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Do New Zealand firms catch up to the domestic productivity frontier?

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Abstract

New Zealand has a poor productivity track record at the level of the aggregate economy and there is little evidence of productivity "catching up" towards that of leading economies. At the same time, there is a very wide distribution of productivity levels among firms within the same industries and it is at least possible that some New Zealand firms are among the most productive in their industry globally. In this case, the relevant question is why new technologies and production techniques do not diffuse from high- to low-productivity firms within New Zealand.

As such, this paper explores technological diffusion among New Zealand firms using a model of convergence in which a firm's multi-factor productivity (MFP) growth depends on its ability to catch up to its industry's productivity frontier. We find that convergence to the frontier is statistically and economically important, indicating a tendency for technology to diffuse from high- to low-productivity firms. The results also indicate that firms in the services sector have slower convergence speeds than firms in the primary and goods-producing sectors. This raises questions about the extent to which firms in some parts of the services sector are exposed to, and influenced by, the domestic productivity frontier.

We also extend the base model to assess the impact of exporting and foreign ownership on MFP growth and the speed of convergence. This allows for the possibility that by exposing firms to new technologies and larger markets, international openness may enhance incentives and opportunities to adopt leading production techniques, thereby increasing the speed with which firms catch up to the productivity leader. The results suggest that firms that are more open internationally experience faster MFP growth and speed of convergence. However, greater international openness at the industry level can slow the speed with which low-productivity firms converge towards the frontier. This may reflect the fact that exporting or foreign-owned firms tend to have relatively high productivity levels, so that faster MFP growth in these firms increases the average "distance to frontier" for other firms in the industry.

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1 Introduction

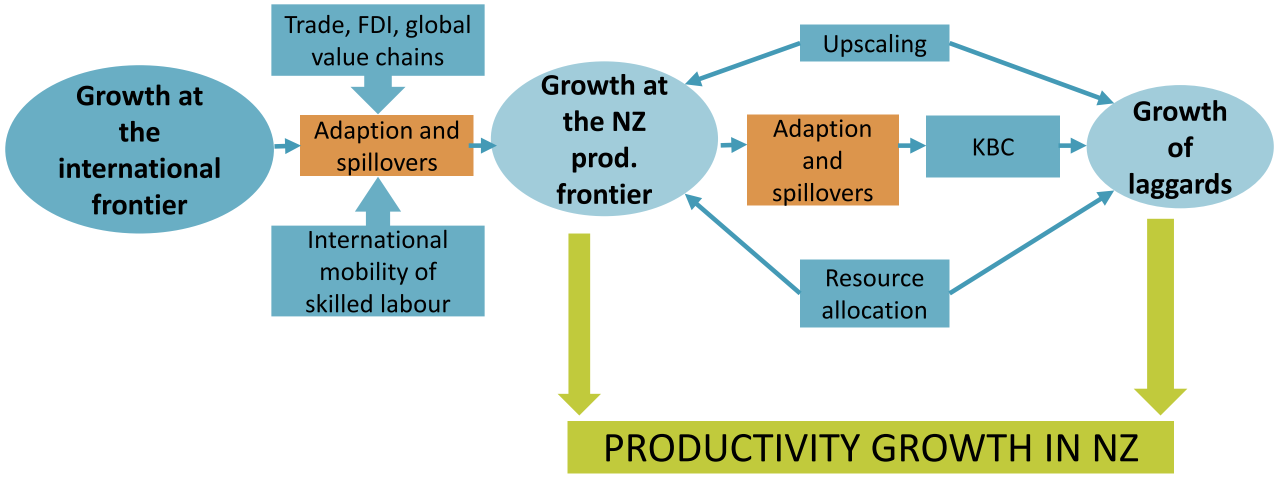
New Zealand has a poor productivity track record at the level of the aggregate economy and has failed to "catch-up" to higher productivity countries. This is unusual internationally and New Zealand has the dubious distinction of being the only OECD country that had both a below-average level of labour productivity in 1980 and below-average productivity growth since 1980 (Conway & Meehan, 2013). On the face of it, this suggests that New Zealand is not converging to the international productivity frontier and that there are issues with the extent to which new technology and production techniques diffuse across the border into the New Zealand economy.

However, large productivity dispersions across firms within narrowly-defined industries complicate the basic aggregate-level convergence story. For example, given productivity differences at the firm-level, it is possible that the most productive firms in a laggard country such as New Zealand are more productive than at least some of the firms in a leading country. Some domestic firms may even be operating at, or close to, the international technological frontier in their industry even though economy-wide data indicate that New Zealand's productivity has been falling further behind in aggregate. Indeed, differences in the extent to which new technologies spread across firms within an economy are an important source of cross-country income differences. For example, while adoption lags for new technologies across countries have fallen, penetration rates once technologies are adopted have diverged (Comin & Ferrer, 2013).

Reflecting the importance of going beyond the aggregates, Figure 1 sketches out broad economic drivers that influence firm productivity growth. It differentiates between firms that are at the international frontier, firms that are at the domestic frontier (but behind the international frontier) and laggard firms.

