi_j - \psi_j) + (\phi_{j,t=3} - \psi_{j,t=3}) \tag{7}$$

The relative simplicity of this definition is aided by the fact that the base group of moderately-skilled NZ-born is normalised to have a zero gap in all time periods – ie, the S_0 share in equation (6) isn't interacted with time period indicators. While the individuals in the moderately-skilled group change over time, we expect the within-year normalisation of the NZ-born skill categories to minimise the risk that differences in the base group drive the estimated differences in gaps over time. If changes in base group composition or some other factor affected the contribution of the base group to output and/or wages, estimated changes in productivity-wage gaps would move in the same direction for all subgroups, which we do not observe in our empirical results, though we cannot completely exclude this as a potential issue.

Table 9 reports estimated effective labour weights (in columns 1 and 2) and estimated period-specific productivity-wage gaps (column 3, following the example of equation (7)). The reported productivity-wage gaps are directly comparable to those reported in column (5) of Table 8, where the latter is an average across the three periods. Comparing across time periods for a particular labour type, the final column of Table 9 reports the differences in the gap between 2005-2009 and 2015-2019. Focussing on this last column, only one labour type – other residents – has a (statistically significant) declining productivity-wage gap (decrease of 78pp), while three labour types have (significantly) increasing productivity-wage gaps: low-skilled NZ-born (increase of 9.4pp); long-term migrants (increase of 16pp); and skilled non-residents (increase of 74pp).

Table 9 Productivity-wage gap ($\phi - \psi$) – variation over time

	Output ϕ	Wages ψ	*Gap* $\phi - \psi$	Change in gap (t=1 to t=3)
Low-skilled NZ-born ($t = 1$)	-0.401***	-0.387***	-0.014	0.094***
	[0.032]	[0.008]		
$\times\ \delta(t = 2)$	-0.023	-0.026***	-0.011	
	[0.020]	[0.005]		
$\times\ \delta(t = 3)$	0.076**	-0.018**	0.080***	
	[0.032]	[0.007]		
High-skilled NZ-born ($t = 1$)	1.704***	1.258***	0.446***	-0.044
	[0.087]	[0.022]		
$\times\ \delta(t = 2)$	-0.190***	-0.043***	0.299***	
	[0.057]	[0.013]		
$\times\ \delta(t = 3)$	-0.095	-0.051***	0.402***	
	[0.084]	[0.018]		
Long-term migrant ($t = 1$)	0.033	0.150***	-0.117***	0.160***
	[0.036]	[0.012]		
$\times\ \delta(t = 2)$	0.027	-0.075***	-0.015	
	[0.037]	[0.010]		
$\times\ \delta(t = 3)$	0.152***	-0.008	0.043	
	[0.043]	[0.012]		
Skilled resident t=1	-0.034	0.462***	-0.496***	-0.054
	[0.127]	[0.039]		
$\times\ \delta(t = 2)$	0.322**	0.225***	-0.399***	
	[0.159]	[0.050]		
$\times\ \delta(t = 3)$	0.506**	0.560***	-0.550***	
	[0.204]	[0.059]		
Skilled non-resident ($t = 1$)	-0.180	0.432***	-0.612***	0.744***
	[0.209]	[0.041]		
$\times\ \delta(t = 2)$	0.276	-0.218***	-0.118	
	[0.220]	[0.042]		
$\times\ \delta(t = 3)$	0.550**	-0.194***	0.132**	
	[0.218]	[0.043]		
Other resident ($t = 1$)	0.022	-0.354***	0.376***	-0.782***
	[0.129]	[0.036]		
$\times\ \delta(t = 2)$	-0.211	-0.034	0.199	
	[0.172]	[0.043]		
$\times\ \delta(t = 3)$	-0.795**	-0.013	-0.406	
	[0.313]	[0.049]		
Other non-resident ($t = 1$)	-0.157*	-0.254***	0.097	0.027
	[0.093]	[0.019]		
$\times\ \delta(t = 2)$	-0.055	0.090***	-0.048	
	[0.115]	[0.019]		
$\times\ \delta(t = 3)$	0.097	0.070***	0.124***	
	[0.096]	[0.020]		
N	174,555	174,555		
R^2	0.950	0.974		

Notes: Translog production function and firm-level wage bill equation jointly estimated as a pair of non-linear seemingly unrelated regressions. Only effective labour input coefficients (following equation (*6*)) reported. Long-term migrants include Australian-born. Robust standard errors (clustered on firm) in brackets. ***;**;* indicates coefficient significantly different from zero at 1;5;10% level respectively. Industries are pooled and each specification includes production-function industry linear time trends and intercepts (excluding the largest industry, MN11).

The decline in the gap for other residents is substantial and is primarily due to a large decrease in the productivity weight from an approximate equivalence to moderately-skilled NZ-born, to a point estimate weighting other residents as approximately equivalent to 23% (=1+0.022-0.795) of base group employees. The $t = 3$ estimated productivity weight change has a relatively large standard error and we cannot reject the possibility that the gap in that period is zero, despite the point estimate being large. Overall, the implied change may reflect the small size of this group and, therefore, difficulty in pinning down coefficients when the group is disaggregated over time. From an economic perspective, small group size is also grounds for being less concerned about actual changes since the contribution of the group to aggregate productivity is also small. Furthermore, around half of this group is partnership residents (Table 1), suggesting that any policy considerations for this group shouldn't be considered in isolation and need to be thought of in concert with the partner status.

The three groups with increasing gaps all appear to experience increases in their relative contribution to productivity, and a decline in their share of firm-level wages (for low-skilled NZ-born and skilled non-residents) or a static share of wages (long-term migrants). Long-term are the largest migrant group and their share of total employment has grown significantly over time (Figure 2). From 2005-2009 to 2015-2019, their productivity weight grew by 15pp leading to the gap with moderately-skilled NZ-born increasing to become insignificantly different from zero (at the 10% level). From a firm perspective, long-term migrants' relative contribution to output has caught up to their relative wage share, implying an increased return for firms from this migrant type.

Skilled non-residents saw a 55pp increase in their production function weight, but a 19pp decline in the wage bill equation weight from the first to last five-year period. As with long-term migrants, this is a significantly increasing group, who appear to have become an increasingly valuable input relative to their wage cost.

From the worker perspective, these trends are consistent with a loss in bargaining power over time, particularly for groups that may have had relatively low bargaining power initially. In particular, for low-skilled NZ-born, the productivity wage gap increases by 9.4pp to a statistically significant 8% in 2015-2019. This change places the group in a similar category to other non-residents, who also have a significant positive productivity-wage gap in 2015-2019 (of 12.4%) resulting from below-base level contributions to both productivity and wages.

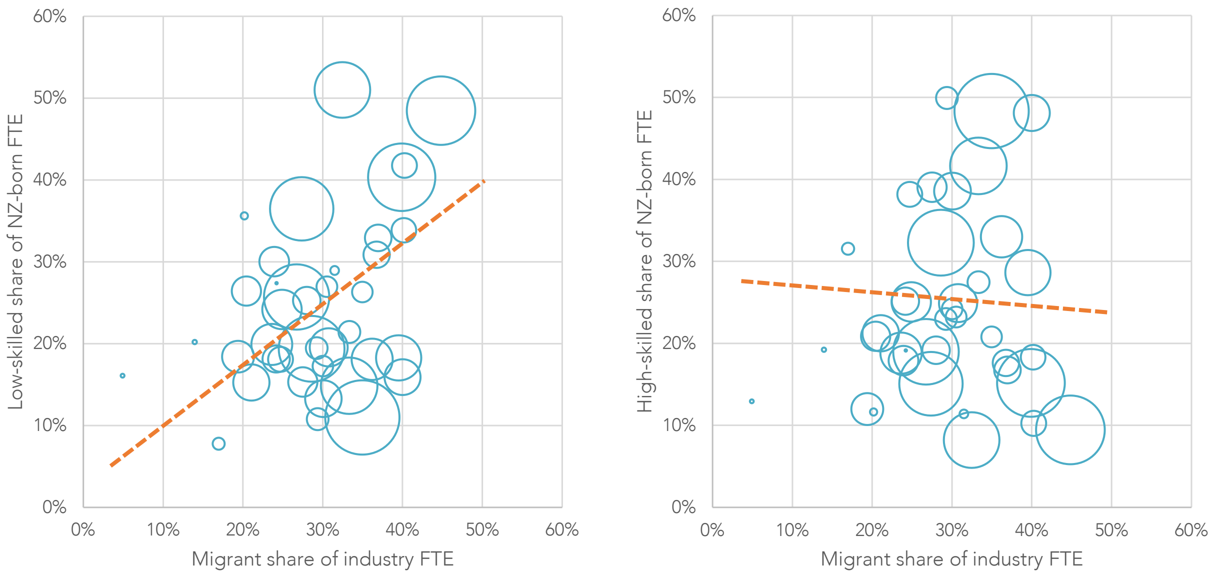
These results link to the burgeoning wage inequality literature that shows that a substantial driving force of increasing wage inequality is due to worker sorting and differing pay practices across firms (see, eg, Criscuolo et al., 2020, for cross-country evidence for the OECD). It also relates directly to the literature on rent-sharing between firms and workers with heterogeneous characteristics, which implies that workers of different types have unequal ability to capture rents generated by their employer (see Dostie et al., 2020, for findings specifically related to migrants, and Allan & Maré, 2022, for NZ-specific results covering other forms of worker heterogeneity).

5.4 Industry-specific models

It is likely that the relative contribution of migrants to output is related to the industries and sectors that employ them, which may be explicitly specified by the migrant visa (eg, essential skills and RSE), or restricted by limitations on the scope of work (eg, hours restrictions on student visas) or the intent of the stay in New Zealand (eg, working holiday schemes). Beyond selection effects, migrant skills may be more beneficial in some industries than others, and relative skills availability in New Zealand and wage-setting practices across industries may influence the wages available to attract migrants. Aside from the potential for migrants to differ substantially across industries (as in Figure 9 and Figure 10), we expect the production technology that firms utilise to be industry-specific, and for other inputs (such as the mix of skilled and unskilled native labour, and the capital-labour ratio) to vary considerably across industries, suggesting that industry-specific estimates may yield results that are closer to the true firm-level production function. Figure 11 shows the correlation between the aggregate migrant share at the industry level and the share of NZ-born total FTE that is low- and high-skilled NZ-born (left and right panels respectively). Bubble size indicates the relative total migrant FTE across industries, and the dashed line plots the linear relationship between the two measures weighted by total migrant FTE. The left panel of Figure 11 suggests that migrants are more concentrated in industries where NZ-born workers are more likely to be low-skilled. Conversely, the relationship between migrant concentration and NZ-born workers being high-skilled is slightly negative.

