Firm Productivity Growth and Skill

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Motu Working Paper 15-18
Motu Economic and Public Policy Research

October 2015

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Acknowledgements

Initial work on this project was undertaken while the authors were on secondment to Statistics New Zealand and was funded by the Department of Labour. Subsequent work has been supported by the Productivity Hub (Productivity Commission, MBIE, Treasury, and Statistics New Zealand).The results in this working paper are not official statistics, they have been created for research purposes from the Integrated Data Infrastructure (*IDI*), managed by Statistics New Zealand. The opinions, findings, recommendations, and conclusions expressed in this working paper are those of the author(s), not Statistics NZ, Motu Economic and Public Policy Research Trust, or any of the organisations acknowledged in the previous paragraph. Access to the anonymised data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organisation, and the results in this working paper have been confidentialised to protect these groups from identification. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the *IDI*. Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz.The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes. Any person who has had access to the unit record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the *IDI* for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

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ISSN 1176-2667 (Print), ISSN 1177-9047 (Online).

Abstract

This paper examines the relationship between firm multifactor productivity growth (*mfp*) and changing skill levels of labour in New Zealand, over the period 2001-12, using longitudinal data from Statistics New Zealand's Longitudinal Business Database (*LBD*) and Integrated Data Infrastructure (IDI). We estimate that the average skill of workers declined by 1.8% over the period, reflecting strong employment growth for workers with lower than average skill levels. The net decline was the combined effect of a 3.6% decline in unobserved skill outweighing a 1.8% increase in observed skill, resulting in 1.8% slower estimated skill-adjusted labour growth (13.3%) than the 15.0% growth in full-time equivalent (*FTE*) employment. Mirroring the skill-dilution, skill-adjusted *mfp* growth averaged 0.24% per annum over the period compared to 0.14% pa for unadjusted growth. The patterns were stronger over the pre-*GFC* period to 2008, during which adjusted and unadjusted *mfp* grew 0.57% pa and 0.42% pa respectively. Our analysis of the effect of changing skill on *mfp* growth finds that the impact of skill adjustment was almost entirely due to changing skill composition within continuing firms.

JEL codes
D24, J24

Keywords
Productivity, reallocation, decomposition; *LBD*, Linked Employer-Employee Data, firm turnover.

Haiku

When the rains arrive
The brackish lake grows deeper
But is less salty

Quals are increasing
Job growth draws in new workers
But they are less skilled

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1 Introduction

The greater availability of business microdata over recent decades has facilitated a much richer understanding of the economic adjustment processes that generate productivity growth. Most microdata-based labour and multi-factor productivity (*mfp*) analyses measure labour inputs in firm production functions using pure quantity measures, such as the (total) number of workers, a weighted average of full-time and part-time workers, or the total number of hours worked.[1] Such analyses implicitly assume there is no change in the quality of labour over time which, in the context of the increasing levels of training and qualifications in New Zealand over the past decades, is open to question.[2]

This paper is concerned with the relationship between changes in skill and the measurement of productivity growth in New Zealand. Specifically, we focus on the impact of skill changes on estimated *mfp*, and on how these changes in workforce composition have played out across firms. Our analysis uses a rich longitudinal panel of businesses that supports annual productivity estimates covering a high proportion of the New Zealand economy over the period 2001–2012. The data are drawn from Statistics New Zealand's Longitudinal Business Database (*LBD*), combined with skill estimates derived from linked employer-employee data in Statistics New Zealand's Integrated Data Infrastructure (*IDI*).

First, we develop a proxy for skill that is derived more directly from workers' earnings than usual observable measures of skill such as educational qualifications.[3] This is partly by necessity, as the *IDI* does not provide coverage of observable skill

[1] Recently published New Zealand studies include: Grimes et al (2009), Fabling & Sanderson (2013), Maré & Graham (2013); Maré & Fabling (2013), Doan et al (2014), and Fabling & Grimes (2014).

[2] There were substantial increases in both employment and the average qualifications in New Zealand between the 2001 and 2013 censuses. The proportion of those aged 20 and over with a degree qualification or higher increased from 15% to 25%, while the proportion with no school qualifications declined from 19% to 14%. The increase in degree qualifications was particularly strong for younger workers. In contrast, older workers, with lower average qualifications, experienced the strongest employment growth (e.g. workers aged 60 and over accounted for more than half of the increase in employment), reflecting both increasing cohort sizes associated with the baby boom generation, and increases in labour force participation rates. (NZ Census data)

[3] Statistics New Zealand (2008) produced a labour-quality adjusted official productivity series, based on the observed qualifications-based labour quality-adjusted approach of Szeto and McLoughlin (2008). Reflecting the recent increase in qualifications, these studies estimate increasing labour quality in New Zealand, and lower quality-adjusted productivity growth.

measures throughout the sample period for the full population of workers;[4] in addition, observable qualifications provide only partial measures of relevant skills. Our skill proxy consists of two components: an observable component of skill estimated from life cycle patterns of earnings reflecting skill associated with labour market experience; and an unobservable component of skill for each individual, derived from their average earnings premium (or penalty) conditional on their sex and phase of the life cycle.

We estimate that the average skill of workers declined 1.8% over the period 2001-2012 as employment growth disproportionately drew in workers with lower than average skill levels. The net decline arose from a 3.6% decline in unobserved skill outweighing a 1.8% increase in observed skill.[5] Also, broadly consistent with Maré and Hyslop's (2008) finding of cyclically-based skill composition changes, we estimate a net 3.0% dilution of skill during the business cycle upswing until the global financial crisis (*GFC*) struck in 2008, followed by 1.4% skill-concentration during the next two years of contraction, and a further mild 0.2% skill dilution over the final two years of the sample period.

Second, we use these measures of skill to derive skill-adjusted labour input and *mfp* measures for each firm, which adjust the firm's labour quantity and *mfp* measures for changes in the average skill of workers employed by the firm. Compared to the estimated 15.0% growth in full-time equivalent (*FTE*) employment over the period, the 1.8% decline in average skill means that estimated skill-adjusted labour input grew by 13.3%. Also, mirroring the patterns of skill-dilution and skill-adjusted labour input over the period, skill-adjusted *mfp* growth was stronger than unadjusted growth. Over the full period, the estimated growth of skill-adjusted *mfp* was 2.7% (0.24% pa) compared to growth in unadjusted *mfp* of 1.5% (0.14% pa); while, over the 2001–2008 pre-*GFC*

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[4] Although the *IDI* has detailed information on qualifications and training acquired since 2000, this covers mainly younger cohorts; and while there is broader qualifications data available, this is only for Household Labour Force Survey (*HLFS*) samples of the population since 2006. In addition, overseas study and qualifications information on migrants is largely absent.

[5] Although our results are at odds with Szeto and McLoughlin's (2008), they are not necessarily inconsistent. Our approach is potentially more robust to measuring the effect of an increase in lower-skilled workers within qualification groups, which may cause the average skill level to increase more slowly (or decrease) than measured by a qualifications-based approach. For example, using a similar approach, Maré & Hyslop (2008) found that new workers between 2001 and 2007 had lower than average earnings characteristics on both observable (12% lower) and unobservable (7% lower) dimensions, and the increase in low-earning workers offset the rise in average earnings over time associated with increasing qualifications.

period growth was substantially stronger: adjusted and unadjusted *mfp* grew 4.0% (0.57% pa) and 2.9% (0.42% pa) respectively.

Third, we analyse the effect of changes in skill on *mfp* growth over the sample period, by comparing decompositions of skill-adjusted and unadjusted *mfp* growth into contributions from firm entry and exit, reallocation of inputs between firms within and between industries, and from *mfp* growth within continuing firms. Our main finding is that the impact of skill adjustment is almost entirely accounted for by changing skill composition within continuing firms. This implies that the changes in skill, and hence skill-adjusted impacts on *mfp*, occur mainly for continuing firms.

The paper is organised as follows. In section 2 we document the skill proxy that we use, and the methods for estimating *mfp* using a skill augmented production function. The method that we use for decomposing *mfp* growth follows Griliches & Regev (1995) and is described in section 3. In section 4 we describe key features of the data that we use for productivity estimation, before presenting the main results in section 5. Section 6 summarises and discusses the main findings.

2 Skill and productivity

Multi-factor productivity is an index of how much output a firm can produce for a given level of inputs. In the case of gross output, production is commonly modelled as a function of inputs including labour, capital, and intermediates. Distinguishing different types of labour recognizes that workers with different sets of skills make different contributions to production, and interact differently with other factors of production. Despite the centrality of heterogeneous labour inputs for firm performance and technology adoption, many productivity studies lack suitable data for analysing the contribution of skill to productivity. Syverson (2011) highlights the contribution of labour quality as one of the key questions that still need to be answered if we are to understand firm-level productivity.

Linked employer-employee data, as used in the current paper, have been used to shed light on the relationship between firm performance and the distribution of skill within firms. Abowd and Kramarz (2005) model the role of skill using a worker and firm fixed effects model that provides estimates of wage components associated with observable and unobservable skill characteristics of workers. Using these estimates, the authors estimate an augmented production function that includes both the level and the variance of worker skills within firms. They find that the level of skill raises productivity, as captured by sales per worker. Abowd et al (2007) examine the interactions between production technologies and the use of skilled workers, and find that firms using advanced technologies are more likely to use high-skilled workers and less likely to use more experienced workers.

We model the relationship between productivity and skill using a skill-augmented production function (Griliches, 1970), modelling firm-i's output in year-t (Y_{it}) in terms of its capital inputs (K_{it}), intermediate inputs (M_{it}), and labour inputs (L_{it}). In the absence of skill adjustment, labour input is some quantity measure of labour, such as total hours worked, $ln\, L_{it} = ln(H_{it})$. Skill-adjustment is introduced by noting that effective labour input depends on both total hours of work and skill provided per hour. Indexing skill so that an increase in skill has a proportional impact on labour input, we can denote skill-adjusted labour input as,

$$ln\, L_{it} = ln(H_{it} * (1 + S_{it})) \approx \ln(H_{it}) + S_{it} \quad (1)$$

if relative skill differences, S_{it}, are not large. Both H and S are generally found to be positively related to output, although differences in skill explain little of the variation in productivity across firms. A small number of recent studies have confirmed the relevance of labour quality as a dimension of factor inputs.[6] There are persistent differences across firms both in productivity levels (Bartelsman & Doms, 2000; Foster, Haltiwanger, & Krizan, 2001; Syverson, 2011) and in firms' skill compositions (Haltiwanger, Lane, & Spletzer, 2007). A high degree of persistence in skill composition suggests that firm turnover may play an important role in productivity dynamics in the face of changing aggregate skill composition. Despite this, the inclusion of labour quality measures does not greatly reduce the dispersion of estimated productivity between firms. Accounting for labour quality differences reduces the productivity dispersion within manufacturing industries by around 10 percent and within service industries by around 20 percent (Fox & Smeets, 2011).

[6] See Abowd & Kramarz (2005); Hellerstein, Neumark & Troske (1999); Galindo-Rueda & Haskel (2005); Fox & Smeets (2011); Iranzo et al (2008). Other studies have examined the relationship between firm performance and workforce skill composition, though without controlling for capital inputs (Haltiwanger, Lane, & Spletzer, 2007; Lallemand, Plasman, & Rycx, 2004, 2009).

2.1 Proxies for skill

A key focus of this study is to examine how the levels and changes in productivity relate to worker and firm quality. Worker quality measures are proxied by estimates of worker and firm premiums from regressions of job-year earnings rates using an additive log-linear two-way fixed effects model for the log (*FTE* annual earnings) of worker-n, employed in firm-i, in year-t (w_{nit}). We aggregate monthly employer-employee data to March calendar years and weight annual job observations by annual *FTE* employment. We exclude monthly earnings information for workers who ever receive working proprietor income from the firm where they are employed.[7]

We regress w_{nit} on a vector of worker-level observable characteristics X_{nt}, time-invariant fixed worker (θ_n) and firm (ψ_i) effects:

$$w_{nit} = X'_{\text{nt}}\beta + \theta_n + \psi_i + \varepsilon_{nit} \quad (2)$$

where the residual (ε_{nit}) is an idiosyncratic earnings component. The vector X_{nt} consists of sex-specific age-quartics and time-effects; the worker effect θ_n represents the portable earnings premium of worker-*n* and reflects factors such as their ability and motivation. It also captures the impact of each worker's average qualifications during the period. Similarly, the firm effect (ψ_i) represents the earnings premium paid by firm-i to each of their workers and reflects the firm's pay structure; and the residual term (ε_{nit}) captures match-quality, tenure effects and a random idiosyncratic component.

In order to examine the relationships between earnings components and firm productivity, we aggregate the measures to the firm-year level, by taking the job-*FTE* employment weighted average of the estimated components from equation (2), across all jobs in the firm during a year.[8] Econometric estimates of the worker and firm effects are not unique (Abowd, Creecy, & Kramarz, 2002). We normalise firm effects to have zero mean overall, and worker fixed effects to have zero mean for each sex within each connected group.[9]

Based on the estimates of equation (2), we can express firm-i's earnings rate as,

[7] Fabling and Maré (2015a) explains the *FTE* calculation and identification of working proprietors.

[8] Mechanically, this is done by applying the parameter estimates to monthly firm-level data and then re-aggregating the monthly means to create an annual observation that matches firm balance-date years.