In this framework, innovation at the international frontier leads to new technologies, which can then diffuse to other firms. However, this diffusion process is not costless and is subject to various constraints. Technology transfer is a "sticky process" influenced by a number of factors, such as the degree of economic integration and regulatory barriers. Vintage models of technology also highlight that the uptake of new technology may not necessarily be optimal for firms who have already invested in an older form of technology. In addition, the ability to absorb new technologies varies among firms due to differences in factors such as management quality and workforce skills. Therefore, it is likely that at first, new global technologies are only accessible to the most productive firms in the domestic economy – that is, the domestic frontier firms. Then, once technologies have been adapted to local conditions by domestic frontier firms, these technologies can diffuse to laggard firms. This is consistent with evidence that the productivity growth of laggard firms within a country is more strongly related to productivity developments of the most advanced domestic firms as opposed to those of the globally most advanced (Bartelsman, Haskel, & Martin, 2008; Iacovone & Crespi, 2010; OECD, 2015).

Figure 1 Productivity growth and international-frontier firms, domestic-frontier firms and laggards



Source: Adapted from OECD (2015)

To explore the role of technological diffusion within New Zealand, this paper uses a model of multi-factor productivity (MFP) growth to examine convergence of laggard New Zealand firms to the domestic productivity frontier (ie, the right-hand side of Figure 1). It assesses the extent to which low-productivity firms converge towards firms operating at the domestic productivity frontier in each industry. This process of convergence captures the idea of technology spillovers from high- to low-productivity firms, where a firm's distance from the technological frontier is used as a measure of the potential for productivity-enhancing technological transfer.

This convergence model is estimated both with and without firm-level fixed effects. While this is done mainly for empirical reasons, in broad terms the different specifications are analogous to the idea of absolute-β versus conditional-β convergence in the cross-country growth literature. That is, in the fixed-effects model, firms are assumed to operate with different technologies even in the long run. This is analogous to the way that conditional convergence implies that countries have different long-run growth paths. As such, an important feature of the modelling strategy is that firm-level productivity convergence does not necessarily imply a narrowing in the width of the MFP distribution across firms in the same industry.

Estimating the model on New Zealand firm data shows that convergence to the frontier is statistically and economically important, indicating a tendency for technology to spillover from high- to low-productivity firms. The further a given firm is from the productivity frontier, the greater the scope for productivity improvements arising from technological catch up. Not surprisingly, the speed of convergence to firm-specific steady states (that are some distance behind the technological frontier) is estimated to be much faster than the speed of absolute convergence to the domestic frontier.

The results also indicate some important differences in firm-level productivity dynamics in different parts of the New Zealand economy. Firms in the services sector either have much slower convergence speeds or a much larger dispersion of firm-specific steady states than firms in other parts of the economy. This raises questions about the extent to which firms in some parts of the services sector are exposed to, and influenced by, the productivity frontier in their industry within New Zealand.

Despite the finding of productivity convergence at the firm level, there is no evidence to suggest that the width of the MFP distribution across New Zealand firms has generally become smaller at the industry level. Instead, the number of industries in which the productivity distribution has reduced is about the same as the number of industries in which it has expanded. This suggests that a number of influences – including firm entry and exit, firm-level steady states and productivity shocks – have offset the impact of convergence dynamics in some parts of the New Zealand economy.

As well as assessing convergence among New Zealand firms, the model can be extended to investigate a range of potential drivers of MFP growth. To demonstrate this, the model is used to assess the influence of international openness – as measured by exporting and foreign direct investment (FDI) – on the MFP growth of laggard firms. These two aspects of international openness are modelled as influencing MFP growth of laggards both directly and indirectly via the speed with which firms catch up to the productivity leader in their industry. Reflecting the versatility of the model, these openness measures are assessed at both the firm level and the industry level.

The results suggest that international openness can increase the speed with which new technologies (broadly defined) diffuse from high- to low-productivity firms. At the firm level, increased exporting or foreign ownership increases MFP growth by increasing the speed of convergence to the technological frontier. In addition, firms that export or have significant foreign ownership are more prevalent at the technological frontier, and therefore make an important contribution to productivity growth through shifting out the domestic technological frontier and thus allowing for greater technology transfer.

At the industry level, a greater share of employment in exporting or foreign-owned firms has a positive direct impact on firm productivity performance, consistent with previous work showing that international openness stimulates competition and increases incentives to adopt new technologies. However, greater international openness in an industry can slow the speed with which low-productivity firms converge towards the frontier. This may reflect the fact that exporting or foreign-owned firms tend to have relatively high productivity levels, so that faster MFP growth in these firms increases the average "distance to frontier" for other firms in the industry.

The rest of the paper proceeds as follows. Section 2 outlines the modelling framework and some measurement issues that influence the choice of estimation technique. Section 3 outlines the data and Section 4 presents results. Conclusions are offered in Section 5.

2 Model specification and estimation

This section describes the convergence model used and estimation issues. It then outlines the relationship between productivity convergence and the productivity distribution.

2.1 The model

Following Griffith, Redding, and Simpson (2009), the model used to examine productivity catch-up at the firm level in New Zealand incorporates several important features from the empirical literature on cross-country convergence. First, current productivity levels depend on past productivity levels, which captures the empirical regularity of persistence in productivity. Second, the model allows for the observed regularity of heterogeneous productivity levels across firms, as firms differ in their underlying capabilities. Third, consistent with the theoretical and empirical literature on the role of imitation and technology transfer in driving productivity growth, the model allows for productivity catch-up.