The downsides of industry-specific estimates are primarily two-fold: the difficulty with comparing estimated parameters across industries due to the base group normalisation of the effective labour weights, and small sample size making it hard to pin down non-linear parameters. For the former issue, we focus exclusively on within-industry interpretations of coefficients. We address the latter issue by estimating industry models at level one of the NZSIOC – ie, at a more aggregated level than the production function industry – and restricting attention to the five largest industry groups, which together cover 74% of employment and 80% of firm-year observations in the estimation sample.[12]

Figure 11 Migrant share correlation with NZ-born skill at industry level



Notes: Bubble size reflects the total share of migrant FTE in each industry. Dashed line is weighted ordinary least squares fit, where weight is industry migrant share. Horizontal axis is share of total industry FTE, whereas vertical axis is share of NZ-born total industry FTE.

Table 10 Industry employment composition in five largest industry groups

	Industry (NZSIOC level 1)	NZ Low	NZ Mod	NZ High	Oz	LT	SR	SNR	OR	ONR
CC	Manufacturing	16.1%	37.6%	16.0%	1.3%	22.8%	1.9%	1.2%	1.6%	1.5%
EE	Construction	13.7%	47.3%	16.2%	1.6%	14.2%	2.2%	2.7%	0.8%	1.3%
FF	Wholesale trade	13.8%	34.5%	23.0%	1.5%	21.2%	2.2%	0.9%	1.3%	1.5%
GH	Retail trade & accommodation	28.2%	30.5%	8.3%	1.8%	20.1%	2.2%	1.5%	1.9%	5.6%
MN	Professional, scientific, technical, admin & support services	14.3%	26.6%	22.1%	1.8%	22.5%	3.4%	2.1%	1.9%	5.3%
	Total (all industries)	17.3%	34.7%	17.2%	1.6%	20.8%	2.2%	1.5%	1.5%	3.1%

Notes: Statistics are for productivity estimation sample level 1 industries with at least 15,000 observations (see Table 3 for further notes).

These industries vary substantially in the composition of both their NZ-born and migrant labour input (Table 10, extending the results in Table 5). Manufacturing (NZSIOC industry CC) has an employment mix that is fairly similar to the entire productivity industry average, with a slight tendency towards

[12] Separate estimates for each production function industry are included in Table B.4 for completeness. We include estimates for all industries with at least a thousand firm-year observations, even those results that are implausible (eg, industry KK1_). As in the industry group regressions, we include (industry-specific) year dummies in these specifications, rather than linear time trend terms.

moderately-skilled NZ-born, over low- and high-skilled, and a somewhat higher reliance on long-term migrants than the average. Construction (EE) is most reliant on moderately-skilled NZ-born and has a substantially lower proportion of long-term migrants than the average (14% vs 21% overall). Construction is also the industry most reliant on skilled non-residents, and least reliant on other residents, in this sub-sample of industries. NZ-born workers in wholesale trade (FF) are skewed towards high-skilled and away from low-skilled, and have a relatively low shares of other non-resident visa holders. Retail trade and accommodation (GH) are the opposite, with a NZ-born distribution skewed towards low-skilled workers and an over-representation of other non-resident workers (including working holiday scheme visas and students). Professional services industry (MN) employment is skewed toward high-skilled NZ-born, but also more reliant on all migrant types, at the expense of fewer moderately-skilled NZ-born than average. This diversity of employment mixes provides a good testing ground for the general applicability of the pooled (all industry) findings.

Each of the five industry-specific models is estimated independently following the same specification as the pooled estimates, except that linear productivity industry time trends are replaced by year dummies. Production function, wage bill equation and productivity-wage gap estimates are reported together in Table 11. Focussing initially on the sign of estimated weight coefficients (ie, ϕ and ψ), when significantly different from zero (at the 10% level) the industry-specific coefficients are entirely consistent with the pooled results (Table 6 and Table 7). All NZ-born weights are significant and consistently signed – negative for low-skilled and positive for high-skilled.

Similarly, all long-term migrant weights are positive except in the two instances where they are insignificantly different from zero (at the 10% level) – for manufacturing in the production function, and in retail trade and accommodation for the firm-level wage bill equation. Significant positive productivity weight coefficients for skilled residents are restricted to wholesale trade and professional services with the latter of these groups being the most intensive user of this labour type. Remaining visa types have significant and consistently signed coefficients in three out of five industries in the production function, and four out of five industries in the firm-level wage bill equation. Overall, these results support the hypothesis that the pooled industry findings are a reasonable representation of the broad patterns that play out in the largest industries.

Turning to the implied productivity-wage gaps at the industry level (bottom panel of Table 11), there is greater apparent heterogeneity across industries. For example, the pooled results implied that the gap was insignificantly different from zero for low-skilled NZ-born, since productivity and wage weights were both negative, but not different from each other (at the 10% level). In the industry-level results, two gaps for low-skilled NZ-born are positive and significant, one is negative and significant, and the remaining two are insignificantly different from zero. While this seems at odds with the prior conclusion of consistency across industries, the differences in gaps can be reconciled by recognising that the reference group (and production function/wage bill equation) changes across industries. In other words, the gaps are expressed as within-industry deviations from a normalised zero gap for moderately-skilled NZ-born in each industry.

For example, focussing on professional services, all point estimates for gaps are negative, ranging from -0.188 (and insignificantly different from zero) for high-skilled NZ-born to -1.411 for skilled residents. The fact that all gaps are negative could be due to the productivity-wage gap for moderately-skilled NZ-born in this industry being relatively large compared to the average gap for this group for all industries pooled. In a relative sense, what is important here is the ranking of gaps, where the high-skill NZ-born gap is larger than the gap for long-term and skilled resident migrants, for example, as it the case in the pooled results (Table 8, column 5). A key difference in this industry, therefore, is that high-skilled NZ-born do not have a positive gap, relative to moderately-skilled.

Table 11 Productivity-wage gap $(\phi - \psi)$ – five largest industry groups

	CC	EE	FF	GH	MN
Production function					
$\phi_{NZ,Lo}$	-0.430***	-0.201***	-0.518***	-0.285***	-0.446***
	[0.064]	[0.051]	[0.116]	[0.032]	[0.073]
$\phi_{NZ,Hi}$	1.334***	1.001***	2.722***	1.226***	2.285***
	[0.146]	[0.105]	[0.366]	[0.091]	[0.222]
ϕ_{LT}	-0.008	0.316***	0.428***	0.096**	0.384***
	[0.054]	[0.074]	[0.144]	[0.042]	[0.105]
ϕ_{SR}	0.034	-0.107	0.690**	0.012	1.549***
	[0.202]	[0.201]	[0.332]	[0.107]	[0.282]
ϕ_{SNR}	0.414***	0.117	-0.185	0.164*	0.491**
	[0.148]	[0.222]	[0.385]	[0.084]	[0.227]
ϕ_{OR}	-0.050	-0.225	-1.117***	-0.218*	-0.961*
	[0.185]	[0.264]	[0.374]	[0.112]	[0.561]
ϕ_{ONR}	-0.706***	-0.081	-0.580***	-0.066	-0.305**
	[0.159]	[0.102]	[0.163]	[0.046]	[0.126]
Firm-level wage bill equation					
$\psi_{NZ,Lo}$	-0.496***	-0.323***	-0.612***	-0.461***	-0.211***
	[0.015]	[0.015]	[0.030]	[0.010]	[0.042]
$\psi_{NZ,Hi}$	1.012***	0.918***	1.465***	1.098***	2.474***
	[0.034]	[0.036]	[0.061]	[0.040]	[0.123]
ψ_{LT}	0.024*	0.223***	0.199***	-0.021	0.849***
	[0.015]	[0.021]	[0.036]	[0.013]	[0.070]
ψ_{SR}	0.568***	0.530***	1.072***	0.085**	2.960***
	[0.051]	[0.054]	[0.104]	[0.039]	[0.170]
ψ_{SNR}	0.295***	0.241***	0.596***	0.017	1.084***
	[0.044]	[0.028]	[0.185]	[0.023]	[0.167]
ψ_{OR}	-0.592***	-0.075	-0.687***	-0.374***	-0.309***
	[0.046]	[0.092]	[0.115]	[0.038]	[0.119]
ψ_{ONR}	-0.590***	-0.247***	-0.436***	-0.219***	-0.038
	[0.040]	[0.034]	[0.083]	[0.013]	[0.064]
N	36,264	22,167	17,706	37,386	25,461
R^2 – Prod	0.976	0.979	0.918	0.951	0.897
R^2 – Wage	0.981	0.976	0.965	0.980	0.952
Productivity-wage gap $(\phi - \psi)$					
Low-skilled NZ-born	0.067	0.122***	0.095	0.177***	-0.235***
High-skilled NZ-born	0.322**	0.083	1.257***	0.127	-0.188
Long-term migrant	-0.032	0.093	0.229*	0.117***	-0.465***
Skilled resident	-0.534***	-0.637***	-0.381	-0.073	-1.411***
Skilled non-resident	0.119	-0.124	-0.782**	0.147*	-0.594***
Other resident	0.542***	-0.150	-0.430	0.156	-0.652
Other non-resident	-0.116	0.165*	-0.144	0.153***	-0.267***

Notes: Translog production function and firm-level wage bill equation jointly estimated as a pair of non-linear seemingly unrelated regressions for each industry. Only effective labour input coefficients and productivity-wage gaps reported. Long-term migrants include Australian-born. Robust standard errors (clustered on firm) in brackets. ***;**;* indicates coefficient significantly different from zero at 1;5;10% level respectively. Each specification includes time dummies (base year 2005).