[9] Sex differences in average earnings rates are absorbed in the vector of observable characteristics.

$$\overline{w}_{it} = \overline{\mathrm{X}}_{\mathrm{it}}\hat{\beta} + \bar{\hat{\theta}}_{\mathrm{it}} + \hat{\psi}_i + \bar{\varepsilon}_{it} \quad (3)$$

where a caret (^) denotes an estimate obtained from estimating equation (2), and $\overline{\mathrm{X}}_{\mathrm{it}}\hat{\beta}$ and $\bar{\hat{\theta}}_{\mathrm{it}}$ are the *FTE*-weighted average estimated worker demographic and worker effects across all employees of firm-i in year-t. The first two terms of the equation capture the skill content of a firm's labour input – based on observed $\left(\overline{\mathrm{X}}_{\mathrm{it}}\hat{\beta}\right)$ or unobserved $\left(\bar{\hat{\theta}}_{\mathrm{it}}\right)$ worker attributes. Each of these components has a proportional impact on wages, and hence on labour input. In order to examine the link between firm productivity and worker skill, we substitute these measures in place of the average skill term (S_{it}) that appears in equation (1)

Substituting the estimated mean worker skill proxies, and relaxing the constraint that each component has the same impact on output yields the following expression for skill-adjusted labour input:

$$\left\{\beta_j^H \ln H_{it} + \beta^S S_{it}\right\} = \left\{\beta_j^H \ln H_{it} + \beta_j^X\left(\overline{\mathrm{X}}_{\mathrm{it}}\hat{\beta}\right) + \beta_j^\theta\left(\bar{\hat{\theta}}_{\mathrm{it}}\right)\right\} \quad (4)$$

A doubling of labour input can be achieved by doubling any one of the three components of skill-adjusted labour input.[10]

2.2 Productivity estimation

Productivity is estimated using an industry-specific gross output Cobb-Douglas production function that relates output (Y_{it}) for firm-i (in industry-j) in year-t to labour(L_{it}), capital (K_{it}) and intermediate inputs such as materials (M_{it}) inputs:

$$Y_{it} = \mathrm{a}_{\mathrm{it}}\phi_{\mathrm{j}}(L_{it}, K_{it}, M_{it}) = \mathrm{a}_{\mathrm{it}}L_{it}^{\beta_j^L} K_{it}^{\beta_j^K} M_{it}^{\beta_j^M}.$$

Taking logarithms, gives

$$\ln Y_{it} = \lambda_{\mathrm{j}} + \beta_j^L \ln L_{it} + \beta_j^K \ln K_{it} + \beta_j^M \ln M_{it} + \epsilon_{it} \quad (5)$$

where β_j^L , β_j^K, and β_j^M are production technology parameters for industry-j. This specification allows the production technology to vary across industries but is held constant within industry-j. Firm multifactor productivity (mfp) is the ratio of output (Y_{it})

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[10] Estimated returns to scale will differ depending on which component is increased. The alternative estimates are shown in Appendix table 3. Returns to scale estimates based on increasing observed skills ($\beta_j^X + \beta_x^K + \beta_x^M$) are generally lower than estimates based on increasing hours or unobserved components.

to measured inputs $\phi_j(L_{ijt}, K_{ijt}, M_{ijt})$, and normalised relative to industry-j mean. Specifically, in log form, we estimate *mfp* from equation (5):

$$\epsilon_{it} = ln\, Y_{it} - \left(\lambda_{\mathrm{j}} + \beta_j^L\, ln\, L_{it} + \beta_j^K\, ln\, K_{it} + \beta_j^M\, ln\, M_{it}\right).$$

Substituting in the expression for skill adjusted labour input, as in equation (1), and allowing for unobserved error components, we estimate the following industry-specific production function, adjusting for skill:

$$ln\, Y_{it} = \{\beta_j^H\, ln\, H_{it} + \beta_{\mathrm{j}}^{\mathrm{S}} S_{it}\} + {\beta_j}^K\, ln\, K_{it} + {\beta_j}^M\, ln\, M_{it} + \lambda_j + \underbrace{\tau_{jt} + e_{it}}_{mfp_{it}} \qquad (6)$$

The technology is not constrained to be constant returns to scale; $\left(\beta_j^H + {\beta_j}^K + {\beta_j}^M\right)$ may differ from 1.[11] The residual from equation (6) is a measure of skill-adjusted *mfp*. Within-industry changes in this productivity measure are decomposed, as detailed in section 3, and compared with the decomposition using a measure of labour input that does not adjust for worker skill, obtained by constraining β_j^S to equal zero.

In order to aggregate the contributions of firms to within-industry *mfp* growth, we calculate an index of input use for each industry-year combination. The input-use index is derived from a pooled production function regression, allowing for industry-specific intercepts but constraining other production function parameters to be constant across all firms and industries:

$$ln\, Y_{it} = \underbrace{\{\beta^{\mathrm{H}}\, ln\, H_{it} + \beta^{\mathrm{S}} S_{it}\} + \beta^K\, ln\, K_{it} + \beta^M\, ln\, M_{it}}_{\omega_{\mathrm{it}}} + \underbrace{\lambda_j + \tau_t + e_{it}}_{p_{it}} \qquad (7)$$

The two error components λ_j and τ_t are estimated as fixed effects. This specification is used to derive a consistent set of weights to be used in the decomposition of productivity change, as detailed in section 3.[12] Here, ω_{it} is an index of inputs and p_{it} is an alternative measure of a firm's multi-factor productivity, constrained by the assumption that all firms operate with a common technology. The components of within-industry productivity change are aggregated using the inputs weights (ω_{it}). The

[11] A doubling of labour inputs can be achieved by doubling H_{it}, holding S_{it} constant, or by increasing S_{it} by 1, holding H_{it} constant. $\left(\beta_j^S + {\beta_j}^K + {\beta_j}^M\right)$ is thus an alternative measure of the returns to scale.

[12] For partial productivity measures such as labour productivity (eg: value added per worker), using ω_{it}= labour input leads to exact aggregation of A_{it} = industry value added / industry employment. For *MFP* or *TFP* measures of productivity, output shares are commonly used as weights, leading to inexact aggregation, though potentially with interpretation in terms of aggregate welfare (e.g.: Domar (1961); Baily et al, (1992); Foster et al, (2001)).

input-use index is normalised to sum to one within each year $\sum_i \omega_{it} = 1$, so that weighted mean productivity equals the annual mean.[13]

Equation (7) estimates are also useful for identifying the contribution to productivity growth of changes in industry-composition. The estimated mfp_{ijt} obtained from equation (6) cannot be used to identify whether inputs are being reallocated to more productive industries, since by construction it has zero mean for each industry. However, the estimate of mfp obtained from equation (7) (p_{it}) does identify productivity differences between industries, albeit at the cost of imposing common production function parameters.

Parameter estimates from industry-specific and pooled regressions are included in Appendix table 2 (using *FTE* labour input) and Appendix table 3 (using skill-adjusted labour input).

3 Firm dynamics and skill adjustment

To shed light on the interaction of skill adjustment and productivity at the firm level, we apply standard methods to decompose productivity growth. There are a number of related methods for such decompositions, reflecting differences in assumptions and normalisations (Baily, Hulten, Campbell, Bresnahan, & Caves, 1992; Baldwin & Gu, 2006; Foster et al., 2001; Griliches & Regev, 1995; Petrin & Levinsohn, 2012). These decomposition methods focus primarily on the analysis of within-industry productivity growth, abstracting from inter-industry differences in average productivity. Our study adopts the approach of Griliches and Regev (*GR*), and presents not only a within-industry analysis but also a complementary between-industry analysis of the contribution of changing shares of activity in low and high productivity industries.

A number of studies have identified the important roles played by firm turnover and the reallocation of resources towards more productive firms, even within narrowly defined industry sectors. However, over a five year period, around half of overall productivity growth is the result of improvements within continuing firms (within firm contribution). The contribution from reallocation – high productivity firms increasing

[13] When analysing productivity growth for a specific industry, a different normalisation is used, $(\sum_{i \in j} \omega_{it} = 1 \; \forall$ industries (j)) so that weighted mean productivity equals the industry-year average.

their share of the economy at the expense of lower productivity firms – varies across countries, though is generally positive and small (Bartelsman, Haltiwanger, & Scarpetta, 2004). Net firm turnover contributes positively to productivity growth, with new firms having higher productivity than the exiting firms they replace. Across countries, there are differences in the patterns of entry and exit, though the net positive contribution of firm turnover to productivity growth is a robust finding. In Europe, new firms enter with higher productivity than that of continuing firms in their industries whereas in the United States, the opposite is true, with a relatively high productivity contribution coming from the exit of relatively low productivity firms (Bartelsman et al., 2004).

In a related New Zealand study, Law & McLellan (2005) find that both entering and exiting firms have lower-than-average productivity and that net firm entry contributes negatively to productivity growth. The positive within firm contribution is consequently larger than overall productivity growth.[14]

3.1 Decomposition of within-industry productivity growth

Following the approach of *GR*, the within-industry contribution to productivity change can be decomposed into components arising from firm entry and exit, and from changes in the size and performance of continuing firms. For an industry (j), an index of productivity is obtained as the weighted average of firm (i) productivity (mfp_{ijt} in equation (6)) using weights (ω_{ijt}) as defined in equation (7):

$$A_{jt} = \sum_{i \in j} \omega_{ijt} mfp_{ijt} \tag{8}$$

GR analyse changes around the average industry productivity, and average industry input share, across two years.[15] Using *GR's* approach yields the following decomposition:

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[14] One key difference between the Law and McLellan (2005) approach and that of the other studies summarised by Bartelsman et al (2004) is that Law and McLellan measure the labour productivity of entrants and exiters relative to *overall* average labour productivity rather than to *industry* average labour productivity. The contributions that they estimate will therefore capture the impact of the industry-level correlation between turnover and average labour productivity, which is excluded in other studies.

[15] A commonly used alternative decomposition approach is that of Foster et al (2001) (*FHK*), which takes initial productivity, A_{jt-1}, as the benchmark and weights the change in industry productivity by the firm's initial input share, which includes an additional interaction term. In practice, the *GR* and *FHK* methods yield very similar estimates for the contributions of entering and exiting firms, and when change is measured over longer periods. As noted by *FHK*, when weights are based on inputs, transitory fluctuations in inputs or outputs, or measurement errors in inputs generate a negative correlation between input shares and relative productivity, and thus a negative interaction term. The impact of transitory

$$
\Delta \mathrm{A}_{jt} = \underbrace{\sum_{i \in C} \bar{\omega}_{ij}\, \Delta mfp_{ijt}}_{\substack{Continuers: \\ productivity\ growth \\ [Within]}} + \underbrace{\sum_{i \in C} \Delta\omega_{ijt} \left(\overline{mfp}_{ij} - \bar{\mathrm{A}}_j\right)}_{\substack{Continuers: \\ input\ shares \\ [Reallocation]}}
$$

$$
+ \underbrace{\sum_{i \in N} \omega_{ijt} \left(mfp_{ijt} - \bar{\mathrm{A}}_j\right)}_{Entering\ firms} - \underbrace{\sum_{i \in X} \omega_{ijt-1} \left(mfp_{ijt-1} - \bar{\mathrm{A}}_j\right)}_{Exiting\ firms} \tag{9}
$$

where bars represent two-year averages ($\bar{z} = (z_t + z_{t-1})/2$), C is the set of continuing firms, N is the set of entering firms, and X is the set of exiting firms.

The definition of continuers, entry and exit depend on the length of time over which firm transitions are measured. In our main estimates, we decompose the change in productivity over the full period from 2001 to 2012. Continuers are firms that were operating in each of these two years, whereas entrants and exiters are firms that were operating in one of these years but not in the other, (and firms that entered and exited within the 11 year period are thus excluded from the analysis). We present a complementary decomposition of annual productivity change over this period, where the classification of firms is based on whether they operate in consecutive years.

We augment the decomposition shown in equation (9) to separate the contributions of continuing firms that are not observed in the productivity data in one of the years, but still have employees.[16] Their contribution to the change in measured mean productivity is analogous to that of entrants and exiters, but including them as entrants or exiters would be misleading because they differ from true entrants and exiters. Joiners are continuing firms that are observed in period t but not in period *t-1*. As in the case of entering firms, they make a positive contribution to measured productivity growth if they have productivity that is above mean productivity ($\bar{A}_j$). Leavers are continuing firms that are observed in the productivity data in period *t-1* but not in period *t*. Similar to exiting firms, they contribute positively to measured productivity growth if their productivity (mfp_{ijt-1}) is below mean productivity ($\bar{A}_j$).

3.2 Industry-mix contributions to productivity growth

Aggregate productivity change reflects not only the influence of within-industry changes but also the changing shares of activity in high and low productivity

fluctuations and measurement error is likely to be greater over shorter periods and we consequently rely on the GR decomposition as the more robust approach for analysing both one-year and 11-year changes.

[16] Based on this definition, a producing firm with working-proprietor labour input will be classified as an exiter if it stops employing, and an entrant if it starts employing.

industries.[17] To gauge the contributions from such share changes, we perform a complementary analysis of 'between industry' productivity growth, using industry-level sums of input share weights as defined in equation (7) $\left(\omega_{\mathrm{jt}} = \sum_{i \in j} \omega_{ijt}\right)$, normalised so that $\left(\sum_j \omega_{jt} = 1\right)$. The productivity measure differs from that used for the within-industry productivity growth composition which, by construction, has a mean of zero for each industry. We use instead the estimate of p from equation (7). The weighted mean productivity in year *t* is denoted P_t:

$$P_t = \sum_i \omega_{ijt} p_{ijt} = \sum_j \omega_{\mathrm{jt}} P_{jt} \tag{10}$$

where $P_{jt} = \sum_{i \in j} \omega_{ijt} p_{ijt}$. We decompose annual aggregate productivity growth (ΔP_t) into components attributable to changes in industry productivity growth and changes in the industry-share of total input use. Adopting the *GR* approach of analysing changes around the average aggregate productivity, and average industry input share, across the two years, yields the following decomposition:

$$\Delta P_t = \underbrace{\sum_j \bar{\omega}_j \Delta P_{jt}}_{\substack{within\ industry \\ productivity\ growth}} + \underbrace{\sum_j \Delta \omega_{jt} \left(\bar{P}_j - \bar{P}\right)}_{Industry\ mix} \tag{11}$$

Note that the remaining entry and exit terms that appeared in the within-industry equation (9) are zero here because the industry classification we choose ensures that each industry appears in each year and there is therefore no industry entry and exit.