Consider a general model of convergence in which MFP in a laggard firm is related to the MFP in frontier firms according to the following auto-regressive distributed lag (1,1) co-integrating relationship:

$$lnA_{ijt} = \gamma_i + \alpha_1 lnA_{ijt-1} + \alpha_2 lnA^F_{jt} + \alpha_3 lnA^F_{jt-1} + u_{ijt} \tag{1}$$

where i indexes firm, j indexes industry and t indexes time. The variable lnA_{it} is the MFP of a laggard firm and lnA^F_{jt} is MFP at the technological frontier, which is the productivity level of the leading firms in the industry (see Section 3.1 for details). The variable γ_i is a firm-specific fixed effect. A full set of time dummies, T_t, is included in the model to control for common technological shocks and macroeconomic fluctuations, and ε_{it} is idiosyncratic error, so:

$$u_{ijt} = T_t + \varepsilon_{ijt} \tag{2}$$

Equation (1) can be transformed into an error correction model of productivity catch-up by assuming long-run homogeneity between lnA_{it} and lnA^F_{jt-1}. That is, $1-\alpha_1 = \alpha_2 + \alpha_3$. This yields:

$$\Delta lnA_{ijt} = \gamma_i + \rho \Delta lnA^F_{jt} + \lambda ln\left(\frac{A^F_j}{A_{ij}}\right)_{t-1} + u_{ijt} \tag{3}$$

where $\rho = \alpha_2$ and $\lambda = \alpha_1 + \alpha_2 = 1-\alpha_1$.

In words, productivity growth in laggard firms is modelled as a function of changes in the industry's technological frontier, ΔlnA^F_{jt}, and the "distance to frontier", $ln\left(\frac{A^F_j}{A_{ij}}\right)_{t-1}$. The first of these captures the direct effect of MFP growth at the frontier on MFP growth in laggard firms. The second is the size of the gap between a laggard firm's level of productivity and that of the productivity frontier for its industry. The parameter λ is therefore the speed of convergence. A positive estimated coefficient on the distance to the frontier means that the productivity growth of laggard firms is faster than the productivity growth of firms that are at, or close, to the frontier. This implies that technology is diffusing from frontier firms to laggard firms, with firms that are further behind the frontier having the most potential to benefit.

In Section 4.2, this base model is extended to assess the impact of exporting and foreign ownership at the firm and industry levels on firm-level productivity growth. These variables are modelled as having a direct effect on firm productivity growth (η), as well as an indirect effect via the speed of convergence (τ):

$$\Delta lnA_{ijt} = \gamma_i + \rho \Delta lnA^F_{jt} + \lambda ln\left(\frac{A^F_j}{A_{ij}}\right)_{t-1} + \sum_k \tau_k \left[X_{it-1} ln\left(\frac{A^F_j}{A_{ij}}\right)_{t-1}\right] + \sum_k \eta_k X_{it-1} + u_{ijt} \tag{4}$$

2.2 Estimation issues

There are a number of issues in estimating Equations (3) and (4), including: measurement error, endogeneity and selection bias.

Measurement error and mean reversion

Measures of MFP growth at the firm level are noisy – while the median of $\Delta ln A_{it}$ is 0.3%, the range is ±500%. For a number of firms, this high degree of variation is unlikely to reflect true changes in MFP.

This measurement error could result in a positive estimated speed of convergence due to mean reversion rather than productivity catch-up. Firms that recently experienced negative transitory shocks (whether caused by measurement error or other factors) are more likely to experience productivity growth, while firms that recently experienced positive transitory shocks are more likely to experience poor productivity growth. Note that the situation is worse in the case of fixed effects than OLS estimation since the fixed effects method removes long-term variation, leaving only short-term variation, which may mean it is more vulnerable to short-term shocks and mean reversion (Iacovone & Crespi, 2010).

To mitigate measurement error, we identify approximately 4% of observations as outliers using Cook's distance from the OLS estimation of Equation (3), and remove these observations from our analysis. Outliers tend to be smaller, younger, and are more likely to be exporters and foreign owned (see Appendix A for details).

We also run of number of robustness tests. First, we find that the estimated speeds of convergence are robust to the inclusion of lagged variables in the model to account for short-term mean reversion. These specifications indicate that some of the positive estimated convergence coefficient is due to mean reversion (see Section 4). We also test the relationship between MFP growth and initial MFP levels using a categorical measure of productivity rather than a continuous one, following Griffith et al. (2009). While it is difficult to measure a firm's precise level of MFP, we can be more confident in identifying which productivity decile the firm belongs to. Using this decile measure, we find faster convergence speeds for firms that are further from the frontier (see Table B.2 in Appendix B**Error! Reference source not found.** for details). Finally, since measurement error tends to decrease with firm size, we run weighted regressions, with firm weights proportional to employment size. We find that the results from these weighted regressions are qualitatively the same as results from the unweighted regressions.[1]

Co-integration, endogeneity and bias

Another challenge in estimating Equation (3) is that $ln\, A_{ijt}$ appears on both the left- and right-hand sides. In this situation, unless $ln\, A_{ijt}$ and $ln\, A^F_{jt}$ are co-integrated, OLS is likely to underestimate the true speed of convergence while fixed-effects methods are likely to overestimate the convergence speed. A two-step residual-based co-integration test indicates co-integration. However, the short time series and unbalanced nature of the data suggests caution in taking this result at face value.[2] Therefore, OLS and fixed effects estimators can be thought of as providing lower and upper bounds respectively on the true convergence speed.