5.5 Variation by intensity of migrant share

Sorting of migrants across firms with different characteristics – including industry – may reflect migration policy decisions but may also be influenced by complementarities between migrants and those firm characteristics, including the prevalence of NZ-born workers at particular skill levels. To test this latter hypothesis, we estimate a pooled industry model that allows the output and wage effective labour weights of NZ-born to vary by the proportion of migrant employment at the firm. For simplicity we consider only the overall migrant share as relevant (rather than, say, the proportion of skilled migrants). Further, since the migrant share and NZ-born shares are mechanically related (sum to one), straight interaction of the two is equivalent to adding a quadratic term in the NZ-born share. To simplify the interpretation of the estimates, we interact the NZ-born shares with an indicator variable for whether the employing firm is a "migrant-intensive" – ie, above median share – employer of migrants, which helps break the tautological relationship between the two variables being interacted. For the production function, the effective labour input term takes the following form:

$$\tilde{L} = L\left(\left(1 + \phi_{0,hi\,mig} \times \delta\left(S_{mig} > \tilde{S}_{mig}\right)\right).S_0 + \sum_j \left[\left(1 + \phi_j + \phi_{j,hi\,mig} \times \delta\left(S_{mig} > \tilde{S}_{mig}\right)\right).S_j\right]\right) \qquad (8)$$

where $\delta\left(S_{mig} > \tilde{S}_{mig}\right)$ is the indicator variable for high migrant share firms, and $\tilde{S}_{mig}$ is the median migrant share. The inclusion of the $\phi_{0,hi\,mig}$ parameter shifts the base group to moderately-skilled NZ-born workers in low migrant share firms and allows moderately-skilled NZ-born workers in migrant-intensive firms to have a productivity-wage gap that differs from zero.

This analysis is only suggestive of complementarities between NZ-born and migrants since the model provides no way of distinguishing complementarities from alternative explanations of a positive coefficient on an interaction term, for example, worker sorting due to heterogeneity observed by potential employees but not captured by regression variables. In this alternative interpretation of the interaction term coefficients migrants and high-skilled NZ-born workers have a preference to sort into firms where they know their wages (productivity) will be higher which has the potential to cause a correlation between output and co-location of those labour types. The employer, presumably, has better information than the researcher as to the relative productivity of different workers and potential complementarities between worker types. The mediating role of managers in the appointment process leads us to place more weight on the complementarity interpretation of the estimates over the sorting interpretation.

Bearing this caveat in mind, Table 12 reports jointly-estimated weights and gaps, where the latter are constructed in the manner outlined in the time-varying coefficients subsection. Because of the interaction term for moderately-skilled NZ-born, we include the base group weights as a placeholder in the table (fixed at one in each equation). The results suggest that moderately-skilled NZ-born workers in migrant-intensive firms have significantly lower effective labour weight in both the production function (10.8pp lower) and the firm-level wage bill equation (3.7pp lower). In terms of the productivity-wage gap, these differences imply that moderately-skilled workers receive a higher wage premium in high migrant share firms compared to low migrant share firms, after controlling for productivity differences.

For low-skilled NZ-born workers, both ϕ and ψ are significantly lower in migrant-intensive firms, though the productivity-wage gap is economically small and insignificantly different from zero for low-skilled NZ-born workers in either firm type – consistent with the pooled results. Conversely, high-skilled NZ-born workers have markedly higher weights in both the production function (44pp) and firm-level wage bill equation (62pp) when they work in migrant-intensive firms, yielding a lower but still positive and significant gap for these workers (relative to the base group). While the migrant share coefficients change somewhat from the model without interaction terms (Table 6-Table 8, column 5) as would be expected due to the change in the base group, the two sets of results display similar patterns.

Together the results in Table 12 provide tentative evidence that migrant workers are complements to high-skilled NZ-born workers. However, we are cautious not to over-interpret these results, given the corelation between the employment share variables and the difficulty of identifying effects without an exogenous source of variation that might control for the endogenous employment choices of both employers and workers.

Table 12 Productivity-wage gap $(\phi - \psi)$ – high vs low migrant share firms

	Output ϕ	Wages ψ	Gap $\phi - \psi$
Low-skilled NZ-born	-0.389***	-0.389***	-0.001
	[0.030]	[0.007]	
$\times\, \delta(S_{mig} > \tilde{S}_{mig})$	-0.065**	-0.106***	0.041
	[0.033]	[0.009]	
Moderately-skilled NZ-born	1.000	1.000	0.000
	[.]	[.]	
$\times\, \delta(S_{mig} > \tilde{S}_{mig})$	-0.108***	-0.037***	-0.071***
	[0.027]	[0.008]	
High-skilled NZ-born	1.354***	0.945***	0.409***
	[0.075]	[0.020]	
$\times\, \delta(S_{mig} > \tilde{S}_{mig})$	0.436***	0.617***	0.228***
	[0.063]	[0.020]	
Long-term migrant	0.051*	0.027***	0.024
	[0.030]	[0.009]	
Skilled resident	0.092	0.497***	-0.405***
	[0.083]	[0.028]	
Skilled non-resident	0.177***	0.225***	-0.048
	[0.065]	[0.018]	
Other resident	-0.301***	-0.332***	0.031
	[0.114]	[0.022]	
Other non-resident	-0.132***	-0.175***	0.043
	[0.043]	[0.011]	
N	174,555	174,555	
R^2	0.950	0.975	

Notes: Translog production function and firm-level wage bill equation jointly estimated as a pair of non-linear seemingly unrelated regressions. Only effective labour inputs coefficients (following equation (*8*)) and productivity-wage gaps reported. Long-term migrants include Australian-born. Robust standard errors (clustered on firm) in brackets. ***;**;* indicates coefficient significantly different from zero at 1;5;10% level respectively. Industries are pooled and each specification includes production-function industry linear time trends and intercepts (excluding the largest industry, MN11).

6 Conclusion

In this paper we look at the relationship between migrant employment, productivity and wages in New Zealand firms. New Zealand has a high proportion of its workforce born overseas and the migrant share in total labour input increased substantially over the fifteen-year analysis period, driven by growth in the number of long-term migrants (ie, migrants who have been in New Zealand for at least five years). Long-term migrants account for 15% of full-time equivalent employee labour input in 2004, rising to 24% in 2019. For recent migrants, there is a decline in the proportion of skilled residents (including skilled migrant and entrepreneur visa categories). At the same time there has been an increase in workers on skilled non-resident visas (such as essential skills), and other non-resident visas (including recognised seasonal employer, and working holiday scheme visas).

We present novel – full-time equivalent employment-weighted – evidence of the variable concentration of migrants across different sectors of the economy. Industries such as horticulture, accommodation and food, or telecommunications rely on migrant workers for a third of their labour input, whereas for industries such as road transport, and forestry and logging the figure is more like 5-10%. There is also a wide variety in the migrant visa types that industries employ. Recent migrants on skilled resident visas are important for telecoms, and for professional, scientific and technology services, whereas the majority of the migrant labour for horticulture and accommodation are on other non-resident visas.

Treated as a homogeneous group, migrant workers appear to produce slightly less than the average NZ-born worker but capture a larger share of the firm-level wage bill (Table 6 and Table 7, column 1). However, this simplistic comparison hides considerable heterogeneity between migrants. Migration is not a random flow of people into and out of the country. Firms employ migrants in response to business needs, and there is no reason to expect these requirements to be the same across all firms. The detailed administrative data available in the IDI allow us to examine this heterogeneity by visa type and by length of time within New Zealand (long-term vs recent). Once we account for this variation, we find that long-term and skilled recent migrants are generally more productive than moderately-skilled NZ-born workers, and that this higher productivity is largely accounted for by effort or skill differences – evidenced by wages also being higher for these groups – relative to moderately-skilled NZ-born. Industry-specific models for the five largest industries confirm these findings (Table 11), and analysis of changes over time suggest that the long-term migrant contribution to firm-level productivity has been increasing (Table 9).

It seems likely that migrant workers provide something in addition to their direct labour input to firms that their employers value. For example, the knowledge they bring with them – be it knowledge of their home market, or of products and services and ways of working foreign to New Zealand workers and firms – is an addition to the stock of intangible capital at the firm. Interacting an indicator for migrant-intensive firms with NZ-born worker employment shares we generate preliminary evidence that high-skilled NZ-born workers extract some of these potential benefits from working intensively with migrants (Table 12).

Disclaimer

Acknowledgements David Maré acknowledges support through the MBIE Endeavour Fund research programme "WERO: Working to End Racial Oppression"

References

Abowd, J. M., Kramarz, F., & Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, *67*(2), 251–334.

Alesina, A., Harnoss, J., & Rapoport, H. (2016). Birthplace diversity and economic prosperity. *Journal of Economic Growth*, *21*(2), 101–138.

Allan, C., & Maré, D. C. (2022). *Who benefits from firm success? Heterogeneous rent-sharing in New Zealand* (Working Papers 22_03). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/22_03.html

Andersson, F., Burgess, S., & Lane, J. I. (2007). Cities, matching and the productivity gains of agglomeration. *Journal of Urban Economics*, *61*(1), 112–128.

Aslund, O., Bratu, C., Lombardi, S., & Thoresson, A. (2021). *Firm productivity and immigrant-native earnings disparity* (IZA Discussion Papers No. 14960). Institute of Labor Economics (IZA). https://ideas.repec.org/p/iza/izadps/dp14960.html

Beerli, A., Ruffner, J., Siegenthaler, M., & Peri, G. (2021). The Abolition of Immigration Restrictions and the Performance of Firms and Workers: Evidence from Switzerland. *American Economic Review*, *111*(3), 976–1012.

Bianchi, M., Buonanno, P., & Pinotti, P. (2012). Do immigrants cause crime? *Journal of the European Economic Association*, *10*(6), 1318–1347.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics*, *118*(4), 1335–1374.

Borjas, G. J. (2013). The analytics of the wage effect of immigration. *IZA Journal of Migration and Development*, *2*(1), 1–25.

Boubtane, E., Dumont, J.-C., & Rault, C. (2016). Immigration and economic growth in the OECD countries 1986–2006. *Oxford Economic Papers*, *68*(2), 340–360.

Campo, F., Forte, G., & Portes, J. (2018). *The impact of migration on productivity and native-born workers' training* (IZA Discussion Papers No. 11833). Institute of Labor Economics (IZA). https://ideas.repec.org/p/iza/izadps/dp11833.html

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, *19*(1), 22–64.

Card, D. (2012). Comment: The elusive search for negative wage impacts of immigration. *Journal of the European Economic Association*, *10*(1), 211–215.

Criscuolo, C., Hijzen, A., Schwellnus, C., Barth, E., Chen, W.-H., Fabling, R., Fialho, P., Grabska-Romagosa, K., Kambayashi, R., Leidecker, T., Skans, O. N., Riom, C., Roth, D., Stadler, B., Upward, R., & Zwysen, W. (2020). *Workforce composition, productivity and pay: The role of firms in wage inequality* (OECD Economics Department Working Papers No. 1603). OECD Publishing. https://ideas.repec.org/p/oec/ecoaaa/1603-en.html

Data1850. (2019). *Data1850 dataset: People*. Retrieved from https://data1850.nz/documents/11/Economic_Activity_Series_hzdNReH.xlsx

Delacroix, A. (2003). Heterogeneous matching with transferable utility: Two labor market applications. *International Economic Review*, *44*(1), 313–330.