4 Data description

The data for the study are drawn from two databases assembled and held by Statistics New Zealand. The first is the Longitudinal Business Database (*LBD*), which contains a wide range of administrative and survey information on New Zealand businesses. The second is linked employer-employee *PAYE* data, which forms a part of the Integrated Data Infrastructure (*IDI*), and contains monthly job-level information from income tax returns, supplemented with additional information on worker characteristics from the *IDI*.

We create and analyse an annual panel of enterprises ('firms'), containing firm demographics, firm performance, and a measure of skill at the level of the firm. Each

[17] We assign a permanent industry to each firm, so industry change at the firm level does not occur. Given the level of industry aggregation that we adopt, very few firms are observed to ever change industry.

annual observation relates to a firm's financial year, with observations assigned to a notional March year based on the firms' balance dates. The *LBD* contains financial data from the year to March 2000 to the year to March 2012. For convenience, we refer to years by their end-date (2000 to 2012). To ensure consistent data definition and availability, we do not use production data for the 2000 year (Fabling & Maré, 2015b). Productivity estimation is carried out for the twelve years, 2001 to 2012, allowing us to observe 11 annual changes – from 2001-2002 to 2011-2012. The data that we use are not necessarily representative of all firms in the economy, due to limitations in data availability and coverage, especially for smaller firms.

4.1 Longitudinal Business Database (*LBD*)

The core of the *LBD* dataset is the Longitudinal Business Frame (*LBF*), which provides longitudinal information on all businesses in the Statistics New Zealand Business Frame/ Business Register since 1999, combined with information from the tax administration system. The *LBF* population includes all economically significant businesses.[18]

Our unit of analysis is the enterprise, restricted to industries that are part of the 'measured sector', identified by Statistics New Zealand as "industries that mainly contain enterprises that are market producers. This means they sell their products for economically significant prices that affect the quantity that consumers are willing to purchase" (Statistics New Zealand, 2014) (see Appendix table 1). We further restrict our analysis to private sector, for-profit firms. We follow Fabling (2011) and repair enterprise number links using plant-level employment information.

The *LBD* includes not only the *LBF* but also a range of administrative and survey data that can be linked to the *LBF*. We use business demographic information from the *LBF*, linked with financial performance measures (from the Annual Enterprise Survey, and administrative tax data, including *IR10*s).

The preferred source of value added measures is the Annual Enterprise Survey (*AES*). The *AES* is a postal sample survey, supplemented with administrative data from

[18] A business is economically significant if it a) has annual Goods and Services Tax (*GST*) turnover of greater than $30,000; or b) has paid employees; or c) is part of an enterprise group; or d) is part of a *GST* group; or e) has more than $40,000 income reported on tax form IR10; or f) has a positive annual *GST* turnover and has a geographic unit classified to agriculture or forestry.

tax sources. We use postal returns from *AES* to provide annual gross output and factor inputs for each enterprise's financial year. This information is available for around ten percent of enterprises, which are disproportionately larger firms, accounting for around 50 percent of total employment in New Zealand. Where *AES* information is not available, we derive comparable measures from annual tax returns (*IR10*s).

4.1.1 Production function variables[19]

Gross output is measured as the value of sales of goods and services, less the value of purchases of goods for resale, with an adjustment for changes in the value of stocks of finished goods and goods for resale. Capital input is measured as the cost of capital services rather than as the stock of capital. There are three components to the cost of capital services: depreciation costs; capital rental and leasing costs; and the user cost of capital. The inclusion of rental and leasing costs (including rates) ensures consistent treatment of capital input for firms that own their capital stock and firms that rent or lease their capital stock. The user cost of capital is calculated as the value of total assets, multiplied by an interest rate equal to 10 percent, to approximate the combined cost of interest and depreciation. Intermediate consumption is measured as the value of other inputs used up in the production process, with an adjustment for changes in stocks of raw materials.

Nominal measures of gross output and factor inputs are separately deflated using price indices. Gross output is deflated using an average of four quarters of the Producer Price Index (Outputs), which is available separately for 46 industry groupings within the measured sector. Similarly, intermediate inputs are deflated by the *PPI* (Inputs). Capital inputs are deflated by a four-quarter average of the Capital Goods Price Index (All Groups).

The *LBD* sample is restricted to exclude firms with missing or implausible production data. We exclude firms with unusually large changes in any of gross output, total employment, capital services, or intermediate consumption. Specifically, firms with log changes greater than 4 or less than -4 in any year are dropped, with the exceptions of employment changes in firms employing fewer than 20 employees and changes in financial variables with a magnitude of less than $50,000.

[19] The methods for deriving production function variables is described in detail in Fabling and Maré (2015b).

4.2 Linked employer-employee *PAYE* data

Employment and worker data are derived from the *IDI*, which uses information from tax and statistical sources to construct a record of paid jobs. Since April 1999, all employers in New Zealand are required to file a monthly record, the Employer Monthly Schedule (*EMS*), with Inland Revenue (*IRD*), which lists all paid employees at that firm during the month, the earnings they received and the amount of tax that was deducted at source. Working proprietors and employees are both counted in our measure of a firm's labour input, but we exclude firms without employees from our analysis as it is not possible to construct the skill proxies for a subset of these. Firm entry and exit is identified on the basis of whether a firm has employees. An entrant is thus a firm that is observed with production data but which had no employees in the previous year. Similarly, an exiting firm is one that does not report any employees in the following year.[20]

Conceptually, the *PAYE* data cover the universe of employment relationships and earnings in New Zealand over the period. One limitation of the data, though, is that it does not contain a measure of hours of work. We use the algorithm described in Fabling and Maré (2015a) to derive a labour input measure that adjusts the count of workers to a full-time equivalent measure.[21] We estimate a 'full-time-equivalent' (*FTE*) monthly employment measure for each worker, using information on multiple jobs, minimum wage rates, job spells, and notified job end dates. The *FTE* measure is aggregated to an annual firm-level measure of labour input.

The estimation of skill proxies (two way worker and firm fixed effects estimation) is based on all the available data on *PAYE* employee jobs in New Zealand during the fifteen March-years from April 1999 to March 2014.

[20] Around 5 percent of entrants had employees in an earlier period and 5 percent of exiters were employers in a later period. A one-year horizon for identifying entry and exit was maintained to ensure consistent definitions could be used in the first and last years. A very small number of firm-year observations are dropped because worker fixed effects cannot be estimated due to missing worker demographic information.

[21] The algorithm used in the current paper includes an additional adjustment based on the receipt of non-employment income, which slightly lowers the *FTE* estimate for relatively few workers.

5 Results

5.1 Annual growth rates of inputs, outputs and *mfp*

The period of our study, 2001-2012, was one of overall growth, though with a sharp slowdown in 2009, in the wake of the Global Financial Crisis (*GFC*). Table 1 summarises the annual movements in output, inputs, and estimated *mfp*. Output by firms in the sample grew by 12.1 percent, while capital grew by 34.5 percent and intermediate inputs by 6.7 percent.

Given our focus on the role of skill and labour inputs, the table shows four different labour-related input measures. First, unadjusted labour input, as measured by full-time equivalent workers, grew by 15.0 percent. Second, this growth in labour input was accompanied by an increase in worker observable skill ($\overline{\mathrm{X}}_{\mathrm{it}}\hat{\beta}$ in equation (3)), which grew by 1.8 percent, largely reflecting the ageing of the employed workforce. Third, in contrast, there was a dilution in unobserved worker skill, as measured by average worker fixed effects ($\bar{\theta}_{jt}$), which declined by 3.6 percent over the sample period. The combined effect of the changes in observed and unobserved skill was a net 1.8% decline in average worker skill over the period.

The pattern of declining unmeasured skill is consistent with the findings of Maré and Hyslop (2008), who document a substantial decline in average worker 'quality' over the 2000-2007 period as sustained employment growth drew in workers with lower-than-average skill and earning capacity. In particular, the results in Table 1 show a steady decline in average unobserved skill until 2008, when the domestic recession and *GFC* struck, resulting in a cumulative 3.6% decline from 2001 to 2008. Unobserved skill then increased 0.4% in the two years following the *GFC* (2008/9 and 2009/10) as employment contracted, before a slower rate of decline (-0.2% per year) in the final two years of the period as employment gradually increased. In addition, observed skill increased 1.0% over the two post-*GFC* years, and a further 0.2% in the following year, largely reflecting the drop in youth employment over that period.

Figure 1 illustrates the relationship between skill dilution and broader labour market measures, as captured by the Household Labour Force Survey (*HLFS*). Skill dilution is measured as the cumulative impact of skill adjustment, multiplied by -1 to convert it to a measure of skill *dilution*. The extent of skill dilution is positively correlated with the employment rate (employment / working age population), consistent with employment growth disproportionately drawing in workers with lower than average skill. Skill dilution is reversed during the *GFC* due to the disproportionate loss of workers with lower than average observable and unobservable skill. We believe the consistent cyclical patterns of our measures of changing skill provides support for their validity and robustness, and for our interpretation of them as indicators of compositional change.

The fourth labour input measure in Table 1 is an overall skill-adjusted labour input measure. This is constructed as the sum of the log (*FTE* labour input), the average unobserved worker fixed effects, and the average worker observable skill. The 1.7% decline in average worker skill means that the growth in skill adjusted labour input (13.3%) is correspondingly lower than the growth in *FTE* labour input (15.0%).

A consequence of downward revision in input growth is that a higher proportion of output growth is attributed to growth in *mfp*. Table 1 compares two productivity growth measures. The first, *mfp*(*FTE*), is estimated using *FTE* labour input and grew by 1.5 percent between 2001 and 2012. The skill-adjusted measure, *mfp*(skill-adjusted), grew by 2.7 percent over the same period. The final panel of Table 1 compares the growth of *FTE* and skill-adjusted measures of labour input and *mfp*. Using a skill-adjusted labour input measure yields 1.8 percentage point lower estimated growth of labour input, and 1.1 percentage point higher growth in *mfp*.

Figure 2 plots the cumulative changes in labour input (with and without skill adjustment) and the implied cumulative *mfp* growth paths. Although we would not expect labour input or productivity growth for our estimation sample to match that of the entire measured sector, as estimated in official statistics, we include cumulative growth in these for comparison.[22] The dark upper line in panel (a) shows the 15 percent cumulative growth in *FTE* labour input, reaching a peak in 2009 of 21.9 percent above 2001 levels before declining in the subsequent three years. Adjusting for skill lowers growth throughout the sample period, as shown by the growing gap between *FTE* growth and the skill-adjusted growth (lower dark line). Labour input as measured in official

[22] The series are not expected to be the same, though there are clear similarities, especially in the timing and magnitude of the impact of the *GFC*. Our measure is not intended to be an accurate measure of overall productivity but focuses instead on productivity variation across the firms that are included in our sample. Our measure excludes some firms, as outlined above, and does not attempt to make aggregate adjustments that are implemented by Statistics New Zealand to improve the coverage and accuracy of the official measure.

productivity statistics grew more slowly than *FTE* labour input for our sample, increasing by 11.8 percent (lower solid line) by 2012, with a recovery between 2010 and 2012, which is not evident in the *FTE* or skill-adjusted measures. An alternative measure of *FTE* employment comes from the Quarterly Employment Survey. This shows labour input increasing by 18.7 percent through to 2012, higher than the 13.3 percent increase in our measure.

Official statistics contain a 'composition-adjusted' measure of labour input (lower dashed line), which controls for the changing qualification and age mix of employed workers (Statistics New Zealand, 2008; Szeto & McLoughlin, 2008). In contrast to our skill-adjusted labour input measure, the official composition-adjusted labour input measure grew faster (13.1 percent) than the unadjusted (11.8 percent). The different direction of impact reflects different definitions of skill. The rise in qualifications captured by the official composition adjustment contrasts with the dilution arising from the relative growth of workers with low average earnings capacity. The apparently conflicting trends can be reconciled if dilution were to occur across the qualification distribution.[23]

The impact of the alternative measures of labour input on estimated within-industry mfp growth is shown in panel (b) of Figure 2. Aggregate mfp growth is calculated as $(\sum_i \omega_{it} mfp_{it} - \sum_i \omega_{it-1} mfp_{it-1})$, using weights from equation (7) and alternative measures of mfp from equation (6), with and without β^s constrained to be zero. The relatively slow growth in skill-adjusted labour input is reflected in estimated mfp growth of 2.7 percent, which is 1.2 percentage points higher than that estimated using *FTE* labour input (as in Table 1). In contrast, the composition adjustment in the official statistics lowers estimated mfp growth from 4.2 percent to 3.5 percent. All mfp series show a pronounced decline in 2008 – 2009 and recovery in the subsequent three years.

[23] Because our measure estimates worker earning capacity as a time-invariant worker characteristic, any changes in earning capacity associated with increased qualifications over time for particular workers would show up as *mfp* growth. The entry of more qualified workers would contribute positively to growth in our skill-adjusted measure as long as qualifications and earnings are positively related.

5.2 Firm dynamics

The analysis of the interaction between changing skill composition and firm dynamics relies on the classification of firms as entrants, exiters and continuers. Table 2 summarises the distribution of firms across these transition groups. The net change in the number of firms in our sample between 2001 and 2012 was an increase of 4,101, from 89,676 to 93,777. Of the firms observed in the data in 2012, 26,625 (28.4%) were continuers who were also observed in 2001. A further 7,029 firms (7.5%) were 'joiners' - continuers who were operating but who were not observed in the productivity data in 2001. Almost two thirds (64.1%) of firms in 2012 were entrants who had started operating at some point in the 11 years between 2001 and 2012. The increase due to entrants and joiners was almost balanced by reductions due to 53,784 exiters (60.0 percent of the 2001 total) and 9,264 leavers (10.3%).