We also estimate Equations (3) and (4) using generalised method of moments (GMM), with additional lags used as instrumental variables to control for endogeneity bias. Given the unbalanced nature of our panel and the possibility of multiple endogenous variables, we would ideally use difference-GMM (Arellano & Bover, 1995) and/or system-GMM (Blundell & Bond, 1998). Unfortunately, our data do not meet the assumptions of these methods.[3] However, we do use fixed-effects GMM (FE-GMM), by instrumenting A_{ijt-1} with deeper lags (in particular, A_{ijt-2} and/or A_{ijt-3}). Tests suggest that these lag variables are good instruments and thus FE-GMM may eliminate some of the endogeneity bias from the fixed-effects estimation. However, an issue with using deeper lags as instruments is that it worsens the selection effect as firms now have to be present for three or four years to be included in the analysis.

Selection bias

As touched on above, selection bias poses another challenge in estimating Equations (3) and (4) as firms must be economically active at both time *t* and *t-1* to be included in the analysis. Exiting firms will generally be poor performers with lower productivity than surviving firms. This result holds empirically for a wide range of countries including New Zealand (Doan, Devine, Nunns, & Stevens, 2012; Law & McLellan, 2005).

We do not control for selection bias in this paper, although it is possible to do so using a Heckman selection correction model (Heckman, 1976). Nishimura, Nakajima, and Kiyota (2005) and Griffith et al. (2009) apply such a model to Japanese and UK data respectively, and both find significant selection bias, although the impact on the convergence speed in the case of the UK is very small. The Japanese

[1] These robustness results are not reported here, but are available by request.

[2] Tests of non-stationary and co-integration tend to be designed for strongly balanced panels with a long time dimension and relatively few cross-sectional units. In contrast, we have a very large number of cross-sectional units but a relatively short time-series. The data are also unbalanced due to firm entry and exit and uneven data coverage across firms. Over the 11 year period of 2000 to 2011, each firm has on average only four observations.

[3] Based on Arellano-Bond tests for autocorrelation of the residuals, our data violates the difference-GMM moment condition $\mathrm{E}\left[ln\, A_{ijt-l}\Delta\varepsilon_{ijt}\right]=0$ for each $t \geq 3, l \geq 2$. That is, the past productivity of laggards is correlated with changes in the current transitory shock. As discussed in, Roodman (2009b), system-GMM is almost always overidentified and most of our regressions fail the Hansen test for validity of additional instruments. Moreover, the additional moment condition of $\mathrm{E}\left[\Delta\, ln\, A_{ijt-1}\varepsilon_{ijt}\right]=0$ for each $t \geq 3$ is often validated. That is, the lagged difference of the productivity of laggards is correlated with the current transitory shock.

analysis finds a more substantial impact, and estimates that not taking into account firm exits results in a 1.5 percentage point downward bias in the speed of convergence (8.8% a year versus 10.3% a year).

2.3 Convergence and the productivity distribution

An important feature of the above modelling strategy is that firm-level productivity convergence does not necessarily imply a narrowing in the width of the MFP distribution across firms in the same industry. Depending on the relationship between the initial productivity distribution and the steady-state distribution, the standard deviation of productivity across firms in the same industry may increase, decrease or remain constant over time, irrespective of convergence dynamics (Griffith, Redding, & Simpson, 2005).

This is analogous to the cross-country convergence literature at the macro level in which absolute β-convergence is necessary but not sufficient for σ-convergence (Young, Higgins, & Levy, 2008).[4] Specifically, cross-country productivity levels can exhibit absolute β-convergence without exhibiting σ-convergence if random shocks to the growth process are relatively large. There is an even wider set of circumstances under which conditional β-convergence is not sufficient for σ-convergence given different balanced growth paths due to cross-country differences in factors such as institutional settings (Young et al., 2008). In this scenario, countries converge towards their own steady-state productivity levels, resulting in long-run productivity dispersion.

Although the different approaches to estimating Equations (3) and (4) are taken mainly for empirical reasons, there is a conceptual difference between the firm-level convergence models with and without fixed effects that is broadly analogous to absolute- versus conditional-β convergence. OLS assumes that all firms are converging towards a common steady-state level of MFP, consistent with absolute convergence. Fixed-effects estimation, however, assumes that firms have different long-run steady-state levels of MFP, consistent with the idea of conditional convergence. As with the macroeconomic literature, this admits the possibility of a long-run steady state in which laggard firms stay an equilibrium distance behind the frontier due to differences in innovative capabilities and other firm-specific characteristics. As such, the estimated speed of convergence is likely to be faster in the case of fixed-effects estimation than in the case of OLS.

3 Data and descriptive statistics

This section first outlines the data used in the estimation. It then provides some descriptive statistics, including information on: the change in industry MFP distributions, transitions of firm productivity and the characteristics of frontier firms versus laggard firms.

3.1 Data

The model is estimated using data from the Longitudinal Business Database (LBD) component of Statistics New Zealand's Integrated Data Infrastructure from 2000 to 2011. LBD is a rich source of firm-level data with employment and financial information from the Inland Revenue Department, merchandise exports from Customs and various business surveys from Statistics New Zealand (Fabling, 2009).

[4] β-convergence explores the cross-sectional relationship between productivity growth and initial productivity levels while σ-convergence examines the evolution of cross-sectional measures of the productivity dispersion. β-convergence is used in much of the macroeconomic literature on cross-country and regional convergence (see for example Barro & Sala-I-Martin, 1991, 1992). β-convergence has also been applied in the firm convergence literature by Chevalier, Lecat, and Oulton (2012).

The population of the LBD is all economically significant firms.[5] The model is estimated across private-sector firms only.[6] Firms with no employees are also excluded, given that working-proprietor-only firms are subject to a higher degree of measurement error.[7] In addition, the method developed in Fabling (2011) is used to correct for "broken" longitudinal firm identifiers.