Dostie, B., Li, J., Card, D., & Parent, D. (2020). *Employer policies and the immigrant-native earnings gap* (IZA Discussion Papers No. 13245). Institute of Labor Economics (IZA). https://ideas.repec.org/p/iza/izadps/dp13245.html

Dustmann, C., Frattini, T., & Preston, I. P. (2013). The effect of immigration along the distribution of wages. *Review of Economic Studies*, *80*(1), 145–173.

Dustmann, C., Schönberg, U., & Stuhler, J. (2017). Labor supply shocks, native wages, and the adjustment of local employment. *The Quarterly Journal of Economics*, *132*(1), 435–483.

Edo, A. (2019). The impact of immigration on the labor market. *Journal of Economic Surveys*, *33*(3), 922–948.

Edo, A., Ragot, L., Rapoport, H., Sardoschau, S., Steinmayr, A., & Sweetman, A. (2020). An introduction to the economics of immigration in OECD countries. *Canadian Journal of Economics/Revue Canadienne d'économique*, *53*(4), 1365–1403.

Fabling, R. (2011). *Keeping it together: Tracking firms on New Zealand's Longitudinal Business Database* (Working Papers 11_01). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/11_01.html

Fabling, R. (2018). *Entrepreneurial beginnings: Transitions to self-employment and the creation of jobs* (Working Papers 18_12). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/18_12.html

Fabling, R., & Maré, D. C. (2015a). *Production function estimation using New Zealand's Longitudinal Business Database* (Working Papers 15_15). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/15_15.html

Fabling, R., & Maré, D. C. (2015b). *Addressing the absence of hours information in linked employer-employee data* (Working Papers 15_17). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/15_17.html

Fabling, R., & Maré, D. C. (2019). *Improved productivity measurement in New Zealand's Longitudinal Business Database* (Working Papers 19_03). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/19_03.html

Fabling, R., & Sanderson, L. (2014). *Productivity distributions in New Zealand: The dangers of international comparison* (Working Papers 14_16). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/14_16.html

Friedberg, R. M., & Hunt, J. (1995). The impact of immigrants on host country wages, employment and growth. *Journal of Economic Perspectives*, *9*(2), 23–44.

Glaeser, E. L., & Maré, D. C. (2001). Cities and skills. *Journal of Labor Economics*, *19*(2), 316–342.

Hanson, G. H. (2009). The economic consequences of the international migration of labor. *Annual Review of Economics*, *1*(1), 179–208.

Hellerstein, J. K., & Neumark, D. (1995). Are earnings profiles steeper than productivity profiles? Evidence from Israeli firm-level data. *The Journal of Human Resources*, *30*(1), 89–112.

Hellerstein, J. K., & Neumark, D. (1999). Sex, wages, and productivity: An empirical analysis of Israeli firm-level Data. *International Economic Review*, *40*(1), 95–123.

Hellerstein, J. K., & Neumark, D. (2007). Production function and wage equation estimation with heterogeneous labor: Evidence from a new matched employer-employee data set. In E. R. Berndt & C. R. Hulten (Eds.), *Hard-to-measure Goods and Services: Essays in Honor of Zvi Griliches* (Vol. 67, pp. 31–71). University of Chicago Press.

Hellerstein, J. K., & Neumark, D. (2008). Workplace segregation in the United States: Race, ethnicity, and skill. *The Review of Economics and Statistics*, *90*(3), 459–477.

Hellerstein, J. K., Neumark, D., & Troske, K. R. (1999). Wages, productivity, and worker characteristics: Evidence from plant-level production functions and wage equations. *Journal of Labor Economics*, *17*(3), 409–446.

Huber, P. J. (1967). The behavior of maximum likelihood estimates under nonstandard conditions. In L. M. Le Cam & J. Neyman (Eds.), *Proceedings of the Berkeley Symposium on Mathematical Statistics and Probability: Vol. 5.1* (pp. 221–233). University of California Press.

Hunt, J., & Gauthier-Loiselle, M. (2010). How much does immigration boost innovation? *American Economic Journal: Macroeconomics*, *2*(2), 31–56.

Jacobs, V., Rycx, F., & Volral, M. (2022). *Does over-education raise productivity and wages equally? The moderating role of workers' origin and immigrants' background* (IZA Discussion Papers No. 15074). Institute of Labor Economics (IZA). https://ideas.repec.org/p/iza/izadps/dp15074.html

Jaumotte, F., Koloskova, K., & Saxena, S. C. (2016). *Impact of migration on income levels in advanced economies* (IMF Spillover Notes No. 2016/008). International Monetary Fund. https://ideas.repec.org/p/imf/imfsns/2016-008.html

Kerr, S. P., & Kerr, W. R. (2019). Immigrant networking and collaboration: Survey evidence from CIC. In I. Ganguli, S. Kahn, & M. MacGarvie (Eds.), *The Roles of Immigrants and Foreign Students in US Science, Innovation, and Entrepreneurship* (pp. 173–205). University of Chicago Press.

Kerr, W. R., & Lincoln, W. F. (2010). The supply side of innovation: H-1B visa reforms and US ethnic invention. *Journal of Labor Economics*, *28*(3), 473–508.

Lewis, E. (2011). Immigration, skill mix, and capital skill complementarity. *The Quarterly Journal of Economics*, *126*(2), 1029–1069.

Lewis, E. (2013). Immigration and production technology. *Annual Review of Economics*, *5*(1), 165–191.

Lewis, E., & Peri, G. (2015). Immigration and the economy of cities and regions. In G. Duranton, J. V. Henderson, & W. C. Strange (Eds.), *Handbook of Regional and Urban Economics* (Vol. 5, pp. 625–685). Elsevier.

Longhi, S., Nijkamp, P., & Poot, J. (2005). A meta-analytic assessment of the effect of immigration on wages. *Journal of Economic Surveys*, *19*(3), 451–477.

Longhi, S., Nijkamp, P., & Poot, J. (2010). Joint impacts of immigration on wages and employment: Review and meta-analysis. *Journal of Geographical Systems*, *12*(4), 355–387.

Maré, D. C., & Fabling, R. (2013). Productivity and local workforce composition. In R. Crescenzi & M. Percoco (Eds.), *Geography, institutions and regional economic performance* (pp. 59–76). Springer-Verlag.

Maré, D. C., Hyslop, D. R., & Fabling, R. (2017). Firm productivity growth and skill. *New Zealand Economic Papers*, *51*(3), 302–326.

Maré, D. C., & Stillman, S. (2009). *The impact of immigration on the labour market outcomes of New Zealanders* (Working Papers 09_11). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/09_11.html

MBIE. (2020). *Introduction to the immigration system: Data and evidence (briefing to the incoming minister)*. Wellington: Ministry of Business, Innovation & Employment.

McLaren, J. (2003). Trade and market thickness: Effects on organizations. *Journal of the European Economic Association*, *1*(2–3), 328–336.

McLeod, K., Fabling, R., & Maré, D. C. (2014). *Hiring new ideas: International migration and firm innovation in New Zealand* (Working Papers 14_14). Motu Economic and Public Policy Research. https://ideas.repec.org/p/mtu/wpaper/14_14.html

Mitaritonna, C., Orefice, G., & Peri, G. (2017). Immigrants and firms' outcomes: Evidence from France. *European Economic Review*, *96*(C), 62–82.

Nickell, S. (2009). Immigration: Trends and macroeconomic implications. In D. Mihaljek (Ed.), *Globalisation, labour markets and international adjustment: Essays in honour of Palle S Andersen* (pp. 51–63). Bank for International Settlements.

Ortega, F., & Peri, G. (2014). Openness and income: The roles of trade and migration. *Journal of International Economics*, *92*(2), 231–251.

Ottaviano, G. I. P., & Peri, G. (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association*, *10*(1), 152–197.

Ottaviano, G. I. P., Peri, G., & Wright, G. C. (2018). Immigration, trade and productivity in services: Evidence from UK firms. *Journal of International Economics*, *112*(C), 88–108.

Peri, G. (2012). The effect of immigration on productivity: Evidence from US states. *The Review of Economics and Statistics*, *94*(1), 348–358.

Peri, G., & Sparber, C. (2009). Task specialization, immigration, and wages. *American Economic Journal: Applied Economics*, *1*(3), 135–169.

Productivity Commission. (2021). *International migration to New Zealand: Historical themes & trends* (Working Paper No. 2021/04). Productivity Commission. https://www.productivity.govt.nz/research/immigration-history/

Schloss, D. F. (1891). Why working-men dislike piece-work. *The Economic Review*, *1*(3), 311–326.

Sin, I., Stillman, S., & Fabling, R. (2020). What drives the gender wage gap? Examining the roles of sorting, productivity differences, bargaining and discrimination. *The Review of Economics and Statistics*, 1–16. https://doi.org/10.1162/rest_a_01000

Timmins, J., Mason, G., Mok, P., Nunns, P., & Stevens, P. (2012). *To make or buy (skills): An analysis of training decisions using microdata* (Occasional Papers No. 12/6). Ministry of Economic Development. https://ideas.repec.org/p/ris/nzmedo/2012_006.html

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, *48*(4), 817–838.

White, H. (1982). Maximum likelihood estimation of misspecified models. *Econometrica*, *50*(1), 1–25.

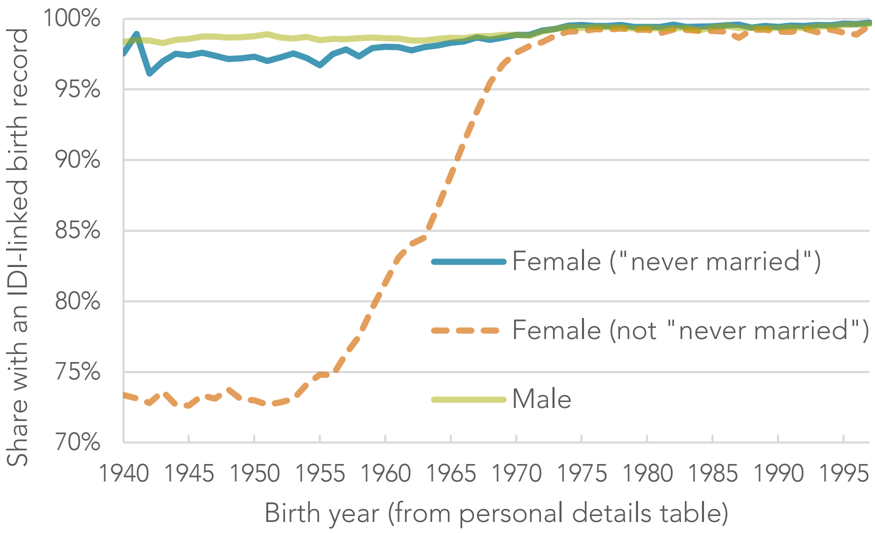
Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *Journal of the American Statistical Association*, *57*(298), 348–368.