Although continuers accounted for only 28.4 percent of the 2012 firms, they were relatively large firms, and contributed 60.5 percent of gross output in that year. In contrast, the contributions of entrants and exiters to gross output was only around half of their contribution to firm counts. Joiners and leavers accounted for between 7 and 10 percent of both firm counts and gross output.

Table 3 reports input-weighted means of inputs, outputs, and productivity for each transition group, expressed relative to overall means. The weights (ω_{it} as defined in equation (7)) are the same weights as are used for calculating mean productivity, and reflect each firm's share of inputs.[24] Continuing firms are relatively large, with output and labour inputs that are roughly double the weighted mean across all firms. In contrast, the mean size of entrants is only around a third the size of the overall mean. Exiters are larger than entrants, but still only about half as large as the overall mean. Leavers comprise relatively small labour-intensive firms, with output and capital levels around 20% of the overall mean, and labour inputs about 25% of the mean. Joiners, on the other hand, are more similar in size to entrants and exiters but, like leavers, are

[24] This weighting leads to different statistics than those shown in Table 2, which are based on sums of output. In contrast, the statistics underlying Table 3 are input-weighted geometric means. Whereas Table 2 joiners and leavers have output shares that are similar to their share of firms, Table 3 shows that they have relatively low (weighted) mean output, consistent with some high-output joiners and leavers having low employment shares. The geometric means used in Table 3 further lower the statistical influence of high-output firms.

relatively labour intensive. Continuers are the most capital intensive group of firms, with capital labour ratios about 10% higher than the overall average.

There is limited variation in unobserved skill and worker observables, with no group differing by more than 3.6 percentage points from the mean level. Within that range, entrants and exiters have lower levels of observable and unobserved skill than continuing firms, with exiters having the lowest level of unobserved skill (96.4% of overall mean). The difference between continuers and other firms in the size of labour inputs is magnified by skill adjustment.

Mean productivity differences are also relatively small, with only the low productivity leavers group having mean productivity that differs from the overall mean by more than 3.1 percent. Entrants are the group with the highest mean productivity (101%), whereas exiters have lower mean productivity of 98%.[25] Comparing *mfp* estimated using a skill-adjusted labour input measure with *mfp* estimated using *FTE* does not greatly change the relative *mfp* across the transition groups.

5.3 Decomposition of within-industry *mfp* growth

A key focus of this paper is on whether the productivity impact of skill adjustment differs across transition groups. Table 4 compares the contributions to estimated productivity growth made by each transition group, with and without skill adjustment of labour input. The contributions are calculated as weighted sums of within-industry contributions, summed across all industries.[26] Annual average growth in *mfp* was 0.14 percent using *FTE*-based labour input, and 0.24 percent using skill-adjusted labour input (Total growth over 11 years of 1.5 percent and 2.7 percent respectively, as shown in Figure 2 and Table 1).

The difference of 0.1 percent growth per year is almost entirely accounted for by the impact of skill adjustment on changes in productivity for continuing firms (bottom row of Table 4). Put simply, the reduction in average worker skill was absorbed almost entirely by continuing firms. The contribution of inputs being reallocated from high-

[25] Entrants may have been operating for up to 10 years, so they are not necessarily very young firms.

[26] Weights are year-specific industry shares of inputs. Industry-specific decompositions are shown in Appendix table 4 (for mfp based on unadjusted labour input) and Appendix table 5 (for skill-adjusted mfp).

productivity continuers to lower-productivity continuers differs only slightly between the two different *mfp* measures (-0.05 percent and -0.06 percent). Similarly the positive contributions made by high-productivity entrants and low-productivity exiters do not differ appreciably. The net entry contribution of 0.16 percent is the same whether calculated using the *FTE* or the skill-adjusted specification.

These contributions are shown in panel (a) of Figure 3, with leavers and joiners combined in the final block. Only for overall growth and within-firm changes are there appreciable differences between the *FTE*-based contributions and the skill-adjusted contributions. For other components, the difference (shown as the third, striped bar in each block) is small.

Single-year transition groups

The finding that the productivity impact of skill adjustment is confined almost entirely to productivity changes for continuing firms is confirmed, when transition groups and productivity changes are measured over one year intervals. For annual changes, continuers are firms that are observed with employment and production data in two consecutive years. 'Entrants' are identified as firms who reported neither employment nor production data in the prior year and 'exiters' are firms that have no employment or production data in the subsequent year. A firm could appear in each of these categories in different years, and could even appear as a continuer, joiner and leaver multiple times.

When measured this way, the transition groups capture quite different sets of firms. Continuers that survive for 11 years are quite different from those that survive from one year to the next. Based on annual transitions, 75 percent of firms each year are classified as continuers, and they account for over 90 percent of output. In contrast, entrants and exiters in a year account for only 13 and 10 percent of firms respectively, and only 2-3 percent of gross output. These patterns are shown in Table 5. It also shows that joiners and leavers account for roughly the same proportion of employment in a year when they are measured annually as when they are measured over 11 years, consistent with transitory absences from the data. Table 6 shows some of the key differences between the one-year transition groups. Compared with the 11-year transition group summary in Table 3, single-year entrants and exiters, and single-year joiners are much smaller, and continuers are not as large relative to the mean firm. Entrants and exiters are also shown to have relatively high productivity in their first (last) year of operation.[27]

Table 7 shows annual productivity growth decompositions using the two different *mfp* definitions. The overall productivity change of 0.14 percent using *FTE* labour input and 0.24 using skill-adjusted labour input is, by definition, the same as in Table 4. As was the case with 11-year transitions, the impact of skill adjustment is confined largely to productivity changes within continuing firms. This implies that the dilution of skill was primarily taking place within continuing firms. The lack of difference between the *FTE* and skill-adjusted contributions from the other components indicates that skill dilution was not differentially affecting entrants and exiters and that differential growth rates of continuing firms were not systematically linked to differences in skill dilution. Skill-adjustment has only a minor effect on the estimated contribution of reallocation of inputs between continuers, of entry and exit, or of joiners and leavers. The final row of Table 7 summarises the differences in estimated *mfp* growth between the *FTE* and skill-adjusted specifications. Within-firm productivity change contributed 0.13 percentage points to the 0.10 percent annual average growth. Net entry balances to make a zero contribution, as does net joining and leaving transitions. The patterns of annual contributions in Table 7 also reveal that year-to-year variation in *mfp* is largely due to year-to-year changes in the contribution of within-firm productivity changes from continuers.

Compared with the 11-year transitions summarised in Table 4, the contributions of joiners and leavers are much larger when transitions are based on annual changes. Year-on-year joiners and leavers have consistently low relative productivity, so joiners make a sizeable negative average contribution to *mfp* growth (-0.20 percent for *mfp*(*FTE*) and -0.25 percent for *mfp*(skill)) and leavers make a sizeable positive contribution (0.36 and 0.41). Exiters in their final year of operation make an average negative contribution (-0.07 percent and -0.05 percent in Table 7), though this includes an atypically strong negative impact of high-productivity exiting firms in 2003. Another key difference between Table 4 and Table 7 is that year-to-year reallocation of inputs among continuing firms contributes positively to *mfp* growth, whereas reallocation

[27] High productivity in first and last years may be in part due to input and output measurement and timing issues in firms that are incurring setup costs or running down inventories when they cease operation. See Fabling & Maré (2015b) for details of end-period adjustments made to the production and employment data.

among firms continuing for 11-years makes a negative contribution. The positive year-to-year reallocation is particularly positive in 2009 and 2010, in the immediate wake of the *GFC*. The impact of skill adjustment is small in either case – 0.01 percent for 11-year continuers, and -0.02 percent for year-on-year continuers.

The contributions based on single-year transitions are summarised in panel (b) of Figure 3. Although the pattern of contributions differs across *FTE* and skill-adjusted specifications, the pattern of differences between the specifications (ie, the striped bars) is similar to that shown in panel (a) based on 11-year transitions.

5.4 Between industry decomposition

The decompositions presented so far capture the patterns of productivity growth within industries, controlling for differences across industries in technologies and in productivity levels. As discussed in section 1, estimating cross-industry differences in productivity levels requires a more constrained production function specification. Table 8 summarises the estimated contribution of the reallocation of inputs across industries (i.e., equation (11)), under the imposed assumption of a common technology with industry fixed effects, as shown in equation (7). With this specification, overall productivity growth captures both within-industry growth, and the impact of input reallocation between industries with different mean levels of *mfp*. Table 8 shows the decomposition of productivity growth into these two components.

Measuring labour input as *FTE*, annual average productivity growth is estimated to be 0.19 percent. About half of this (0.9 percent per year) is attributed to within industry productivity shifts, and about half (0.9 percent per year) to changing industry mix. The estimated within-industry growth is lower than that estimated from industry-specific regressions, and shown in Table 4.

When *mfp* is estimated using skill-adjusted labour inputs, a greater rate of growth is attributed to within-industry productivity shifts (0.17 percent per year) compared with the *FTE*-based estimate. The analysis of within-industry productivity growth presented in the previous section demonstrated that this effect is dominated by changes for continuing firms within industries. Overall, the impact of skill adjustment on inter-industry reallocation is small relative to its impact on estimated within-industry growth. The impact of reallocation is, however, positive in most years in both *FTE*-based and skill-adjusted estimates. Over the 2001-2012 period, high-productivity industries increased their share of productive inputs. Skill adjustment also slightly lowers the rate of growth attributed to reallocation across industries, to 0.07 percent per year compared with 0.09 percent using *FTE*-based *mfp* estimates. This implies that the decline in average skill levels disproportionately affects high-productivity industries, though the differences are relatively small.

The patterns in Table 8 are summarised in Figure 4. The figure also shows the differences between the estimates of within-industry productivity growth obtained from industry-specific regressions (shown in Table 4) and those presented in this section from pooled industry fixed effect regressions.

6 Summary and discussion

The main objective of this study was to gauge the role of skill composition in productivity measurement and growth, and to identify whether skill composition affects particular sources of productivity growth. We used an indirect measure of worker skill, derived from linked employer-employee data and employing a two-way fixed effects estimation method. Using this measure, we found that the 15 percent growth in full-time equivalent labour input between 2001 and 2012 was accompanied by an overall decline in average worker skill, contrary to the trends observed in skill measures based on formal qualifications. Adjusting our estimates of *mfp* productivity for this slower increase in labour input results in more of output growth being attributed to growth in productivity rather than growth in inputs.

The impact of using skill adjusted labour inputs in the estimation of *mfp* is accounted for almost entirely by the impact on estimated productivity growth for continuing firms. Despite the persistence of firms' personnel practices as identified by Abowd et al. (2007), it appears that continuing firms are flexible enough to adapt to changing labour quality.

The skill-adjusted production function estimates capture the relationship between skilled labour input and gross output. We would expect output growth to have been lowered by the drop in average labour quality over the study period. Continuing firms were, however, more able to maintain output in the face of slower growth in skill-adjusted labour content than other transition groups. In contrast, for entrants and exiters, output change reflects lower labour quality, and estimated *mfp* is affected less.

Our study also sheds light on the contribution to productivity growth made by reallocation. The findings are similar for *FTE*-based *mfp* estimates and skill-adjusted estimates, but differ when we vary the timeframe over which we observe transitions. Using transition groups defined across an 11-year window, and looking within industries, net entry contributed 0.16 percent per year to *mfp* growth, with positive contributions from both entrants and exiters. In contrast, within-industry reallocation of inputs from more-productive to less-productive continuing firms made a negative contribution to *mfp* growth (-0.05 to -0.06 percent per year) (Table 4).

When estimated using single-year transitions to identify transition groups (Table 7), net entry makes a smaller average annual contribution of 0.03 percent, with a negative average contribution from exiting firms. Joiners and leavers account for a sizeable proportion of year-to-year productivity growth (0.16 percent per year), reflecting discontinuously observed mainly low-productivity firms. In contrast with the 11-year transition group results, year-to-year reallocation of inputs within industries makes a positive contribution to *mfp* growth. In addition to the within-industry reallocation, reallocation from less-productive to more-productive industries also contributed to productivity growth, adding an average of 0.07 to 0.09 percent per year (Table 8).

There are a number of possible extensions to this study. First, other dimensions of labour quality could be examined. The IDI contains educational attainment data for a substantial subset of workers, and it would be possible to analyse whether the dynamics of qualification adjustment are similar to that of the more general skill adjustment analysed in the current paper. The role of firm dynamics in qualification adjustment may differ for particular types of qualification, such as those related to *STEM* (science, technology, engineering, and mathematics) skills.

Second, the sensitivity of *mfp* estimates to alternative functional forms of production function, or alternative approaches to estimation could be investigated. Extensions could include the use of more flexible functional forms, such as translog production functions, or estimation approaches that deal explicitly with the challenges of unobserved firm heterogeneity and the endogeneity of input choices (Ackerberg, Caves, & Frazer, 2006; Griliches & Mairesse, 1998).