Firm-level data on gross output and capital, labour and intermediate inputs is derived from the Annual Enterprise Survey (AES) supplemented with tax (IR10) data. Because the primary purpose of AES is the production of National Accounts, it is the most comprehensive source of financial statistics in the LBD. All large firms and a sample of small firms are included in AES, which amounts to about 16,000 firms or around 4% of the firm population each year. For firms not covered by AES, the equivalent data is drawn from IR10 tax forms.

Each firm is assigned to one industry over its lifetime based on its predominant employment share. About 50 different industry classifications are used in the study, which generally correspond to Australian and New Zealand Standard Industrial Classification (ANZSIC) 2- or 3-digit industries. The level of industry disaggregation is largely determined by the availability of suitably disaggregated producer price indexes and an adequate numbers of firms within an industry. The industries included in the analysis are across the primary, goods-producing and services sectors of the New Zealand economy.[8]

Firm-level MFP is calculated using industry-level Cobb-Douglas production functions. These equations allow for the possibility of non-constant returns to scale and include labour, capital and intermediate inputs as well as firm-specific fixed effects and year dummies. Further details are given Appendix C.

The domestic technology frontier in each industry is defined as the 90th percentile of firm-level MFP in that industry. That is, the top 10% of an industry's firms are defined to be at the technological frontier. Although there are several options for defining an industry's technological frontier – such as the average of the top quartile of firm MFP (Bartelsman et al., 2008) or the MFP of the top firm or the average MFP of the top three firms (Griffith, Redding, & Simpson, 2006; Griffith et al., 2009) – the advantage of using the 90th percent is that it is less sensitive to outliers and therefore fluctuates less over time.

Firm characteristics – variables X_{it} in Equation (4) – include: firm size, age, exporter types and foreign ownership. Firm size is the sum of working proprietors and the rolling-mean employee count. Firm age is the current year minus the firm's year of birth.[9]

Firms are classified as either domestic- or foreign-owned using the method outlined in Sanderson (2013). That is, a firm is classified as foreign-owned if it reports majority foreign ownership or a positive response to the company tax return question: "Is the company controlled or owned by non-residents?". However, coverage rates for these data sources are positively correlated with firm size, suggesting that the extent of foreign-ownership may be understated or infrequently updated for small firms. This could generate missing values and cause discontinuity or gaps in our FDI measure. To mitigate against this issue, firms are classified as foreign owned firms if they have a positive response to the foreign-

[5] We refer to what Statistics New Zealand terms "enterprises" as "firms" throughout this paper. A firm is economically significant if it meets any one of the following criteria: 1) annual expenses or sales (subject to goods and services tax (GST)) of more than $30,000; 2) 12-month rolling mean employee count of more than 3; 3) a GST-exempt industry except residential property leasing and rental; 4) part of a group of enterprises; 5) positive annual GST turnover and involved in agriculture or forestry.

[6] Production input and output variables and other supplementary variables are mainly collected at the enterprise level. Enterprises which are classified as "public administration and safety", "education and training" and "health care and social assistance" under the 2006 Australia New Zealand Standard Industrial Classification (ANZSIC) are excluded from the analysis.

[7] For example, the capital input of a working-proprietor firm may include a specific proportion of the proprietor's housing expenses as well as the physical capital associated with the business.

[8] We use Statistics New Zealand terminology: a sector is a group of related-industries.

[9] Year of birth data for firms born after 1986 is likely to be more reliable than for firms born before 1986. A goods and services tax (GST) was introduced in October 1986 and after this date, birth year is recorded as the first time a firm filed a GST return. Before 1986, information from the Economic Master Register is used. There is a noticeable spike in the number of businesses with a recorded birth year of 1986, likely due to the introduction of GST.

ownership variable for 50% or more of their longitudinal tax records. As a result, the measure of foreign ownership used in the paper is time-invariant.

Three data sources from LBD are used to measure the extent to which firms export: customs data, the survey of international trade in services and goods & services tax (GST) filings. Customs provides firm-level information on international merchandise exports. The international trade in services census collects information on trade in commercial services and royalties.[10] Information on zero-rated GST provides dollar values of goods and services sold overseas (Fabling & Sanderson, 2014).

These data sources are collected by different government agencies for particular purposes and the resulting information is not necessarily consistent.[11] Therefore, these different sources of exporting information are combined to derive an indicator of exporting at the firm level. A firm is considered to engage in exporting activity if at least one of these data sources reports a non-zero number. Then, firms that do not report exporting activity in any year are classified as non-exporters; firms reporting exporting activity in more than half of all years are classified as frequent exporters; and all others firms are classified as occasional exporters. That is, the measure of exporting is also time invariant.

As mentioned, the relationship between foreign ownership and exporting at the industry level on firm-level MFP growth is also estimated using Equation (4) above. These industry-level variables are constructed from the firm-level data.[12] The FDI measure is the industry share of employment in foreign-owned firms while the exporting measure is the industry share of employment in exporting firms. As a robustness test, the share of value add in foreign-owned firms and exporting firms were also used, and were found to not materially change the results.

3.2 Descriptive statistics

Table 1 provides Summary statistics for the key variables in Equation (3). There is substantial variation in productivity growth rates and the distance to the frontier across firms and industries. After excluding outliers, MFP growth across all firms in the sample averages about 0.9% a year with a standard deviation of 16.9%. Although much reduced, this indicates that there is still substantial variation in MFP growth in the sample even after outliers have been discarded. However, this variation is similar to UK firms from Griffith et al. (2009) (0.3% mean and 12.9% standard deviation).