Zellner, A. (1963). Estimators for seemingly unrelated regression equations: Some exact finite sample results. *Journal of the American Statistical Association*, *58*(304), 977–992.

Appendix A Unlinked DIA records

Linking NZ-born individuals in Census to Department of Internal Affairs (DIA) birth records, we observe significant under-coverage in the DIA data for people born prior to 1970. Figure A.1 illustrates this for the ever-employed subpopulation with a Census 2013 response, restricted to individuals born between 1940 and 1997 (according to the IDI "personal details" table), and disaggregated by sex.

Figure A.1 Proportion of Census NZ-born who have a linked DIA birth record



Notes: Restricted to labour table ever-employed individuals with observed characteristics (sex/age) and with an unimputed NZ-born response in Census 2013. Having an IDI-linked birth record means the Census record is linked to a DIA birth record via the IDI spine.

The absence of matching DIA birth records appears to be due to the IDI's inability to link records for women who change their surname following marriage – consistent with a constant match rate for men, but declining match rate for most women, but not for never-married women. This is also consistent with the match rate only declining for birth dates prior to 1970, since DIA data was fully digitised in 1998, so that missing names changes should only arise from marriages that pre-dated digitisation. For example, a missing 1997 marriage-related name change is likely to predominantly affect women older than 27 in 1997 (ie, born prior to 1970). Stats NZ metadata supports these assumptions about the timing of data quality changes, stating: "Name changes registered in New Zealand are also added to birth records if the person is NZ-born" provided that name changes on pre-digitisation birth records are unobserved.[13] Stats NZ are aware of the issues with linking married women on the IDI, and are in the process of adding new data and additional linking passes to correct the issue.

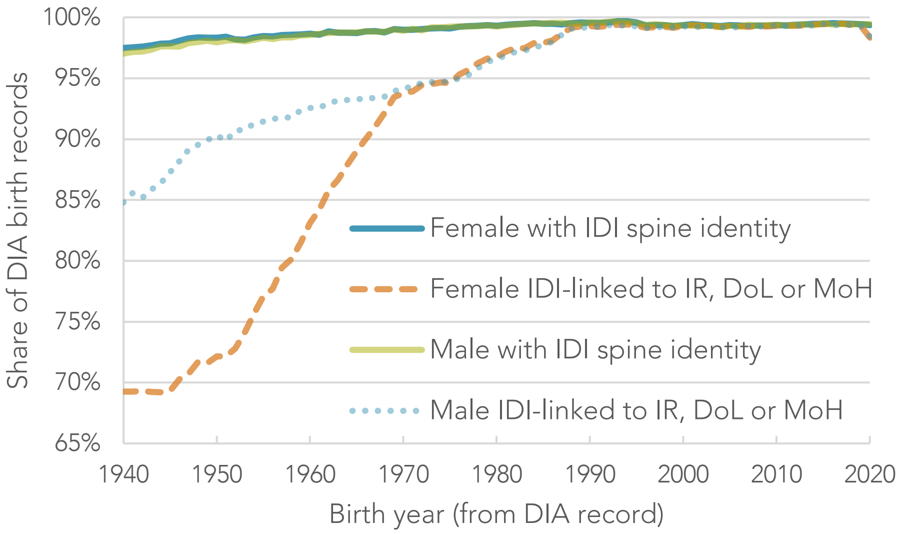
In our population of ever-employed individuals, we estimate from the Census 2013 comparison to DIA records, that DIA fails to identify 90,366 women as NZ-born, with 86,328 of those women born pre-1970 and, therefore, likely to have missing name change data that prevents complete record linking on the IDI. In contrast, 9,333 men who are NZ-born in Census 2013 have missing DIA records, reflecting false matches in the IDI or misreporting in Census.

Since DIA birth records are one of the three data components that feed into the construction of the IDI spine, non-matching of DIA records to other IDI component should also result in duplication of individuals on the spine through the presence of other data sources (eg, tax data) under the individuals' married name. Since duplication of individuals occurs because of non-matching surnames, duplicate (DIA-based) spine records will be unmatched to other IDI datasets. Figure A.2 demonstrates this phenomenon, now using the DIA births data as the base population and comparing the match rate of DIA records to the spine, and to other large datasets in the IDI – Inland Revenue, Department of

[13] The metadata does not state the start date of the DIA name change data used by the IDI (presumably because these data are not available to IDI users).

Labour (border movements and visas), and Ministry of Health.[14] This approach provides an alternative lens with which to estimate the scope of non-matches, without relying on an overlap with Census.[15]

Figure A.2 Link rate of DIA birth records to other datasets in the IDI



Notes: Restricted to DIA birth records with observed characteristics (sex/age). Having an IDI spine identity means that the birth record is linked to the IDI spine. IR, DoL, MoH links are links to Inland Revenue, Department of Labour, and Ministry of Health records respectively.

Regardless of birth year and sex, at least 97% of DIA birth records result in the creation of spine identities (solid lines) – ie, are treated by the IDI as unique individuals in the population of interest (approximately an ever-resident population). However, as we look back at earlier birth years, we see a decline in the match rate of DIA birth records to other datasets in the IDI for both women and men (dashed lines). This is to be expected since those other datasets only have data from the late 1990s, meaning that individuals born prior to the late 1990s may not generate any administrative data in the future (either due to emigration, or due to death). However, the match rate for women drops off far more rapidly prior to 1970 than it does for men, reflecting the duplication of individuals on the spine from non-matched women who changed surname when they married (prior to 1998). Using the match rate to other datasets for males as a guide for what population attrition-based decline in matches should look like in the absence of matching issues, we estimate the number of duplicate female pre-1970 birth spine records at 89,830, similar in magnitude to the shortfall in Census-DIA matches reported earlier, but based on the full population of (DIA-based) NZ-born.

In the absence of explicitly needing pre-1970 DIA birth records linked to other data, these spine duplicates are unproblematic, since they do not result in other data being split across multiple spine identities for the same individual.[16] Unfortunately, we do require linked DIA data since we use DIA births as our primary source for identifying NZ-born. Our solution to DIA under-coverage is to have a secondary step that identifies NZ-born from reported Census (2013 and 2018) responses. This approach identifies 78,864 (4,290) NZ-born ever-employed women (men) who are missing an IDI-linked DIA record. Comparing this total to the DIA-based estimates suggests we do a reasonably complete job of correcting for the under-coverage of linked DIA records. Where we misidentify NZ-born women as migrants, these individuals are most likely to be classified as long-term migrants. This misclassification will have the tendency to make long-term migrants appear more similar to NZ-born than they actually are. Since the true long-term migrant group is large, and we estimate our misclassification to be minimal, any resulting bias is likely to be small.

[14] The first two of these datasets – IR and DoL – constitute the other two components of the IDI spine.

[15] At the expense of not being able to restrict to a population of interest (ever-employed) nor directly assess the causes of non-linkage (ie, marriage-based name changes).

[16] It would be problematic if duplicates were counted in resident population estimates, though current admin-based methods for identifying the resident population rely on data linking across sources to establish residence (see, eg, Fabling, 2018).

Appendix B Additional results

Table B.1 Productivity sample coverage rate by productivity industry

	Production function industry	Firm-years	FTE	WP	L
AA11	Horticulture & Fruit Growing	2.7%	36.2%	2.2%	23.0%
AA12	Sheep, Beef Cattle & Grain Farming	0.2%	8.1%	0.1%	2.0%
AA13	Dairy Cattle Farming	0.5%	6.7%	0.3%	3.3%
AA14	Poultry, Deer & Other Livestock Farming	0.8%	33.8%	0.5%	12.9%
AA21	Forestry & Logging	3.3%	52.8%	1.4%	23.5%
AA31	Fishing & Aquaculture	0.7%	22.8%	0.3%	9.1%
AA32	Agriculture, Forestry & Fishing Support Services, & Hunting	3.6%	47.5%	3.9%	33.8%
BB11	Mining	14.1%	75.0%	3.6%	72.0%
CC1	Food & Beverage Manufacturing	14.5%	77.3%	9.6%	75.1%
CC21	Textile, Leather, Clothing & Footwear Manufacturing	8.8%	70.2%	5.8%	61.1%
CC3	Wood & Paper Product Manufacturing	13.0%	72.2%	8.6%	66.8%
CC41	Printing	9.9%	66.4%	8.2%	59.2%
CC5	Petrochemical Product Manufacturing	23.0%	80.4%	14.4%	78.2%
CC61	Non-Metallic Mineral Product Manufacturing	10.7%	72.9%	7.8%	68.1%
CC7	Metal & Metal Product Manufacturing	13.5%	66.4%	10.1%	60.2%
CC81	Transport Equipment Manufacturing	9.1%	63.6%	7.0%	55.8%
CC82	Machinery & Other Equipment Manufacturing	9.9%	71.5%	7.3%	63.9%
CC91	Furniture & Other Manufacturing	6.0%	57.3%	4.8%	44.1%
DD1	Electricity, Gas, Water & Waste Services	9.8%	88.1%	2.8%	83.8%
EE11	Building Construction	1.9%	43.5%	1.8%	27.3%
EE12	Heavy & Civil Engineering Construction	13.6%	81.7%	12.1%	78.3%
EE13	Construction Services	2.9%	43.3%	3.0%	28.7%
FF11	Wholesale Trade	8.6%	62.7%	5.5%	56.1%
GH11	Motor Vehicle, Motor Vehicle Parts & Fuel Retailing	10.5%	61.0%	9.7%	55.7%
GH12	Supermarket, Grocery Stores & Specialised Food Retailing	6.2%	77.2%	6.5%	69.1%
GH13	Other Store-Based Retailing & Non-Store Retailing	4.6%	65.0%	3.8%	56.0%
GH21	Accommodation & Food Services	6.0%	47.9%	4.4%	41.1%
II11	Road Transport	4.1%	66.2%	3.6%	51.6%
II12	Rail, Water, Air & Other Transport	5.9%	88.5%	1.8%	84.8%
II13	Postal, Courier & Warehousing Services	4.1%	80.7%	1.7%	70.7%
JJ11	Information Media Services	3.1%	69.0%	1.2%	58.7%
JJ12	Telecommunications, Internet & Library Services	6.9%	88.2%	2.8%	86.0%
KK1_	Finance & Insurance	5.1%	88.1%	0.7%	85.5%
KK13	Auxiliary Finance & Insurance Services	2.7%	56.7%	0.7%	44.0%
LL11	Rental & Hiring Services (except Real Estate)	3.4%	56.5%	2.2%	45.2%
MN11	Professional, Scientific & Technical Services	2.4%	53.6%	3.7%	37.5%
MN21	Administrative & Support Services	3.2%	64.6%	2.0%	53.7%
RS11	Arts & Recreation Services	2.0%	48.1%	0.8%	33.3%
RS21	Other Services	2.2%	30.0%	2.1%	20.9%
	Total (productivity industries)	3.8%	61.9%	3.0%	49.1%

Notes: Permanent production function industry comes from the Fabling-Maré productivity dataset on the LBD. Productivity estimation sample covers the 2005-2019 financial years for firms with: measured non-zero productivity components; 10+ FTE employees; incumbent (non-entrant/exiter) status; and firm FTE with observed characteristics at least 75% of total L.