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Table 1: Annual growth in production components

	2001 - 2002	2002 - 2003	2003 - 2004	2004 - 2005	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	Total: 2001-2012
Gross Output	2.6%	4.9%	2.9%	11.0%	-3.5%	-1.7%	4.3%	-5.8%	-3.4%	1.8%	-1.1%	12.1%
Capital	1.6%	8.1%	5.4%	3.5%	4.4%	3.2%	4.2%	2.3%	-1.2%	2.2%	0.8%	34.5%
Intermediates	2.4%	4.8%	2.5%	13.6%	-8.1%	-2.2%	4.2%	-7.4%	-3.1%	1.5%	-1.5%	6.7%
Capital-labour (*FTE*) ratio	-0.1%	3.5%	0.1%	0.4%	0.7%	3.0%	1.4%	1.9%	3.8%	3.8%	1.0%	19.5%
Labour inputs												
FTE Labour input	1.8%	4.6%	5.3%	3.1%	3.7%	0.3%	2.8%	0.3%	-5.0%	-1.6%	-0.2%	15.0%
Worker observables	0.5%	0.3%	-0.2%	0.0%	0.0%	0.0%	0.0%	0.4%	0.6%	0.2%	0.0%	1.8%
Worker fixed effects	-0.8%	-0.3%	-0.8%	-0.2%	-0.5%	-0.6%	-0.4%	-0.1%	0.5%	-0.2%	-0.2%	-3.6%
Skill-adjusted labour input	1.5%	4.5%	4.3%	2.8%	3.2%	-0.3%	2.5%	0.7%	-3.9%	-1.6%	-0.4%	13.3%
Productivity growth												
mfp(*FTE*)	0.9%	0.5%	-0.4%	1.8%	-0.4%	-0.2%	0.8%	-3.2%	0.8%	1.1%	-0.1%	1.5%
mfp(skill-adjusted)	1.0%	0.6%	-0.1%	2.0%	-0.3%	-0.2%	1.0%	-3.3%	0.6%	1.2%	0.1%	2.7%
Impact of skill adjustment												
On labour input growth	-0.3%	-0.1%	-1.0%	-0.3%	-0.5%	-0.5%	-0.4%	0.3%	1.1%	0.0%	-0.2%	-1.8%
On productivity growth	0.2%	0.1%	0.3%	0.1%	0.1%	0.1%	0.2%	-0.1%	-0.2%	0.1%	0.2%	1.1%

Note: Changes are expressed as percentages but calculated as changes in logged variables. For output, capital, FTE and intermediates, changes are changes in logged aggregates. Worker fixed effects and observables, and mfp measures are calculated as changes in annual weighted means, using estimates of equation (7).

Table 2: Firm turnover – defined for 11 year transitions: 2001-2012

Period	End-of-period Sample	Continuers	Entrants	Joiners	Exiters	Leavers
Number of firms	93,777	26,625	60,126	7,029	53,784	9,264
		Share of period t			*Share of period t-1*	
Share of firms	100.0	28.4	64.1	7.5	60.0	10.3
Share of gross output	100.0	60.5	30.9	8.6	34.5	7.3

Note: Enterprise counts have been randomly rounded to base 3. There were 89,676 firms in the sample in 2001.

Table 3: Weighted means, by 11-year transition group (relative to overall)

Period	Period mean	Continuers	Entrants	Join Sample	Exiters	Leave Sample
		Relative to period t			*Relative to period t-1*	
Gross output	100.0%	206.6%	34.5%	41.3%	53.3%	17.8%
Capital	100.0%	209.4%	34.0%	39.8%	53.9%	17.7%
Capital-*FTE* ratio	100.0%	109.5%	92.9%	73.4%	96.7%	65.7%
Labour inputs						
FTE labour input	100.0%	191.3%	36.6%	54.2%	55.8%	26.9%
Unobserved skill	100.0%	101.0%	98.7%	98.1%	96.4%	96.8%
Worker observables	100.0%	100.6%	98.7%	100.9%	98.8%	99.3%
Skill adjusted	100.0%	194.4%	35.7%	53.7%	53.1%	25.8%
Productivity						
mfp(*FTE*)	100.0%	99.7%	101.4%	97.1%	98.0%	95.4%
mfp(Skill)	100.0%	100.1%	100.8%	96.9%	98.4%	95.1%

Note: Weighted means of logged measures are calculated for each transition group, using the weights (ω_{it}) derived from estimating equation (7). Relative means are calculated as the difference from the overall weighted mean of the logged measures, converted to percentage differences.

Table 4: Average annual productivity growth – within-industry decomposition (11 year transition groups)

		Continuers		Entrants		Exiters	
Period: 2001-2012	Average annual within-industry *mfp* growth	Within-firm change in productivity	due to differential growth of high v low productivity firms	Entrants	Joining sample	Exiters	Leaving sample
	mfp growth contribution						
mfp(FTE)	0.14%	0.02%	-0.05%	0.07%	-0.02%	0.09%	0.04%
mfp(skill adjusted)	0.24%	0.11%	-0.06%	0.06%	-0.02%	0.10%	0.05%
Difference in contributions	0.10%	0.09%	-0.01%	-0.01%	0.00%	0.01%	0.01%

Note: Growth rates are annual average growth rates over 11 years. Decomposition based on the method of Griliches & Regev (1995) as described in the text.

Table 5: Firm turnover – defined for single-year transitions: 2001-2012

Period	Pooled Sample	Continuers	Entrants	Joiners	Exiters	Leavers
Number of firms	1,076,937	813,360	144,789	118,788	108,621	150,870
		Share of period t			*Share of period t-1*	
Share of firms	100.0	75.53	13.44	11.03	10.12	14.06
Share of gross output	100.0	90.30	3.13	6.56	2.19	7.85

Note: Enterprise counts have been randomly rounded to base 3.

Table 6: Weighted means, by single-year transition group (relative to overall)

Period	End-of-period Sample	Continuers	Entrants	Join Sample	Exiters	Leave Sample
Gross output	100.0%	125.5%	6.1%	18.7%	14.6%	14.1%
Capital	100.0%	124.5%	6.7%	19.9%	16.7%	14.5%
Capital-labour ratio	100.0%	101.5%	112.5%	80.2%	133.4%	71.4%
Labour input						
FTE labour input	100.0%	122.6%	6.0%	24.8%	12.6%	20.3%
Unobserved skill	100.0%	100.3%	97.0%	97.2%	96.9%	96.6%
Worker observables	100.0%	100.3%	95.2%	98.8%	97.2%	98.0%
skill adjusted input	100.0%	123.3%	5.5%	23.8%	11.9%	19.4%
mfp(*FTE*)	100.0%	100.1%	103.5%	97.1%	102.7%	95.9%
mfp(Skill)	100.0%	100.2%	102.8%	96.6%	102.0%	95.4%

Note: Weighted means of logged measures are calculated for each transition group, using the weights derived from estimating equation (7). Relative means are calculated as the difference from the overall weighted mean of the logged measures.

Table 7: Annual Productivity change – within-industry decomposition

Period	Total within-industry Productivity growth	Continuers: Within-firm change in productivity	Continuers: due to differential growth of high v low productivity firms	Entrants: Entrants	Entrants: Joining sample	Exiters: Exiters	Exiters: Leaving sample
		mfp growth contribution (*FTE* labour input specification)					
2001 - 2002	0.87%	-0.06%	-0.07%	0.25%	-0.25%	0.09%	0.90%
2002 - 2003	0.47%	0.63%	0.11%	0.02%	-0.14%	-0.84%	0.69%
2003 - 2004	-0.42%	-0.44%	0.03%	0.12%	-0.11%	-0.13%	0.09%
2004 - 2005	1.83%	0.81%	0.19%	0.47%	0.00%	0.02%	0.33%
2005 - 2006	-0.41%	-0.40%	0.20%	-0.02%	-0.18%	-0.06%	0.04%
2006 - 2007	-0.24%	-0.51%	-0.17%	0.13%	-0.13%	0.06%	0.37%
2007 - 2008	0.81%	0.62%	-0.16%	0.13%	-0.06%	0.01%	0.28%
2008 - 2009	-3.19%	-3.07%	0.25%	-0.07%	-0.46%	-0.02%	0.18%
2009 - 2010	0.84%	0.22%	0.35%	-0.02%	-0.18%	0.07%	0.40%
2010 - 2011	1.09%	1.01%	-0.09%	0.00%	-0.19%	0.00%	0.36%
2011 - 2012	-0.12%	-0.23%	0.19%	0.10%	-0.49%	0.01%	0.29%
Annual average	0.14%	-0.13%	0.08%	0.10%	-0.20%	-0.07%	0.36%
		mfp growth contribution (Skill-adjusted labour input specification)					
2001 – 2002	1.03%	0.18%	-0.13%	0.23%	-0.25%	0.11%	0.89%
2002 – 2003	0.59%	0.79%	0.04%	0.02%	-0.21%	-0.79%	0.74%
2003 – 2004	-0.14%	-0.27%	0.10%	0.11%	-0.13%	-0.11%	0.16%
2004 – 2005	1.95%	1.03%	0.19%	0.44%	-0.05%	0.03%	0.32%
2005 – 2006	-0.28%	-0.25%	0.17%	-0.04%	-0.21%	-0.05%	0.10%
2006 – 2007	-0.16%	-0.40%	-0.20%	0.12%	-0.16%	0.07%	0.42%
2007 – 2008	1.02%	0.85%	-0.17%	0.11%	-0.14%	0.03%	0.35%
2008 – 2009	-3.27%	-3.01%	0.18%	-0.10%	-0.55%	0.00%	0.21%
2009 – 2010	0.64%	0.04%	0.31%	-0.03%	-0.21%	0.08%	0.46%
2010 – 2011	1.22%	1.15%	-0.08%	-0.02%	-0.26%	0.01%	0.41%
2011 – 2012	0.05%	-0.09%	0.18%	0.08%	-0.53%	0.02%	0.39%
Annual average	0.24%	0.00%	0.05%	0.08%	-0.25%	-0.05%	0.41%
Difference in contributions over 11 years	0.10%	0.13%	-0.02%	-0.02%	-0.05%	0.02%	0.05%

Notes: The decomposition is based on the Griliches and Regev (1995) method, as summarised by equation (9) and discussed in the text.

Table 8: Productivity growth contribution – between-industry decomposition

	Total Productivity growth	due to within-industry productivity shifts	due to changing industry mix
		FTE labour input specification	
2001 - 2002	0.45%	0.57%	-0.12%
2002 - 2003	0.69%	0.39%	0.30%
2003 - 2004	-0.15%	0.01%	-0.16%
2004 - 2005	1.84%	1.47%	0.37%
2005 - 2006	-0.15%	-0.37%	0.21%
2006 - 2007	-0.36%	-0.31%	-0.05%
2007 - 2008	1.18%	0.99%	0.19%
2008 - 2009	-3.78%	-3.89%	0.11%
2009 - 2010	1.05%	0.95%	0.10%
2010 - 2011	1.26%	1.34%	-0.08%
2011 – 2012	0.01%	-0.15%	0.16%
Total	0.19%	0.09%	0.09%
		Skill adjusted labour input specification	
2001 – 2002	0.59%	0.71%	-0.12%
2002 – 2003	0.70%	0.47%	0.23%
2003 – 2004	0.13%	0.25%	-0.12%
2004 – 2005	1.91%	1.61%	0.30%
2005 – 2006	-0.07%	-0.26%	0.19%
2006 – 2007	-0.32%	-0.25%	-0.07%
2007 – 2008	1.29%	1.15%	0.15%
2008 – 2009	-3.91%	-3.96%	0.05%
2009 – 2010	0.82%	0.69%	0.13%
2010 – 2011	1.35%	1.44%	-0.08%
2011 – 2012	0.12%	0.01%	0.11%
Total	0.24%	0.17%	0.07%
		Difference	
2001 – 2002	0.13%	0.13%	0.00%
2002 – 2003	0.01%	0.09%	-0.07%
2003 – 2004	0.28%	0.24%	0.04%
2004 – 2005	0.07%	0.14%	-0.07%
2005 – 2006	0.09%	0.11%	-0.02%
2006 – 2007	0.05%	0.06%	-0.02%
2007 – 2008	0.12%	0.16%	-0.04%
2008 – 2009	-0.13%	-0.07%	-0.06%
2009 – 2010	-0.23%	-0.27%	0.03%
2010 – 2011	0.09%	0.09%	-0.01%
2011 – 2012	0.10%	0.16%	-0.06%
Total	0.05%	0.08%	-0.02%

Notes: The decomposition is based on the Griliches and Regev (1995) method, as summarised by equation (11) and discussed in the text.

Figure 1: Skill dilution and the employment rate

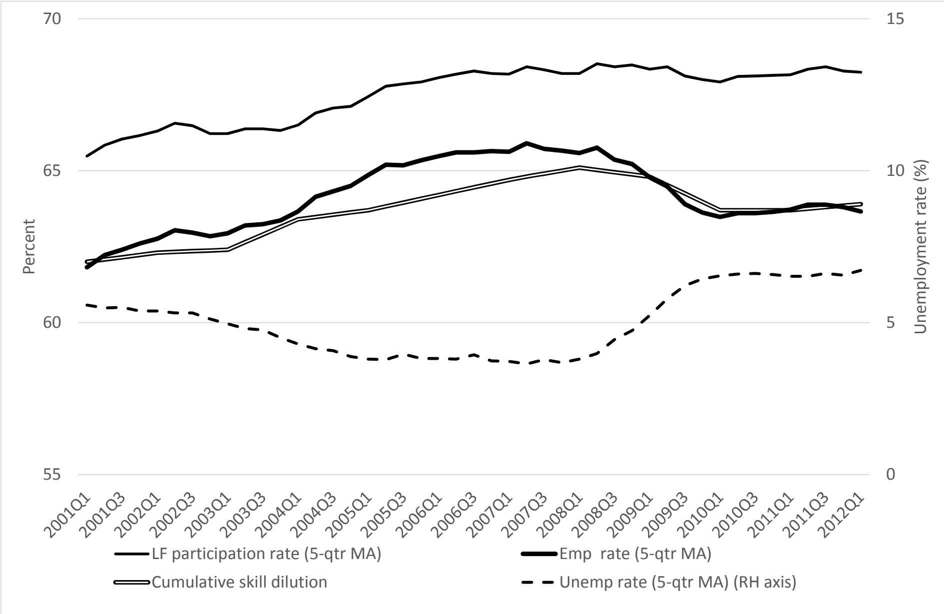
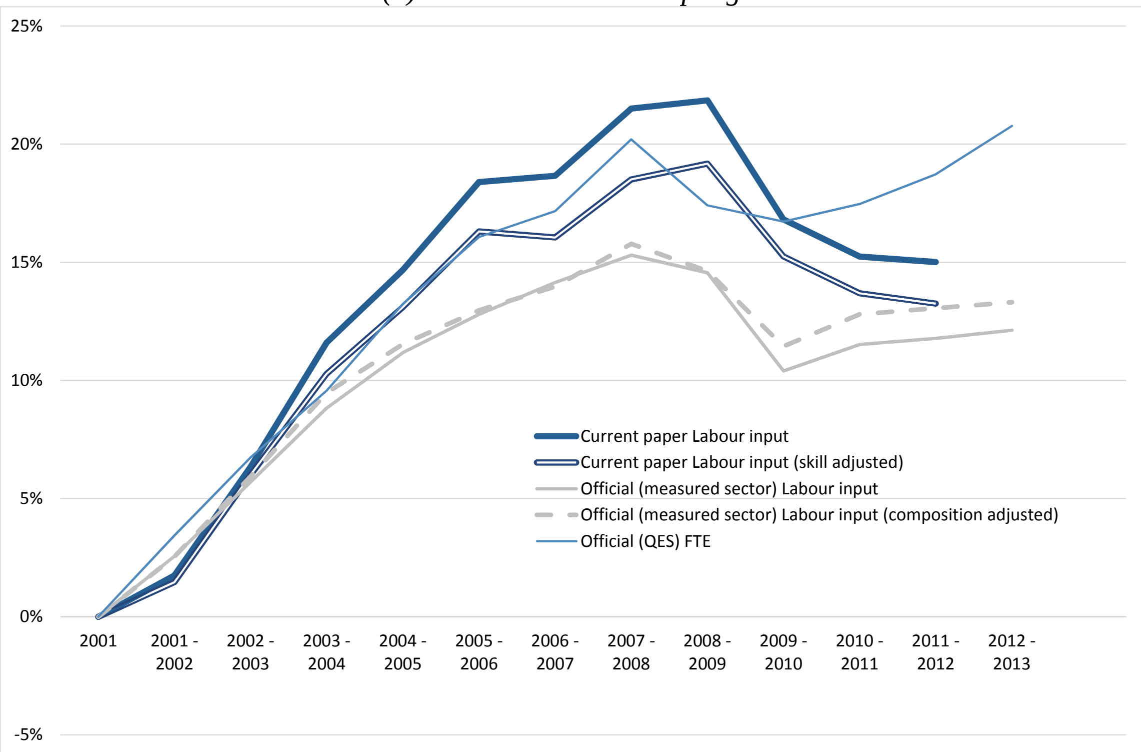