The average MFP level of frontier firms is just over 1.5 times that of laggard firms. The average MFP growth rate for firms at the technological frontier in their industry is 0.26% a year, which is considerably less than for all firms in general. On the face of it, these results suggest that laggard firms generally do converge towards frontier firms.

Table 1 Descriptive statistics

Variable	Mean	Standard deviation
MFP growth $\Delta \ln A_{ijt}$	0.0094	0.1694
Distance-to-the-frontier $\ln\left(\frac{A_j^F}{A_{ij}}\right)_{t-1}$	0.4260	0.3058
Change in the frontier $\Delta \ln A_{jt}^F$	0.0026	0.0208

All industries display persistent productivity dispersion across firms. As discussed in Section 2, these persistent dispersions may reflect variation in firms' innovative capabilities and the fact that it takes time

[10] Commercial services are all services and royalties excluding travel, transportation, insurance, and government services.

[11] For example, some firms in LBD report merchandise exports but their zero-rated GST value is nil.

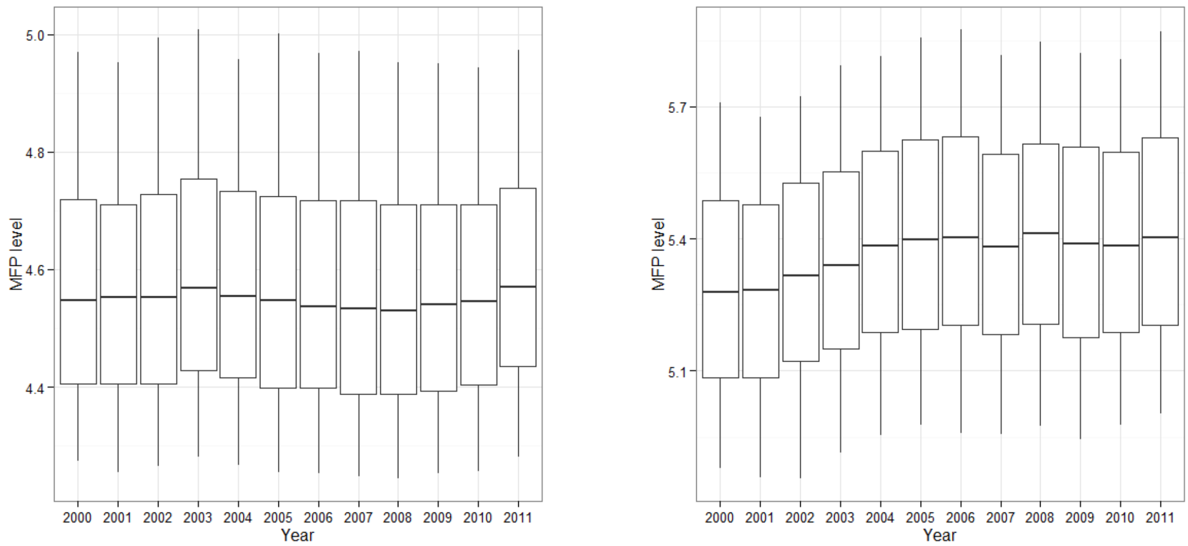
[12] Ideally, other sources of data could be used to measure exporting and foreign ownership at the industry level. However, Statistics New Zealand does not provide this information and it is not available via other data sources (in particular, New Zealand is not included in the EU/WorldKLEMS database).

to catch-up with a constantly advancing frontier. By way of example, Figure 2 shows the evolution of the productivity distribution for two industries: primary product and machinery equipment wholesaling, which exhibits relatively fast productivity growth, and residential and non-residential building construction, with stagnating productivity growth. Both industries exhibit persistent productivity dispersion.

Figure 2 Evolution of the MFP distribution in two selected industries

Residential and non-residential building construction

Primary product and machinery equipment wholesaling



Notes:

1. The line in the middle of the box plot is the median and the edges of the box are the lower and upper quartiles. The low and high points of the lines coming out of the boxes indicate the 10th and 90th percentiles.
2. Primary product and machinery equipment wholesaling includes agricultural product wholesaling (F331); mineral, metal and chemical wholesaling (F332); timber and hardware goods wholesaling (F333); specialised industrial machinery and equipment wholesaling (F341); and other machinery and equipment wholesaling (F349). Building construction includes residential (E301) and non-residential (E302) building construction.
3. Residential and non-residential building constructions includes 8,983 firms a year on average over the 2000-2011 period, and primary product and machinery equipment wholesaling industry includes 3,572 firms.

As discussed in Section 2, the modelling framework used in the paper can accommodate increases, decreases or constant productivity distributions over time. Figure 3 summarises change in the productivity distribution in all industries in the population. In the 50 industries used in the analysis, the standard deviation of MFP was lower in 2011 than in 2000 in 28, while it was higher in 22.