Table B.2 Migrant employment shares by productivity industry

Industry	Annual average N(firms)	L	NZ	Industry employment share Oz	LT	SR	SNR	OR	ONR
AA11	212	5,767	59.8%	1.3%	19.7%	1.3%	1.1%	3.6%	13.3%
AA12	40	807	85.8%	0.7%	6.8%	0.6%	2.1%	0.6%	3.5%
AA13	70	1,107	68.9%	0.8%	11.5%	1.1%	12.7%	0.3%	4.7%
AA14	39	1,227	79.0%	1.6%	11.4%	1.4%	2.5%	1.7%	2.3%
AA21	84	2,007	95.0%	0.9%	3.3%	0.2%	0.1%	0.2%	0.2%
AA31	9	200	76.2%	2.8%	12.9%	0.5%	0.7%	0.3%	6.6%
AA32	233	7,127	63.1%	0.9%	12.6%	0.6%	1.8%	2.0%	19.1%
BB11	55	3,613	82.9%	3.1%	9.2%	1.6%	1.6%	0.6%	1.0%
CC1	431	55,740	73.3%	1.3%	19.3%	1.3%	0.8%	1.9%	2.1%
CC21	162	6,993	63.2%	1.0%	29.4%	1.3%	1.0%	2.4%	1.6%
CC3	272	15,333	79.6%	1.2%	15.6%	1.0%	0.6%	1.0%	1.0%
CC41	128	5,453	66.7%	1.5%	27.1%	2.0%	0.7%	1.1%	1.0%
CC5	252	16,807	63.8%	1.4%	28.5%	2.3%	0.7%	1.8%	1.4%
CC61	82	6,153	70.8%	1.4%	22.0%	1.3%	1.7%	1.4%	1.3%
CC7	440	17,040	69.2%	1.3%	22.8%	2.2%	2.3%	1.2%	1.0%
CC81	134	5,353	69.9%	1.5%	21.0%	3.2%	2.2%	0.9%	1.2%
CC82	361	18,347	60.5%	1.3%	30.1%	4.0%	1.6%	1.4%	1.1%
CC91	157	4,640	65.0%	1.1%	27.6%	1.9%	1.1%	2.0%	1.3%
DD1	80	11,580	72.5%	1.6%	20.9%	2.4%	0.9%	1.0%	0.7%
EE11	339	11,393	75.8%	1.8%	14.6%	2.2%	3.4%	0.8%	1.5%
EE12	198	22,640	78.9%	1.4%	13.6%	2.3%	2.2%	0.7%	0.8%
EE13	940	25,593	76.4%	1.6%	14.5%	2.0%	2.9%	1.0%	1.6%
FF11	1,180	52,973	71.4%	1.5%	21.2%	2.2%	0.9%	1.3%	1.5%
GH11	314	13,520	76.1%	1.3%	15.0%	2.4%	1.2%	1.2%	2.7%
GH12	342	33,533	67.5%	1.4%	20.8%	2.3%	0.7%	2.5%	4.8%
GH13	748	51,453	72.6%	1.9%	19.7%	1.7%	0.6%	1.3%	2.1%
GH21	1,088	36,593	55.2%	2.0%	22.0%	2.6%	3.8%	2.3%	12.2%
II11	382	19,087	80.6%	1.0%	15.1%	0.8%	1.0%	0.8%	0.7%
II12	61	16,160	69.9%	2.2%	23.8%	1.7%	0.7%	1.0%	0.7%
II13	189	22,313	75.1%	1.3%	19.8%	1.3%	0.4%	1.1%	1.0%
JJ11	94	9,393	75.3%	2.2%	18.0%	1.9%	0.7%	1.0%	0.9%
JJ12	43	11,733	60.0%	1.7%	28.9%	4.8%	1.3%	1.5%	1.7%
KK1_	87	33,720	66.7%	1.7%	26.6%	2.5%	0.5%	1.2%	0.9%
KK13	104	6,213	70.6%	2.0%	21.4%	2.5%	0.8%	1.5%	1.2%
LL11	109	5,380	69.6%	1.7%	20.7%	1.9%	1.4%	1.6%	3.1%
MN11	1,221	54,853	65.0%	2.0%	23.3%	4.4%	2.3%	1.2%	1.8%
MN21	477	39,807	60.1%	1.5%	21.5%	2.0%	1.8%	2.9%	10.2%
RS11	122	5,660	59.8%	3.3%	21.4%	2.7%	3.1%	2.0%	7.8%
RS21	367	10,007	72.0%	1.4%	19.1%	2.2%	2.1%	1.4%	1.9%

Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes).

Table B.3 Estimated translog coefficients – pooled industry

	(1)	(2)	(3)	(4)	(5)
			Production function		
β_m	0.482***	0.493***	0.493***	0.493***	0.493***
	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]
β_k	0.123***	0.115***	0.114***	0.114***	0.114***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
β_l	0.419***	0.414***	0.414***	0.414***	0.415***
	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]
β_{mm}	0.081***	0.080***	0.080***	0.080***	0.080***
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]
β_{mk}	-0.041***	-0.041***	-0.041***	-0.041***	-0.041***
	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]
β_{ml}	-0.119***	-0.116***	-0.116***	-0.116***	-0.117***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
β_{kk}	0.028***	0.027***	0.027***	0.027***	0.027***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
β_{kl}	-0.008**	-0.007*	-0.007*	-0.007*	-0.008*
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
β_{ll}	0.052***	0.054***	0.054***	0.054***	0.054***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
			Firm-level wage bill equation		
γ_m	0.088***	0.056***	0.056***	0.056***	0.054***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
γ_k	0.037***	0.020***	0.020***	0.020***	0.020***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
γ_l	0.925***	0.962***	0.963***	0.963***	0.964***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
γ_{mm}	0.009***	0.003***	0.003***	0.003***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
γ_{mk}	0.006***	0.004***	0.005***	0.005***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
γ_{ml}	-0.018***	-0.007***	-0.007***	-0.007***	-0.008***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
γ_{kk}	0.003***	0.003***	0.003***	0.003***	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
γ_{kl}	-0.016***	-0.016***	-0.017***	-0.016***	-0.017***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
γ_{ll}	0.009***	0.012***	0.012***	0.012***	0.013***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]

Notes: Estimated parameters correspond to the five pooled industry specifications in Table 6 and Table 7. See those tables for further notes. Production function inputs (m, k, l) are demeaned prior to estimation to aid interpretation of these coefficients.

Table B.4 Productivity-wage gap $(\phi - \psi)$ – detailed productivity industries

	AA11	AA13	AA21	AA32	CC1	CC21	CC3	CC41	CC5
					Production function				
$\phi_{NZ,Lo}$	0.179	-0.423*	-0.774***	-0.734***	-0.454***	-0.079	-0.350***	-0.048	-0.469**
	[0.301]	[0.251]	[0.104]	[0.153]	[0.150]	[0.181]	[0.109]	[0.198]	[0.210]
$\phi_{NZ,Hi}$	1.784*	1.007	0.312*	0.492*	1.683***	2.342***	0.669***	1.356***	1.668***
	[0.927]	[0.769]	[0.178]	[0.288]	[0.408]	[0.418]	[0.235]	[0.293]	[0.615]
ϕ_{LT}	0.463*	0.032	0.255	-0.281***	-0.062	0.251*	0.170	0.251*	-0.049
	[0.274]	[0.305]	[0.315]	[0.078]	[0.121]	[0.135]	[0.173]	[0.138]	[0.221]
ϕ_{SR}	0.234	1.402	0.257	0.566	-0.819***	0.893	-0.217	0.471	-0.645
	[0.547]	[1.046]	[2.794]	[0.363]	[0.309]	[0.577]	[0.391]	[0.462]	[1.005]
ϕ_{SNR}	-0.165	0.389*	-1.182	-0.470***	0.219	0.439	-0.613	2.427**	-0.453
	[0.806]	[0.235]	[0.764]	[0.128]	[0.226]	[0.463]	[0.374]	[1.006]	[0.734]
ϕ_{OR}	-0.445	-0.319	-0.922***	-0.276*	-0.572	1.340***	0.095	-0.344	0.344
	[0.958]	[1.256]	[0.197]	[0.156]	[0.440]	[0.475]	[0.351]	[0.391]	[0.607]
ϕ_{ONR}	0.541	0.418	-0.065	-0.478***	-0.459**	-0.368	0.140	-0.805***	0.651
	[0.374]	[0.432]	[0.825]	[0.071]	[0.212]	[0.389]	[0.313]	[0.298]	[0.665]
					Firm-level wage bill equation				
$\psi_{NZ,Lo}$	-0.192***	-0.350***	-0.459***	-0.404***	-0.379***	-0.136*	-0.396***	-0.295***	-0.455***
	[0.041]	[0.052]	[0.051]	[0.025]	[0.036]	[0.081]	[0.029]	[0.077]	[0.047]
$\psi_{NZ,Hi}$	0.871***	0.701***	0.534***	0.887***	1.072***	1.342***	0.850***	0.910***	1.023***
	[0.108]	[0.132]	[0.086]	[0.112]	[0.088]	[0.154]	[0.075]	[0.119]	[0.100]
ψ_{LT}	-0.017	0.066	0.113	-0.101***	0.036	0.120**	0.087*	0.230***	0.009
	[0.042]	[0.047]	[0.134]	[0.033]	[0.032]	[0.053]	[0.046]	[0.072]	[0.043]
ψ_{SR}	-0.049	-0.097	0.002	0.280	0.213***	0.529*	0.370**	-0.079	0.327**
	[0.091]	[0.130]	[0.598]	[0.309]	[0.082]	[0.304]	[0.169]	[0.156]	[0.136]
ψ_{SNR}	0.085	-0.008	0.284	-0.164**	0.019	0.183	0.395***	0.474	0.259
	[0.127]	[0.037]	[0.626]	[0.068]	[0.053]	[0.196]	[0.119]	[0.349]	[0.167]
ψ_{OR}	-0.105	-0.276*	-0.369***	-0.222***	-0.445***	0.290**	-0.543***	-0.432**	-0.613***
	[0.083]	[0.153]	[0.141]	[0.059]	[0.074]	[0.129]	[0.150]	[0.207]	[0.126]
ψ_{ONR}	0.071*	-0.014	0.140	-0.180***	-0.234***	-0.338***	-0.351**	-0.787***	-0.333**
	[0.041]	[0.061]	[0.349]	[0.019]	[0.041]	[0.109]	[0.145]	[0.177]	[0.140]
N	3,177	1,044	1,266	3,498	6,465	2,424	4,077	1,926	3,774
R^2 – Prod	0.918	0.925	0.967	0.876	0.980	0.982	0.986	0.983	0.980
R^2 – Wage	0.973	0.943	0.973	0.968	0.991	0.978	0.988	0.982	0.986
					Productivity-wage gap $(\phi - \psi)$				
NZ (Lo)	0.372	-0.073	-0.315***	-0.330**	-0.075	0.058	0.046	0.247	-0.014
NZ (Hi)	0.913	0.306	-0.222	-0.395	0.611	1.000**	-0.181	0.446*	0.645
LT	0.480*	-0.035	0.142	-0.179**	-0.097	0.131	0.083	0.021	-0.057
SR	0.283	1.500	0.255	0.286	-1.032***	0.364	-0.587*	0.550	-0.972
SNR	-0.250	0.397*	-1.466*	-0.306**	0.200	0.257	-1.009***	1.953*	-0.712
OR	-0.340	-0.043	-0.553**	-0.054	-0.127	1.050***	0.638**	0.088	0.958
ONR	0.471	0.432	-0.205	-0.297***	-0.225	-0.031	0.492*	-0.018	0.984