Figure 2: The impact of skill adjustment on labour input and productivity growth

(a) Cumulative labour input growth



(b) Cumulative productivity growth

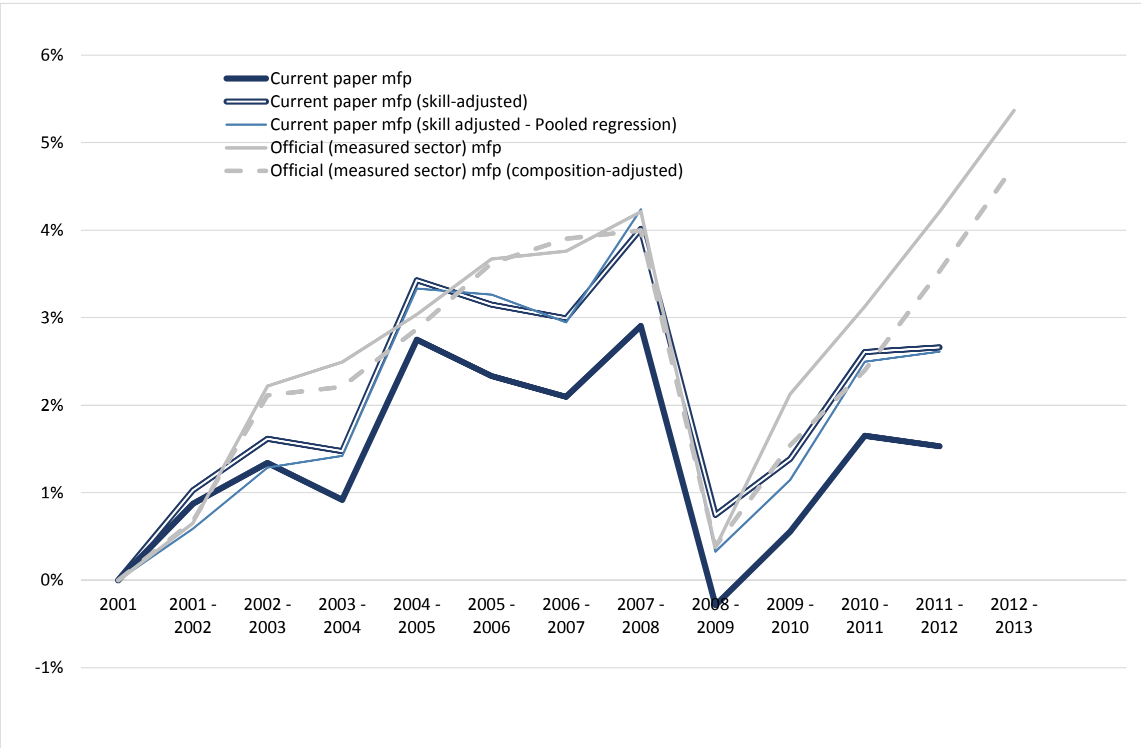
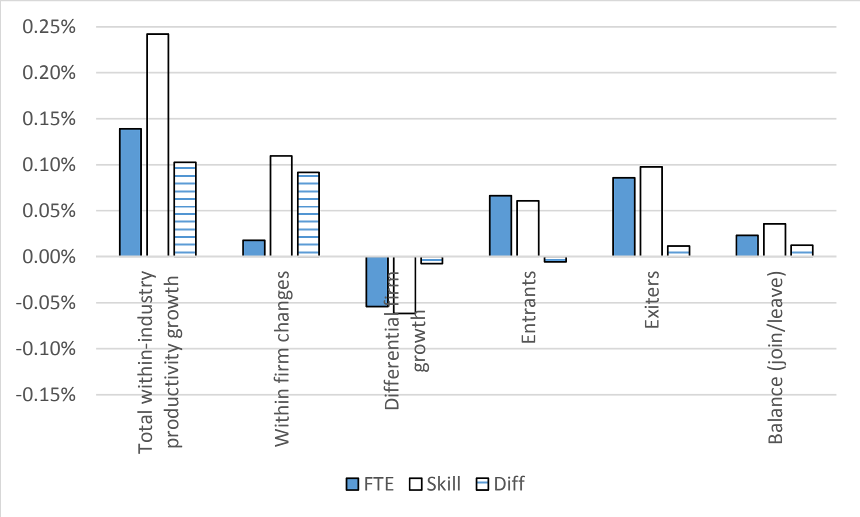


Figure 3: Contributions to within-industry productivity growth

(a) 2001-12 11-year Transitions



(b) Average One-year transitions

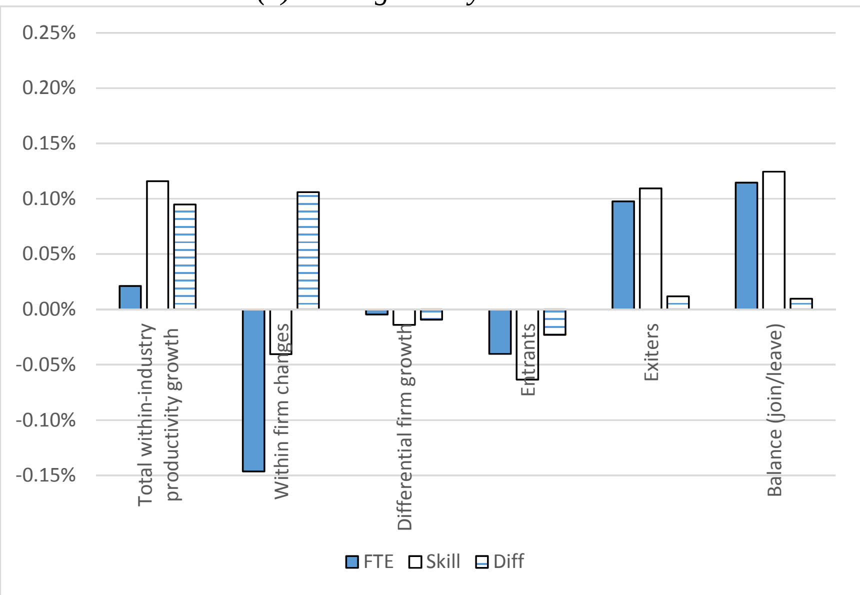
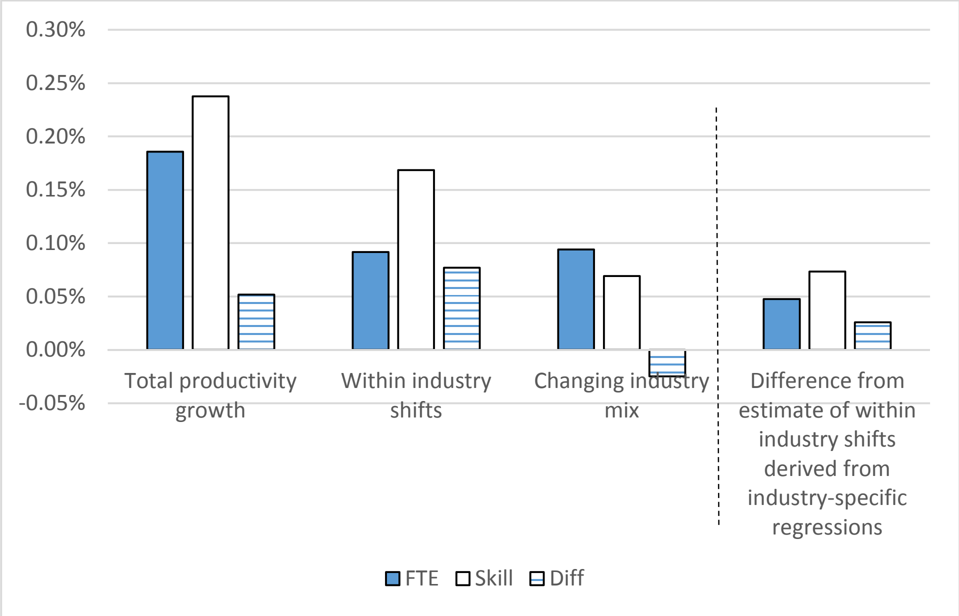


Figure 4: Contributions of industry mix to productivity growth



Note: The final set of 3 bars show the difference between the estimates of within-industry shifts in Table 4 and Table 8. A positive value indicates that the Table 4 estimates based on industry-specific regressions are larger.

Appendix table 1: Industry Groupings

NZSIOC (level 3)	*PPI*	Description	Number of National Accounts Working Inds	*ANZSIC06* industry codes	Measured sector ([a] =formerly excluded)
	AA	Agriculture, forestry, and fishing			
AA11	AA11	Horticulture and fruit growing	1	A011/ A012/ A013	Yes
AA12	AA12	Sheep, beef cattle, and grain farming	1	A014/ A015	Yes
AA13	AA13	Dairy cattle farming	1	A016	Yes
AA14	AA14	Poultry, deer, and other livestock farming	1	A017/ A018/ A019	Yes
AA21	AA21	Forestry and logging	1	A030	Yes
AA31	AA31	Fishing and aquaculture	1	A020/ A041	Yes
AA32	AA32	Agric, forest, fish support services, and hunting	1	A042/ A051/ A052	Yes
BB11	BB	Mining	1	B	Yes
	CC	Manufacturing			
CC11	CC11	Meat and meat product manufacturing	1	C111	Yes
CC12	CC12	Seafood processing	1	C112	Yes
CC13	CC13	Dairy product manufacturing	1	C113	Yes
CC14	CC14	Fruit, oil, cereal, and other food manufacturing	1	C114/ C115/ C116/ C117/ C118/ C119	Yes
CC15	CC15	Beverage and tobacco product manufacturing	1	C12	Yes
CC21	CC21	Textile, leather, cloth, and footwear manufacturing	1	C13	Yes
CC31	CC31	Wood product manufacturing	1	C14	Yes
CC32	CC32	Pulp, paper, and converted paper manufacturing	1	C15	Yes
CC41	CC41	Printing	1	C16	Yes
CC51	CC51	Petroleum and coal product manufacturing	1	C17	Yes
CC52	CC52	Basic chemical and chemical product manufacturing	3	C18	Yes
CC53	CC53	Polymer product and rubber product manufacturing	1	C19	Yes
CC61	CC61	Non-metallic mineral product manufacturing	1	C20	Yes
CC71	CC71	Primary metal and metal product manufacturing	1	C21	Yes
CC72	CC72	Fabricated metal product manufacturing	1	C22	Yes
CC81	CC81	Transport equipment manufacturing	1	C23	Yes
CC82	CC82	Machinery and other equipment manufacturing	2	C24	Yes
CC91	CC91	Furniture and other manufacturing	2	C25	Yes
	DD	Electricity, gas, water, and waste services			
DD11	DD11	Electricity and gas supply	3	D26/ D27	Yes
DD12	DD12	Water, sewer, drainage, and waste services	3	D28/ D29	Yes
	EE	Construction			
EE11	EE11	Building construction	2	E30	Yes
EE12	EE12	Heavy and civil engineering construction	1	E31	Yes
EE13	EE13	Construction services	1	E32	Yes
FF11	FF	Wholesale trade	5	F	Yes
	GH	Retail trade and accommodation			
GH11	GH11	Motor vehicle & parts, and fuel retailing	2	G39/ G40	Yes
GH12	GH12	Supermarket, grocery, and specialised food retailing	2	G41	Yes
GH13	GH13	Other store-based and non-store retailing	4	G42/ G43	Yes
GH21	GH21	Accommodation and food services	2	H	Yes
	II	Transport, postal, and warehousing			
II11	II11	Road transport	1	I46	Yes
II12	II12	Rail, water, air, and other transport	3	I47/ I48/ I49/ I50	Yes

NZSIOC (level 3)	*PPI*	Description	Number of National Accounts Working Inds	*ANZSIC06* industry codes	Measured sector ([a] =formerly excluded)
II13	II13	Post, courier support, and warehouse services	3	I51/ I52/ I53	Yes
	JJ	Information media and telecommunications			
JJ11	JJ11	Information media services	3	J54/ J55/ J56/ J57	Yes
JJ12	JJ12	Telecommunication, Internet, and library services	2	J58/ J59/ J60	Yes
	KK	Financial and insurance services			
KK11	KK11	Finance	1	K62	Yes
KK12	KK12	Insurance and superannuation funds	3	K63	Yes
KK13	KK13	Auxiliary finance and insurance services	1	K64	Yes
	LL	Rental, hiring, and real estate services			
LL11	LL11	Rental and hiring services	1	L66	Yes[a]
LL12	LL12	Property operators and real estate services	3	L67	Yes[a]
	LL21	Ownership of owner-occupied dwellings	1		No
	MN	Professional and administrative services			
MN11	MN11	Professional, scientific, and tech services	5	M	Yes[a]
MN21	MN21	Administrative and support services	3	N	Yes[a]
OO11		Local government administration	1	O753	No
OO21		Central government admin, defence and public safety	3	O except for O753	No
PP11		Education and training	4	P	No
QQ11		Health care and social assistance	3	Q	No
	RS	Arts, recreation, and other services			
RS11	RS11	Arts and recreation services	3	R	Yes
RS21	RS21	Other services	3	S	Yes[a]

Note: The measured sector is defined as in Statistics New Zealand (2010). L77 was subsequently added to the definition of the measured sector (Statistics New Zealand, 2011) but is excluded from our coverage.