Figure 3 Change in the standard deviation of MFP within 50 industries, 2000-2011

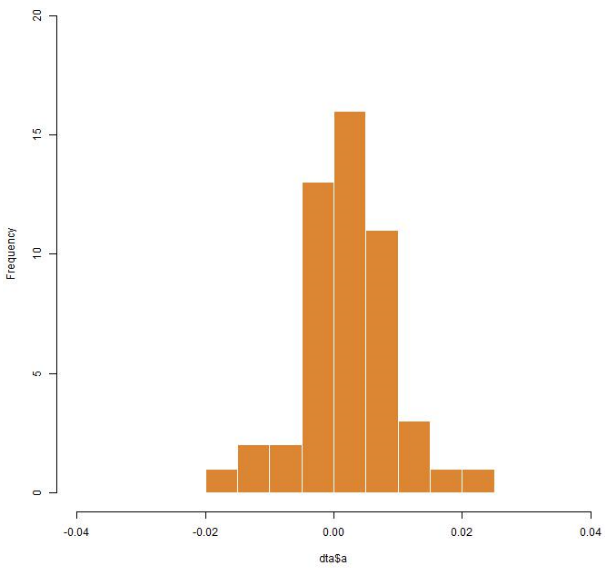


Table 2 shows the proportion of firms that move between deciles in the firm-level distribution of MFP in their industry between 2000 and 2011, as well as the rate of firm exit.[13] As expected, the exit rate is higher among lower productivity firms. For example, only 17% of firms in decile 1 in 2000 are economically active in 2011, compared with 44% of firms in decile 10 in 2000. Many firms that manage to survive do not change their position in the distribution much, with most firms either staying in the same decile or moving to an adjacent decile. For example, slightly more than half of surviving firms that were in decile 2 in 2000 were either still in decile 2 in 2011 or had moved into decile 1 or decile 3. Consistent with the empirical framework, however, the persistence in the cross-sectional dispersion of MFP is accompanied by individual firms changing their position within the productivity distribution.

Firms at the productivity frontier (ie, decile 10 firms) also change over the ten year period. About 41% of firms that were on the frontier in 2000 remain on the frontier in 2011, and about 20% of firms that were in decile 9 in 2000 are on the frontier in 2011. Just 3% of firms that were in the lowest decile in 2000 make it to the frontier by 2011.

Table 2 Transition matrix of firm productivity

		MFP decile, 2011										
		1	2	3	4	5	6	7	8	9	10	Exit rate
MFP decile, 2000	1	0.33	0.18	0.13	0.09	0.07	0.06	0.05	0.04	0.03	0.03	0.83
	2	0.19	0.20	0.15	0.13	0.08	0.08	0.07	0.05	0.04	0.02	0.78
	3	0.13	0.15	0.15	0.15	0.13	0.08	0.08	0.06	0.05	0.02	0.74
	4	0.09	0.13	0.15	0.14	0.13	0.12	0.08	0.07	0.05	0.04	0.69
	5	0.07	0.10	0.11	0.13	0.15	0.13	0.12	0.09	0.08	0.04	0.66
	6	0.05	0.07	0.08	0.12	0.14	0.14	0.14	0.11	0.10	0.05	0.64
	7	0.04	0.05	0.07	0.10	0.11	0.14	0.14	0.15	0.12	0.08	0.62
	8	0.03	0.05	0.06	0.06	0.09	0.12	0.16	0.17	0.15	0.11	0.60
	9	0.02	0.04	0.05	0.05	0.07	0.08	0.11	0.16	0.20	0.20	0.59
	10	0.02	0.03	0.02	0.03	0.04	0.05	0.08	0.12	0.20	0.41	0.56

Notes:

1. Deciles are defined by industries rather than over the whole population.

[13] Firm exits can be temporary or permanent exits. Firms that exit temporarily become economically active in later periods.

3.3 Characteristics of frontier and laggard firms

Firms that have higher MFP levels tend to be larger, more export oriented and more likely to be foreign-owned than firms further down the productivity distribution in the same industry (Table 3). These differences in the characteristics of firms at different points in the MFP distribution are confirmed using a pooled logistic regression, which shows that frontier firms are more likely to be larger, foreign owned, exporters and younger (see Appendix D)

Table 3 Descriptive statistics for laggard and frontier firms

	Average frontier firm	Average laggard firm	Average decile 1 laggard firm	Average decile 9 laggard firm
MFP level	0.397	0.041	-0.72	0.33
Firm size	38.3	13.5	5.0	27.0
Firm age	12	11	11	14
Foreign ownership (time invariant)	7.8%	2.1%	1.8%	4.8%
Occasional exporter (time invariant)	15.1%	17.5%	14.1%	15.7%
Intensive exporter (time invariant)	33.3%	20.9%	18%	27.6%

4 Results

This section presents the results from estimating the base convergence model (Equation (3)), and then looks at whether the speed of convergence differs by sector and industry. It then uses the extended convergence model (Equation (4)) to look at whether international openness influences the convergence speed.

4.1 Base convergence model

In the simplest form of the model (Equation (3)), change in the productivity frontier and distance to the frontier are regressed on firm-level MFP growth. The results from different specifications of this model are given in Table 4.

In all specifications of the model, the distance-to-frontier coefficient is positive and significant. This indicates that all else equal, firms that are further behind the productivity frontier in their industry have faster rates of productivity growth.

As expected and outlined in Section 2, the OLS estimates of the speed of convergence are smaller than the fixed-effects estimates. This is because OLS assumes that all firms are converging towards a common frontier productivity level, while fixed-effects assumes that each firm is converging towards its own steady-state productivity level, reflecting its underlying innovative capability.

The OLS results estimate a speed of convergence of 0.18 a year (column 1). While this appears to be fast, holding the growth in the frontier at its mean value (0.0026), a firm that has the average MFP level for a decile 1 firm (-0.72) will take around 11 years to increase its MFP level to 50% of the frontier level.