Notes: Table continued on next page

	CC61	CC7	CC81	CC82	CC91	DD1	EE11	EE12
				Production function				
$\phi_{NZ,Lo}$	-0.507***	-0.402***	-0.352***	-0.153	-0.071	-0.574***	0.129	-0.160
	[0.128]	[0.093]	[0.124]	[0.170]	[0.199]	[0.193]	[0.243]	[0.178]
$\phi_{NZ,Hi}$	0.952**	0.742***	0.842***	1.031***	1.211***	0.339	1.349***	1.710***
	[0.397]	[0.147]	[0.266]	[0.239]	[0.410]	[0.624]	[0.493]	[0.297]
ϕ_{LT}	0.245	-0.133**	-0.041	0.101	0.012	0.127	0.927*	0.340
	[0.222]	[0.068]	[0.173]	[0.110]	[0.130]	[0.314]	[0.536]	[0.257]
ϕ_{SR}	1.061*	-0.201	0.298	-0.234	0.403	-1.566	1.225	-0.093
	[0.599]	[0.293]	[0.570]	[0.436]	[0.447]	[1.638]	[1.445]	[0.563]
ϕ_{SNR}	1.177*	0.124	-0.253	0.681*	0.551	-0.925	-0.137	0.191
	[0.632]	[0.189]	[0.328]	[0.368]	[0.385]	[1.011]	[0.695]	[0.496]
ϕ_{OR}	-1.141**	0.693*	0.090	0.596	0.177	-0.676	-1.817	0.436
	[0.526]	[0.367]	[0.796]	[0.489]	[0.336]	[0.932]	[1.520]	[1.116]
ϕ_{ONR}	-0.591	-0.429	-0.036	0.506	-1.467**	-0.213	-0.523	1.093*
	[0.529]	[0.371]	[0.371]	[0.598]	[0.748]	[0.603]	[0.562]	[0.572]
				Firm-level wage bill equation				
$\psi_{NZ,Lo}$	-0.406***	-0.471***	-0.490***	-0.592***	-0.391***	-0.431***	-0.293***	-0.384***
	[0.069]	[0.025]	[0.055]	[0.045]	[0.051]	[0.047]	[0.032]	[0.053]
$\psi_{NZ,Hi}$	0.854***	0.785***	0.733***	1.035***	0.863***	1.480***	1.121***	1.065***
	[0.132]	[0.059]	[0.102]	[0.074]	[0.119]	[0.149]	[0.077]	[0.081]
ψ_{LT}	0.200**	0.005	0.079	0.090**	-0.074*	0.281***	0.297***	0.301***
	[0.087]	[0.027]	[0.074]	[0.045]	[0.040]	[0.109]	[0.049]	[0.089]
ψ_{SR}	0.433	0.347***	0.316	0.473***	0.207	1.610***	0.918***	1.031***
	[0.266]	[0.084]	[0.192]	[0.107]	[0.183]	[0.342]	[0.139]	[0.254]
ψ_{SNR}	0.442**	0.236***	0.231**	0.508***	0.407**	0.652	0.273***	0.338**
	[0.216]	[0.054]	[0.111]	[0.125]	[0.161]	[0.445]	[0.051]	[0.141]
ψ_{OR}	-0.719***	-0.416***	-0.318	-0.411**	-0.387***	-0.492*	0.094	0.104
	[0.170]	[0.117]	[0.253]	[0.162]	[0.133]	[0.278]	[0.202]	[0.386]
ψ_{ONR}	-0.292	-0.225**	0.266	-0.445**	-0.661***	-0.302*	-0.129	0.249
	[0.182]	[0.091]	[0.226]	[0.185]	[0.163]	[0.183]	[0.079]	[0.207]
N	1,227	6,597	2,013	5,412	2,352	1,200	5,091	2,976
R^2 – Prod	0.992	0.977	0.971	0.972	0.965	0.990	0.980	0.984
R^2 – Wage	0.990	0.979	0.979	0.979	0.965	0.995	0.969	0.990
				Productivity-wage gap $(\phi - \psi)$				
NZ (Lo)	-0.102	0.069	0.138	0.439***	0.320*	-0.143	0.422*	0.224
NZ (Hi)	0.098	-0.042	0.109	-0.003	0.348	-1.140*	0.228	0.646**
LT	0.045	-0.138**	-0.119	0.011	0.086	-0.154	0.630	0.038
SR	0.628	-0.547*	-0.019	-0.707	0.196	-3.176**	0.307	-1.124**
SNR	0.735	-0.113	-0.484	0.173	0.144	-1.577	-0.409	-0.147
OR	-0.422	1.109***	0.408	1.007**	0.563*	-0.184	-1.911	0.332
ONR	-0.299	-0.204	-0.302	0.951*	-0.806	0.089	-0.394	0.845