Appendix table 2: Production function estimates – *FTE* specification

	Ln(*FTE*)	Ln(*K*)	Ln(*M*)	Observations	*RTS*	R^2
Pooled IndFE	0.301***	0.118***	0.575***	1,166,616	0.993***	0.892
AA11	0.208***	0.0714***	0.776***	32,196	1.055***	0.796
AA12	0.105***	0.118***	0.771***	76,812	0.994	0.845
AA13	0.173***	0.110***	0.604***	65,373	0.887***	0.868
AA14	0.167***	0.104***	0.746***	9,900	1.017*	0.798
AA21	0.281***	0.0612***	0.733***	5,136	1.075***	0.86
AA31	0.144***	0.198***	0.642***	4,827	0.984	0.803
AA32	0.363***	0.0596***	0.556***	23,013	0.979***	0.842
BB11	0.252***	0.228***	0.529***	2,031	1.008	0.908
CC1	0.226***	0.0689***	0.719***	18,132	1.015***	0.964
CC21	0.328***	0.110***	0.557***	10,422	0.996	0.951
CC3	0.303***	0.0484***	0.632***	13,323	0.984***	0.958
CC41	0.255***	0.155***	0.584***	8,070	0.993	0.957
CC5	0.222***	0.117***	0.667***	7,614	1.006	0.961
CC61	0.227***	0.0858***	0.694***	3,882	1.007	0.967
CC7	0.290***	0.0813***	0.601***	18,363	0.972***	0.959
CC81	0.340***	0.0821***	0.556***	7,233	0.978**	0.931
CC82	0.302***	0.0919***	0.579***	17,325	0.973***	0.944
CC91	0.271***	0.0792***	0.639***	11,994	0.989**	0.951
DD1	0.245***	0.207***	0.515***	3,951	0.967***	0.965
EE11	0.213***	0.0588***	0.684***	50,931	0.956***	0.936
EE12	0.277***	0.104***	0.601***	7,326	0.982***	0.963
EE13	0.263***	0.0788***	0.631***	106,728	0.973***	0.929
FF11	0.287***	0.139***	0.602***	74,109	1.027***	0.898
GH11	0.299***	0.176***	0.519***	20,583	0.993*	0.904
GH12	0.323***	0.226***	0.484***	28,071	1.033***	0.902
GH13	0.340***	0.179***	0.531***	90,987	1.049***	0.876
GH21	0.220***	0.195***	0.632***	101,961	1.047***	0.909
II11	0.250***	0.148***	0.596***	28,563	0.994**	0.955
II12	0.275***	0.0735***	0.636***	4,338	0.984*	0.926
II13	0.288***	0.116***	0.610***	12,978	1.014**	0.927
JJ11	0.160***	0.113***	0.696***	7,785	0.969***	0.902
JJ12	0.317***	0.0865***	0.572***	2,496	0.975*	0.903
KK13	0.319***	0.0942***	0.510***	15,879	0.923***	0.789
KK1_	0.327***	0.119***	0.471***	5,607	0.918***	0.796
LL11	0.234***	0.247***	0.497***	12,357	0.979**	0.856
MN11	0.460***	0.0836***	0.416***	117,741	0.96***	0.844
MN21	0.417***	0.0326***	0.528***	44,397	0.978***	0.872
RS11	0.276***	0.0811***	0.585***	14,568	0.942***	0.847
RS21	0.331***	0.141***	0.540***	79,620	1.013***	0.913

Note: Obs counts have been rr3'ed. Each row is from a separate regression. All regressions also include time dummies and an AES dummy to capture differences across data sources. Significance based on robust standard errors. RTS means 'returns to scale' RTS significance indicators denote difference from constant returns to scale.

Appendix table 3: Production function estimates – Skill specification

Covariates	Ln(*FTE*)	Ln(*K*)	Ln(*M*)	Observ skill (*xb*)	Unobs skill (*wfe*)	Observations	*RTS*_Emp	*RTS*_wfe	*RTS*_xb	R^2
Pooled IndFE	0.301***	0.117***	0.567***	0.108***	0.273***	1,166,616	0.985***	0.956***	0.792***	0.894
AA11	0.208***	0.0703***	0.775***	0.0591	0.0117	32,196	1.054***	0.857***	0.904***	0.796
AA12	0.107***	0.116***	0.769***	-0.0263**	0.119***	76,812	0.992*	1.004	0.859***	0.846
AA13	0.172***	0.110***	0.603***	0.0238**	0.113***	65,373	0.885***	0.826***	0.737***	0.868
AA14	0.169***	0.0945***	0.744***	0.204***	0.276***	9,900	1.007	1.114**	1.043	0.8
AA21	0.283***	0.0560**	0.726***	0.203	0.288	5,136	1.065***	1.07	0.986	0.861
AA31	0.145***	0.196***	0.635***	0.0595	0.170***	4,827	0.976*	1.002	0.891**	0.804
AA32	0.367***	0.0529***	0.551***	0.107***	0.299***	23,013	0.971***	0.903***	0.711***	0.844
BB11	0.265***	0.225***	0.514***	-0.0978	0.246	2,031	1.004	0.985	0.641*	0.909
CC1	0.234***	0.0630***	0.709***	0.190***	0.283***	18,132	1.006*	1.055*	0.962*	0.965
CC21	0.337***	0.106***	0.544***	0.261***	0.359***	10,422	0.986***	1.009	0.911**	0.953
CC3	0.306***	0.0500***	0.623***	0.130***	0.262***	13,323	0.979***	0.934*	0.803***	0.958
CC41	0.256***	0.155***	0.570***	0.121***	0.268***	8,070	0.982***	0.993	0.847***	0.958
CC5	0.224***	0.115***	0.664***	0.0064	0.111	7,614	1.003	0.89*	0.786***	0.961
CC61	0.229***	0.0828***	0.688***	0.088	0.221***	3,882	0.999	0.991	0.859**	0.968
CC7	0.291***	0.0782***	0.598***	0.0425	0.300***	18,363	0.967***	0.976	0.718***	0.96
CC81	0.341***	0.0822***	0.550***	0.0651	0.267***	7,233	0.973***	0.899**	0.697***	0.932
CC82	0.305***	0.0903***	0.574***	-0.0287	0.206***	17,325	0.969***	0.871***	0.636***	0.945
CC91	0.273***	0.0815***	0.630***	0.0707*	0.195***	11,994	0.985***	0.907**	0.783***	0.952
DD1	0.254***	0.192***	0.511***	0.0475	0.357***	3,951	0.957***	1.061	0.751***	0.966
EE11	0.211***	0.0585***	0.681***	0.0809***	0.136***	50,931	0.951***	0.876***	0.82***	0.936
EE12	0.281***	0.102***	0.593***	0.0899*	0.274***	7,326	0.976***	0.969	0.785***	0.964
EE13	0.263***	0.0780***	0.626***	0.0667***	0.151***	106,728	0.967***	0.854***	0.771***	0.929
FF11	0.291***	0.143***	0.584***	0.0986***	0.290***	74,109	1.017***	1.016	0.825***	0.899
GH11	0.299***	0.170***	0.517***	0.255***	0.253***	20,583	0.986***	0.94**	0.942**	0.906
GH12	0.325***	0.226***	0.479***	0.107***	0.153***	28,071	1.03***	0.859***	0.812***	0.903
GH13	0.340***	0.184***	0.515***	0.153***	0.257***	90,987	1.04***	0.957***	0.853***	0.877

Covariates	Ln(*FTE*)	Ln(*K*)	Ln(*M*)	Observ skill (*xb*)	Unobs skill (*wfe*)	Observations	*RTS*_Emp	*RTS*_wfe	*RTS*_xb	R^2
GH21	0.220***	0.195***	0.631***	0.0466***	0.0442**	101,961	1.046***	0.87***	0.872***	0.909
II11	0.263***	0.138***	0.583***	0.117***	0.314***	28,563	0.984***	1.035**	0.838***	0.956
II12	0.285***	0.0667***	0.620***	0.0392	0.394***	4,338	0.972***	1.08	0.726***	0.928
II13	0.292***	0.111***	0.593***	0.237***	0.439***	12,978	0.996	1.142***	0.94	0.929
JJ11	0.159***	0.118***	0.685***	0.103	0.287***	7,785	0.962***	1.091**	0.906*	0.904
JJ12	0.316***	0.0946***	0.555***	0.103	0.269**	2,496	0.965**	0.919	0.752*	0.904
KK13	0.315***	0.0893***	0.504***	0.0321	0.399***	15,879	0.909***	0.993	0.626***	0.796
KK1_	0.341***	0.120***	0.465***	0.778***	0.0881	5,607	0.926***	0.673***	1.362**	0.799
LL11	0.245***	0.251***	0.478***	0.202***	0.336***	12,357	0.973***	1.065	0.93	0.859
MN11	0.453***	0.0881***	0.410***	-0.00899	0.398***	117,741	0.951***	0.896***	0.489***	0.851
MN21	0.421***	0.0257***	0.520***	0.151***	0.476***	44,397	0.967***	1.022	0.697***	0.878
RS11	0.278***	0.0840***	0.578***	0.173***	0.325***	14,568	0.939***	0.987	0.834***	0.849
RS21	0.334***	0.144***	0.525***	0.113***	0.207***	79,620	1.004*	0.876***	0.782***	0.914

Note: Obs counts have been rr3'ed. Each row is from a separate regression. All regressions also include time dummies and an AES dummy to capture differences across data sources. Significance based on robust standard errors. 'RTS" means returns to scale, based on alternative ways of increasing labour input. Using the notation from equations (1) and (7), RTS_Emp=$\beta_j^H + \beta_x^K + \beta_x^M$ *(hours margin); RTS_wfe=*$\beta_j^\theta + \beta_x^K + \beta_x^M$ *(unobserved skill margin); RTS_xb=*$\beta_j^X + \beta_x^K + \beta_x^M$ *(observed skill margin).RTS significance indicators denote difference from constant returns to scale.*

Appendix table 4: Industry-specific within-industry decompositions – *FTE* spec

FTE Period	Total within-industry Productivity growth	Continuers Change in productivity	Continuers due to differential growth of high v low productivity firms	Entrants	Join Sample	Exiters	Leave Sample
			GR Decomposition				
AA11: Horticulture and fruit growing	0.19%	0.63%	-0.13%	-0.42%	-1.36%	-0.04%	1.52%
AA12: Sheep, Beef cattle and Grain Farming	0.25%	0.55%	-0.03%	-0.39%	-0.28%	0.15%	0.24%
AA13: Dairy Cattle farming	-1.52%	-1.08%	0.14%	-0.39%	-0.05%	0.32%	-0.45%
AA14: Poultry, deer and Livestock Farming	1.12%	0.59%	0.14%	-0.03%	-0.04%	0.09%	0.37%
AA21: Forestry and Logging	1.81%	-2.20%	1.92%	1.89%	0.14%	-1.07%	1.13%
AA31: Fishing and Aquaculture	1.16%	-0.54%	-0.21%	0.41%	-0.48%	0.40%	1.57%
AA32: Agr, For, Fish Support ad Hunting	0.09%	-0.96%	0.65%	3.55%	-0.65%	0.34%	-2.83%
BB11: Mining	-3.13%	-2.82%	-0.80%	1.15%	-1.55%	-0.34%	1.23%
CC1: Food Beverage and Tobacco Mfrg	-0.70%	-0.40%	0.01%	-0.03%	0.17%	-0.59%	0.15%
CC21: Textile, Clothing, Footwear and Leather Manufacturing	1.06%	0.11%	0.52%	0.10%	-0.05%	-0.11%	0.49%
CC3: Wood and Paper Product Manufacturing	1.05%	0.12%	0.18%	0.55%	-0.42%	-0.06%	0.68%
CC41: Printing	-0.65%	-1.48%	0.38%	0.17%	-0.11%	-0.02%	0.40%
CC5: Petrochemical Mfrg	-0.40%	-0.49%	-0.24%	-0.20%	-0.97%	0.26%	1.25%
CC61: Non-Metallic Mineral Product Manufacturing	0.08%	-0.20%	-0.07%	0.59%	-0.38%	-0.69%	0.84%
CC7: Metal Product Manufacturing	-1.43%	-1.31%	-0.04%	-0.10%	-0.72%	0.08%	0.66%
CC81: Transport equipment mfrg	-0.64%	-2.06%	1.02%	0.16%	-1.36%	0.03%	1.56%
CC82: Machinery and equipment mfrg	0.15%	-0.65%	0.49%	-0.01%	-0.25%	0.01%	0.56%
CC91: Furniture and Other Manufacturing	0.02%	-0.66%	0.37%	0.03%	-0.16%	0.12%	0.32%
DD1: Electricity Gas, Water and Waste Servicesa	-3.35%	-3.29%	0.36%	-0.17%	-0.16%	-0.23%	0.14%
EE11: Building Construction	0.08%	-0.33%	0.11%	-0.01%	-0.32%	0.15%	0.48%
EE12: Heavy and Civil Engineering Construction	0.34%	-0.43%	0.37%	0.33%	0.26%	-0.07%	-0.13%
EE13: Construction Services	0.90%	0.13%	0.30%	0.13%	0.10%	0.07%	0.16%
FF11: Wholesale Trade	1.01%	0.23%	0.32%	0.27%	0.47%	-0.07%	-0.21%
GH11: Motor Vehicle Retailing and Services	0.21%	-0.55%	0.49%	0.04%	0.29%	0.19%	-0.24%
GH12: Food Retailing	2.95%	3.17%	-0.14%	-0.28%	-0.58%	0.03%	0.75%
GH13: Other Retailing	2.51%	1.39%	0.13%	0.08%	0.12%	0.15%	0.64%
GH21: Accommodation and Food Services	0.57%	0.50%	0.08%	0.06%	0.17%	-0.01%	-0.23%
II11: Road Transport	0.01%	-0.31%	0.21%	0.16%	0.06%	-0.02%	-0.08%

FTE Period	Total within-industry Productivity growth	Continuers		Entrants	Join Sample	Exiters	Leave Sample
		Change in productivity	due to differential growth of high v low productivity firms				
II12: Rail, Water, Air and Other Transport	0.63%	0.97%	-0.25%	-0.02%	-0.22%	-0.02%	0.17%
II13: Postal, Courier and Warehousing Services	0.67%	0.09%	0.26%	0.21%	0.40%	-0.06%	-0.23%
JJ11: Information Media Services	0.76%	0.03%	0.15%	0.49%	0.16%	-0.31%	0.25%
JJ12: Telecomms, internet and library services	1.78%	2.67%	-1.21%	0.23%	-0.59%	0.02%	0.65%
KK13: Auxiliary Finance and Insurance	-1.12%	-1.06%	0.70%	-0.03%	-0.99%	0.24%	0.02%
KK1_: Business Services other than Aux. Finance Insurance	2.11%	2.93%	-0.51%	0.28%	-2.11%	0.35%	1.17%
LL11: Rental and Hiring Services	1.48%	1.47%	0.16%	-0.04%	-0.65%	-0.03%	0.57%
MN11: Professional Scientifica nd Technical Services	-0.34%	-0.95%	-0.01%	0.05%	-0.01%	-0.03%	0.61%
MN21: Administrative and Support Services	-0.15%	-0.55%	-0.10%	0.25%	-0.05%	-0.27%	0.55%
RS11: Arts and Recreation Services	1.12%	0.50%	-0.77%	-1.12%	-0.51%	0.57%	2.46%
RS21: Other Services	0.42%	-0.13%	0.25%	-0.01%	-0.04%	0.13%	0.22%

Appendix table 5: Industry-specific within-industry decompositions – Skill spec

Period	Total within-industry Productivity growth	Continuers: Change in productivity	Continuers: due to differential growth of high v low productivity firms	Entrants	Join Sample	Exiters	Leave Sample
			GR Decomposition				
AA11: Horticulture and fruit growing	0.16%	0.64%	-0.13%	-0.43%	-1.37%	-0.03%	1.50%
AA12: Sheep, Beef cattle and Grain Farming	0.18%	0.51%	-0.04%	-0.41%	-0.28%	0.17%	0.23%
AA13: Dairy Cattle farming	-1.56%	-1.10%	0.13%	-0.41%	-0.05%	0.32%	-0.45%
AA14: Poultry, deer and Livestock Farming	1.10%	0.54%	0.13%	-0.07%	-0.01%	0.12%	0.38%
AA21: Forestry and Logging	1.78%	-2.03%	1.81%	1.92%	0.14%	-1.08%	1.01%
AA31: Fishing and Aquaculture	1.18%	-0.40%	-0.18%	0.43%	-0.48%	0.39%	1.42%
AA32: Agr, For, Fish Support ad Hunting	-0.06%	-0.95%	0.60%	3.26%	-0.65%	0.30%	-2.62%
BB11: Mining	-3.12%	-2.50%	-0.37%	1.24%	-2.34%	-0.35%	1.18%
CC1: Food Beverage and Tobacco Mfrg	-0.66%	-0.32%	-0.01%	-0.04%	0.10%	-0.56%	0.18%
CC21: Textile, Clothing, Footwear and Leather Manufacturing	1.04%	0.17%	0.46%	0.07%	-0.14%	-0.09%	0.58%
CC3: Wood and Paper Product Manufacturing	1.10%	0.18%	0.16%	0.50%	-0.40%	0.00%	0.66%
CC41: Printing	-0.59%	-1.39%	0.38%	0.16%	-0.12%	-0.01%	0.38%
CC5: Petrochemical Mfrg	-0.36%	-0.44%	-0.24%	-0.20%	-0.96%	0.25%	1.23%
CC61: Non-Metallic Mineral Product Manufacturing	0.11%	-0.14%	-0.09%	0.59%	-0.36%	-0.70%	0.81%
CC7: Metal Product Manufacturing	-1.46%	-1.24%	-0.13%	-0.11%	-0.72%	0.08%	0.66%
CC81: Transport equipment mfrg	-0.63%	-1.97%	0.98%	0.16%	-1.49%	0.06%	1.63%
CC82: Machinery and equipment mfrg	0.19%	-0.58%	0.44%	-0.03%	-0.31%	0.02%	0.64%
CC91: Furniture and Other Manufacturing	-0.03%	-0.67%	0.34%	0.02%	-0.18%	0.13%	0.34%
DD1: Electricity Gas, Water and Waste Servicesa	-2.82%	-2.65%	0.25%	-0.14%	-0.15%	-0.23%	0.09%
EE11: Building Construction	0.07%	-0.32%	0.11%	-0.02%	-0.32%	0.15%	0.47%
EE12: Heavy and Civil Engineering Construction	0.45%	-0.37%	0.39%	0.32%	0.23%	-0.05%	-0.06%
EE13: Construction Services	0.89%	0.15%	0.28%	0.12%	0.11%	0.08%	0.15%
FF11: Wholesale Trade	1.13%	0.35%	0.26%	0.24%	0.39%	-0.05%	-0.07%
GH11: Motor Vehicle Retailing and Services	0.19%	-0.53%	0.49%	0.02%	0.25%	0.20%	-0.24%
GH12: Food Retailing	2.83%	3.05%	-0.16%	-0.30%	-0.56%	0.04%	0.76%
GH13: Other Retailing	2.58%	1.48%	0.15%	0.03%	0.08%	0.18%	0.66%

Period	Total within-industry Productivity growth	Continuers: Change in productivity	Continuers: due to differential growth of high v low productivity firms	Entrants	Join Sample	Exiters	Leave Sample
GH21: Accommodation and Food Services	0.55%	0.50%	0.07%	0.04%	0.14%	0.00%	-0.20%
II11: Road Transport	0.05%	-0.22%	0.18%	0.14%	0.01%	-0.01%	-0.05%
II12: Rail, Water, Air and Other Transport	0.98%	1.27%	-0.28%	-0.04%	-0.18%	0.00%	0.21%
II13: Postal, Courier and Warehousing Services	0.92%	0.44%	0.13%	0.13%	0.21%	-0.03%	0.04%
JJ11: Information Media Services	0.98%	0.28%	0.11%	0.51%	0.18%	-0.31%	0.21%
JJ12: Telecomms, internet and library services	2.11%	3.10%	-1.28%	0.19%	-0.65%	0.05%	0.70%
KK13: Auxiliary Finance and Insurance	-0.60%	-0.61%	0.62%	-0.07%	-1.05%	0.32%	0.19%
KK1_: Business Services other than Aux. Finance Insurance	2.05%	2.85%	-0.42%	0.24%	-2.28%	0.33%	1.32%
LL11: Rental and Hiring Services	1.50%	1.57%	0.08%	-0.12%	-0.75%	0.01%	0.70%
MN11: Professional Scientific and Technical Services	0.13%	-0.49%	-0.04%	0.03%	-0.09%	-0.03%	0.75%
MN21: Administrative and Support Services	0.10%	-0.22%	-0.11%	0.19%	-0.14%	-0.24%	0.62%
RS11: Arts and Recreation Services	1.10%	0.62%	-0.85%	-1.15%	-0.57%	0.59%	2.46%
RS21: Other Services	0.40%	-0.09%	0.22%	-0.03%	-0.08%	0.14%	0.25%

Appendix table 6: Summary of industry-specific productivity

	FTE specification			Skill specification		
ANZSIOC Industry	Ann average within-industry *mfp* growth (11 years)	Mean weight	Mean *mfp* across 12 years	Ann average within-industry *mfp* growth (11 years)	Mean weight	Mean *mfp* across 12 years
AA11	0.2%	1.0%	-16.6%	0.2%	1.1%	-18.8%
AA12	0.2%	2.0%	-19.2%	0.3%	2.0%	-18.5%
AA13	-1.6%	2.1%	-17.8%	-1.5%	2.1%	-17.3%
AA14	1.1%	0.4%	-13.7%	1.1%	0.4%	-14.9%
AA21	1.8%	0.5%	4.3%	1.8%	0.5%	6.0%
AA31	1.2%	0.2%	-4.4%	1.2%	0.2%	-3.1%
AA32	-0.1%	0.8%	1.4%	0.1%	0.8%	2.7%
BB11	-3.1%	1.1%	31.0%	-3.1%	1.1%	34.3%
CC1	-0.7%	13.5%	3.7%	-0.7%	14.0%	-0.3%
CC21	1.0%	1.2%	-12.8%	1.1%	1.2%	-16.1%
CC3	1.1%	3.8%	-10.3%	1.1%	3.8%	-11.3%
CC41	-0.6%	0.9%	-16.0%	-0.6%	0.8%	-15.3%
CC5	-0.4%	4.8%	27.0%	-0.4%	4.7%	27.3%
CC61	0.1%	1.0%	-5.1%	0.1%	1.0%	-5.5%
CC7	-1.5%	3.2%	-3.2%	-1.4%	3.2%	-3.2%
CC81	-0.6%	0.8%	-16.6%	-0.6%	0.8%	-15.3%
CC82	0.2%	3.0%	-4.9%	0.2%	3.0%	-4.6%
CC91	0.0%	0.8%	-17.6%	0.0%	0.8%	-18.5%
DD1	-2.8%	4.3%	25.6%	-3.4%	4.2%	28.0%
EE11	0.1%	3.5%	16.0%	0.1%	3.4%	18.4%
EE12	0.5%	2.7%	-12.0%	0.3%	2.7%	-12.4%
EE13	0.9%	4.2%	-4.2%	0.9%	4.1%	-2.0%
FF11	1.1%	6.3%	-0.7%	1.0%	6.1%	1.7%
GH11	0.2%	1.1%	-12.9%	0.2%	1.2%	-12.6%
GH12	2.8%	1.3%	-4.0%	3.0%	1.4%	-8.1%
GH13	2.6%	3.4%	-4.6%	2.5%	3.5%	-6.1%
GH21	0.6%	3.9%	-26.0%	0.6%	4.0%	-29.1%
II11	0.1%	2.4%	-11.3%	0.0%	2.4%	-11.8%
II12	1.0%	3.6%	-13.4%	0.6%	3.6%	-13.0%
II13	0.9%	2.4%	1.2%	0.7%	2.5%	-0.2%
JJ11	1.0%	1.6%	1.8%	0.8%	1.6%	3.7%
JJ12	2.1%	2.6%	9.9%	1.8%	2.5%	12.6%
KK13	-0.6%	0.9%	10.5%	-1.1%	0.8%	16.7%
KK1_	2.0%	3.4%	22.3%	2.1%	3.3%	24.9%
LL11	1.5%	0.8%	1.0%	1.5%	0.8%	0.9%
MN11	0.1%	5.7%	3.5%	-0.3%	5.4%	9.8%
MN21	0.1%	2.2%	0.3%	-0.2%	2.3%	-0.6%
RS11	1.1%	0.7%	-6.7%	1.1%	0.7%	-7.7%
RS21	0.4%	1.9%	-12.7%	0.4%	1.9%	-11.9%

Glossary

AES	Statistics New Zealand's Annual Enterprise Survey
ANZSIC06	Australia and New Zealand Standard Industry Classification 2006
EMS	Employer Monthly Schedule: (PAYE tax return submitted to IRD by employers)
FHK	Reference to Foster et al. (2001)
FTE	Full-time-equivalent employment
GFC	Global Financial Crisis
GR	Reference to Griliches & Regev (1995)
GST	Goods and Services Tax
HLFS	Statistics New Zealand's Household Labour Force Survey
IDI	Statistics New Zealand's Integrated Data Infrastructure
IR10	Inland Revenue form for Accounts information and Financial Summary statement
IRD	Inland Revenue Department
LBD	Statistics New Zealand's Longitudinal Business Database
LBF	Statistics New Zealand's Longitudinal Business Frame
mfp	Multi-factor productivity
NZSIOC	New Zealand Standard Industry Output Categories
PAYE	Pay-as-you-earn system of income tax deductions from wages and salaries
PPI	Statistics New Zealand's Producer Price Index
RTS	Returns to scale
STEM	Science, Technology, Engineering and Mathematics
wfe	Worker fixed effects (as described in section 2.1)

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