Notes: Table continued on next page

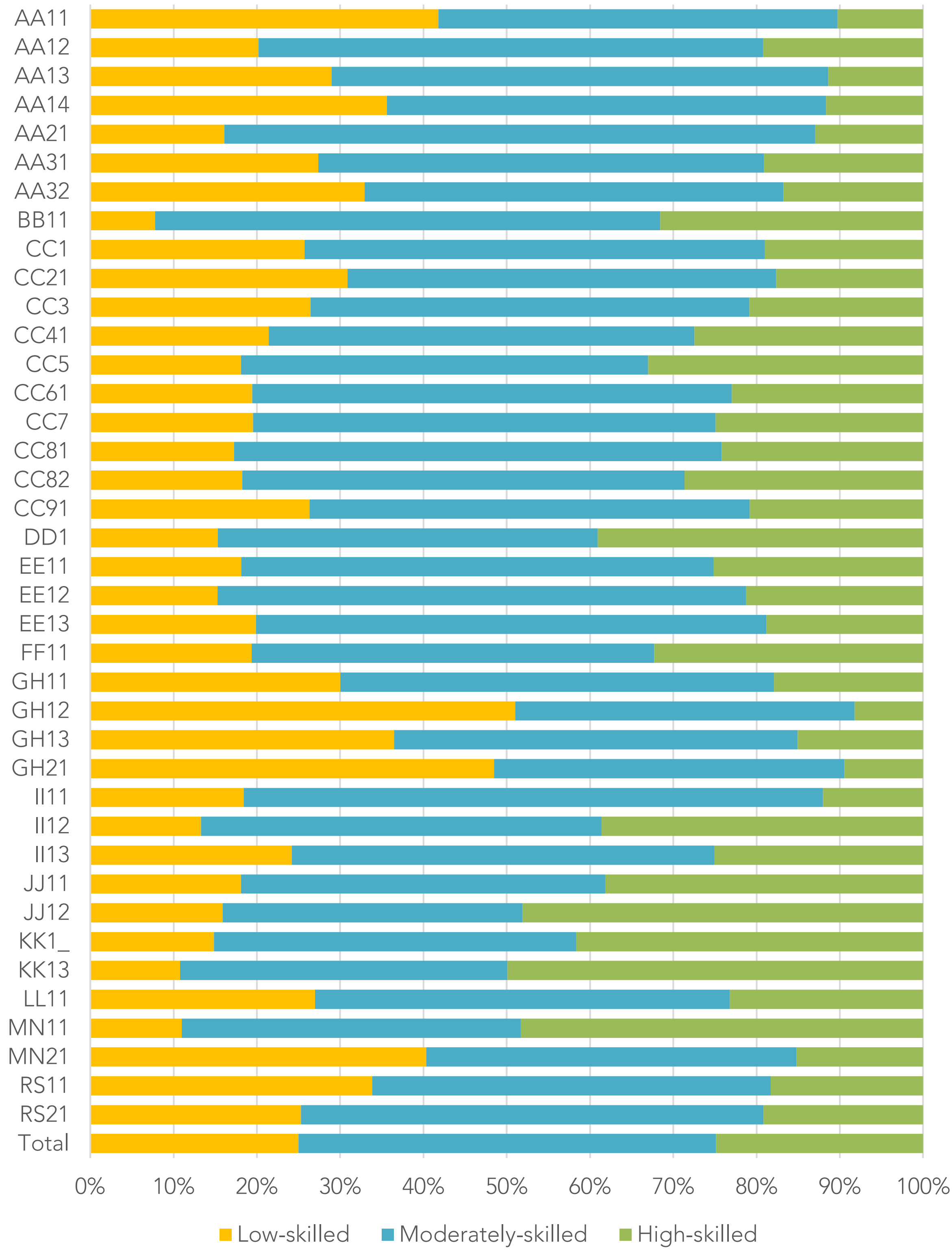
	EE13	FF11	GH11	GH12	GH13	GH21	II11	II13
				Production function				
$\phi_{NZ,Lo}$	-0.263***	-0.518***	-0.321***	-0.400***	-0.500***	-0.260***	-0.807***	-0.527***
	[0.049]	[0.116]	[0.101]	[0.071]	[0.071]	[0.032]	[0.073]	[0.139]
$\phi_{NZ,Hi}$	0.880***	2.722***	1.965***	0.584**	1.079***	0.595***	0.459***	1.503*
	[0.093]	[0.366]	[0.294]	[0.231]	[0.138]	[0.107]	[0.135]	[0.779]
ϕ_{LT}	0.180***	0.428***	-0.037	0.044	0.293***	0.060	-0.432***	0.430
	[0.055]	[0.144]	[0.176]	[0.074]	[0.092]	[0.043]	[0.097]	[0.316]
ϕ_{SR}	-0.073	0.690**	0.003	-0.436**	0.291	-0.200*	-0.813	-1.822*
	[0.141]	[0.332]	[0.263]	[0.187]	[0.287]	[0.107]	[0.550]	[0.951]
ϕ_{SNR}	0.238***	-0.185	0.736	0.053	0.706***	0.130*	0.869*	2.258
	[0.089]	[0.385]	[0.546]	[0.162]	[0.250]	[0.078]	[0.462]	[1.606]
ϕ_{OR}	-0.296*	-1.117***	-0.106	-0.483***	-0.567	-0.176	-0.678*	-0.797
	[0.174]	[0.374]	[0.160]	[0.129]	[0.450]	[0.117]	[0.382]	[0.742]
ϕ_{ONR}	-0.213***	-0.580***	-0.175	0.112	-0.324**	0.135***	-0.019	-0.174
	[0.075]	[0.163]	[0.191]	[0.111]	[0.145]	[0.050]	[0.131]	[0.165]
				Firm-level wage bill equation				
$\psi_{NZ,Lo}$	-0.344***	-0.612***	-0.528***	-0.297***	-0.398***	-0.337***	-0.755***	-0.560***
	[0.017]	[0.030]	[0.030]	[0.030]	[0.025]	[0.013]	[0.028]	[0.041]
$\psi_{NZ,Hi}$	0.786***	1.465***	1.158***	0.894***	0.960***	0.725***	0.440***	1.226***
	[0.043]	[0.061]	[0.101]	[0.150]	[0.063]	[0.035]	[0.043]	[0.104]
ψ_{LT}	0.158***	0.199***	0.131**	0.071**	0.111***	-0.029**	-0.175***	0.220***
	[0.022]	[0.036]	[0.053]	[0.028]	[0.030]	[0.013]	[0.032]	[0.071]
ψ_{SR}	0.359***	1.072***	-0.063	-0.120	0.472***	-0.057	-0.508***	0.035
	[0.055]	[0.104]	[0.105]	[0.075]	[0.114]	[0.037]	[0.168]	[0.225]
ψ_{SNR}	0.216***	0.596***	0.755***	0.175**	0.356**	0.052**	0.240	0.817*
	[0.031]	[0.185]	[0.168]	[0.077]	[0.147]	[0.023]	[0.158]	[0.449]
ψ_{OR}	-0.171*	-0.687***	-0.252***	-0.240***	-0.320***	-0.236***	-0.163	-0.602**
	[0.097]	[0.115]	[0.087]	[0.064]	[0.110]	[0.048]	[0.151]	[0.257]
ψ_{ONR}	-0.308***	-0.436***	-0.483***	-0.028	-0.218***	-0.041**	-0.163**	-0.420***
	[0.032]	[0.083]	[0.049]	[0.046]	[0.042]	[0.016]	[0.080]	[0.085]
N	14,100	17,706	4,716	5,124	11,223	16,320	5,736	2,832
R^2 – Prod	0.971	0.918	0.945	0.965	0.951	0.959	0.973	0.962
R^2 – Wage	0.970	0.965	0.978	0.993	0.981	0.982	0.984	0.986
				Productivity-wage gap $(\phi - \psi)$				
NZ (Lo)	0.081*	0.095	0.207**	-0.103	-0.102	0.078***	-0.052	0.033
NZ (Hi)	0.095	1.257***	0.807***	-0.310*	0.119	-0.131	0.019	0.277
LT	0.022	0.229*	-0.168	-0.028	0.182**	0.089**	-0.257***	0.210
SR	-0.432***	-0.381	0.067	-0.317*	-0.181	-0.143	-0.305	-1.857**
SNR	0.022	-0.782**	-0.019	-0.122	0.350	0.077	0.629	1.441
OR	-0.124	-0.430	0.146	-0.243**	-0.247	0.060	-0.515	-0.195
ONR	0.094	-0.144	0.308*	0.140	-0.106	0.175***	0.144	0.246

Notes: Table continued on next page

	JJ11	KK13	KK1_	LL11	MN11	MN21	RS11	RS21
				Production function				
$\phi_{NZ,Lo}$	-0.754*	-0.140	-2.915	-0.485***	-0.496***	-0.397***	-0.332	-0.533***
	[0.453]	[1.610]	[2.010]	[0.130]	[0.150]	[0.087]	[0.312]	[0.079]
$\phi_{NZ,Hi}$	3.000**	8.490	7.347	2.281***	2.004***	1.398***	0.937	1.240***
	[1.222]	[7.344]	[10.697]	[0.634]	[0.262]	[0.296]	[1.180]	[0.153]
ϕ_{LT}	0.397	-0.432	3.755	-0.305	0.659***	-0.007	0.388	-0.092
	[0.517]	[1.044]	[5.454]	[0.197]	[0.149]	[0.112]	[0.614]	[0.095]
ϕ_{SR}	1.034	-0.080	-3.845	0.253	0.714**	0.876**	1.462	0.043
	[1.254]	[3.417]	[5.417]	[1.018]	[0.285]	[0.375]	[1.212]	[0.199]
ϕ_{SNR}	-0.993	-1.980	-11.828	-0.418	1.437***	0.021	1.477	0.050
	[0.667]	[3.404]	[21.741]	[1.168]	[0.439]	[0.180]	[0.992]	[0.181]
ϕ_{OR}	-2.699*	0.012	0.968	2.703**	0.900*	-0.817	-0.031	0.070
	[1.379]	[1.276]	[10.913]	[1.200]	[0.502]	[0.617]	[2.350]	[0.201]
ϕ_{ONR}	-1.161	0.035	-0.434	-0.914**	-0.187	-0.281**	-0.447	-0.414***
	[0.785]	[0.986]	[1.027]	[0.429]	[0.285]	[0.118]	[0.351]	[0.101]
				Firm-level wage bill equation				
$\psi_{NZ,Lo}$	-0.689***	0.300	64.199	-0.637***	-0.237***	-0.409***	-0.354***	-0.432***
	[0.071]	[0.723]	[890.233]	[0.057]	[0.091]	[0.034]	[0.053]	[0.028]
$\psi_{NZ,Hi}$	1.676***	8.613**	275.615	1.539***	2.785***	1.529***	1.835***	0.934***
	[0.260]	[3.497]	[3764.107]	[0.201]	[0.194]	[0.123]	[0.277]	[0.063]
ψ_{LT}	0.157	2.322**	120.203	-0.023	1.608***	0.025	0.101	0.007
	[0.155]	[1.120]	[1644.239]	[0.078]	[0.133]	[0.041]	[0.113]	[0.036]
ψ_{SR}	1.456***	2.646*	63.184	0.648**	2.732***	0.628***	0.134	0.177**
	[0.451]	[1.445]	[861.923]	[0.270]	[0.203]	[0.167]	[0.199]	[0.082]
ψ_{SNR}	0.274	6.728**	155.618	0.429**	2.375***	0.179**	0.322**	0.138**
	[0.498]	[3.045]	[2103.312]	[0.173]	[0.267]	[0.086]	[0.142]	[0.059]
ψ_{OR}	0.230	0.987	143.543	0.322	1.780***	-0.259***	0.029	-0.294***
	[0.671]	[0.966]	[1981.765]	[0.305]	[0.318]	[0.081]	[0.318]	[0.101]
ψ_{ONR}	-0.766***	0.077	118.172	-0.470***	0.412	-0.195***	-0.053	-0.302***
	[0.255]	[0.632]	[1612.746]	[0.112]	[0.265]	[0.033]	[0.141]	[0.054]
N	1,404	1,563	1,302	1,629	18,309	7,152	1,836	5,502
R^2 – Prod	0.942	0.790	0.784	0.956	0.882	0.931	0.839	0.954
R^2 – Wage	0.982	0.947	0.979	0.971	0.952	0.971	0.971	0.964
				Productivity-wage gap $(\phi - \psi)$				
NZ (Lo)	-0.065	-0.440	-67.114	0.152	-0.259**	0.012	0.022	-0.101
NZ (Hi)	1.323	-0.123	-268.268	0.742	-0.780***	-0.131	-0.898	0.305**
LT	0.240	-2.754*	-116.448	-0.282	-0.950***	-0.031	0.287	-0.100
SR	-0.423	-2.725	-67.029	-0.396	-2.018***	0.248	1.328	-0.134
SNR	-1.267*	-8.708*	-167.446	-0.848	-0.937**	-0.158	1.154	-0.089
OR	-2.929**	-0.975	-142.575	2.382**	-0.880*	-0.558	-0.060	0.364**
ONR	-0.396	-0.043	-118.606	-0.444	-0.599***	-0.086	-0.394	-0.112

Notes: Translog production function and firm-level wage bill equation jointly estimated as a pair of non-linear seemingly unrelated regressions for each industry. Only effective labour input coefficients and productivity-wage gaps reported. Long-term migrants include Australian-born. Robust standard errors (clustered on firm) in brackets. ***;**;* indicates coefficient significantly different from zero at 1;5;10% level respectively. Each specification includes time dummies (base year 2005). The six industries for which there are less than 1,000 observations are excluded.

Figure B.1 NZ-born skill group shares by industry



Notes: Statistics are for the productivity estimation sample (see Table 3 for further notes). NZ-born skill groups are classified using two-way wage fixed effects estimates. Industry definitions are listed in Table B.1.