The coefficient on the frontier growth term is also positive and significant in all specifications. That is, laggard firms in industries where the productivity growth of frontier firms is faster experience faster productivity growth, suggesting greater growth in the frontier increases the opportunities for technological diffusion.

Across the different fixed-effects models, the estimates for the speed of convergence and change in the frontier coefficients are broadly similar. This includes FE-GMM, where additional lags are used as instrumental variables to control for endogeneity bias, suggesting that the results are robust to the specification. In Column (5), lags of the dependent variable (MFP growth) are added to a basic fixed-effects specification. The coefficient on the lag of MFP growth is negative, suggesting some degree of short-term mean reversion.

The estimation results in Columns (1)-(5) of Table 4 assume a linear relationship between the distance to the frontier and MFP growth. Adding a squared distance-to-the-frontier term to the estimations suggests that MFP growth is faster for firms that are further behind the frontier, but that the speed of convergence increases at a decreasing rate (Columns (6) and (7) of Table 4). That is, the difference in the speed of convergence between a decile 9 firm (ie, close to the frontier) and a decile 8 firm is larger than the difference between the speed of convergence for a decile 2 firm and a decile 1 firm.

It is also possible that the speed of convergence may have changed over time. For example, firm dynamism in the USA has reportedly decreased in recent years (see for example Decker, Haltiwanger, Jarmin, & Miranda, 2014), which may have also had implications for firm convergence towards the productivity frontier.[14] To investigate the impact of the Great Recession on the speed of convergence across New Zealand firms, the specifications in columns 8 and 9 of Table 4 include a dummy variable for post-2008 observations. While the speed of convergence has increased slightly post-2008, the change is so small that while statistically significant, it is not economically significant: 0.174 versus 0.180 for the OLS convergence model and 0.685 versus 0.693 for the fixed-effects model.

In addition, this slight increase in the speed of convergence may reflect that our modelling does not explicitly account for patterns of firm exit. That is, the Great Recession may have had a cleansing effect (Foster, Grim, & Haltiwanger, 2014), with the exit rate among low productivity firms increasing and these exit patterns may be driving the slight increase in the measured speed of convergence. Initial investigations suggest that firm exit rates increased post-Recession, although further work is needed to uncover the effect of this increase on productivity growth.[15]

[14] While we are not aware of work that looks at the rate of convergence over time for the USA, work on French firms finds that the speed of convergence decreased between 1992 and 2004 (Chevalier, Lecat, & Oulton, 2012).

[15] In other work, the Productivity Commission is investigating this issue.

Table 4 Base convergence model results

Dep. Var: MFP growth ΔlnA_{it}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance to frontier	0.176*** (0.0013)	0.6875*** (0.0017)	0.5716*** (0.0189)	0.6826*** (0.0306)	0.7113*** (0.005)	0.1968*** (0.0025)	0.801*** (0.0055)	0.174*** (0.0015)	0.685*** (0.0035)
Change in the frontier	0.111*** (0.0121)	0.3723*** (0.0113)	0.3535*** (0.0163)	0.4101*** (0.0218)	0.3181*** (0.0157)	0.1121*** (0.0121)	0.3776*** (0.0114)	0.1096*** (0.012)	0.371*** (0.0115)
Squared distance to the frontier						-0.0147*** (0.0018)	-0.0917*** (0.0048)		
Post-2008 dummy x distance to frontier								0.0054** (0.0023)	0.0082** (00035)
Lag of MFP growth					-0.0205*** (0.0027)				
Lag of change in the frontier					-0.2552*** (0.0153)				
IV for A_{ijt-1}: A_{ijt-2}	No	No	Yes	No	No	No	No		
IV for A_{ijt-1}: A_{ijt-2} and A_{ijt-3}	No	No	No	Yes	No	No	No		
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes
Observations	455,892	455,892	304,383	218,889	326,403	455,892	455,892	455,892	455,892
R^2	0.0812	0.0637	0.3278	0.3523	0.0552	0.0816	0.0766	0.0812	0.0637

Notes:

1. Column 1-5 is the simplest base model. Column 1 is OLS regression, 2 is fixed effects, 3 is FE-GMM with A_{ijt-2} instrumenting for A_{ijt-1}, 4 is FE-GMM with A_{ijt-2} and A_{ijt-3} instrumenting for A_{ijt-1}, 5 is fixed effects with additional lags to account for serial correlation. Columns 6 and 7 include a squared distance-to-the-frontier term: 6 is OLS and 7 is fixed effects. Columns 8 and 9 include an interaction term of a post-2008 dummy (1 for the years 2008 onwards and 0 otherwise) and the distance to the frontier.
2. Regressions are estimated on laggard firms for 2001-2011. Outliers are excluded. Standard errors in brackets are clustered at the firm level.
3. R^2 for column (1) is adjusted R^2, for column (2) and (5) is overall R^2, for column (3) and (4) is centred R^2 from Stata output. Note that these different measures of R^2 are not directly comparable.
4. * significant at 10% level, ** significant at 5% level, *** significant at 1% level

Convergence by sector and industry

The base model estimation results reported in Table 4 pool across industries and thereby impose common coefficients. There may, however, be parameter heterogeneity across industries – for example, knowledge spillovers may occur more easily in some industries than in others. To test for this possibility, Equation (3) is estimated separately for the primary sector, goods-producing sector (and the manufacturing sub-sector) and services sector.[16] The equation is also estimated separately in each of the 50 industries in the sample.

To the best of the authors' knowledge, Nishimura et al. (2005) is the only other paper that explores differences in convergence speed across firms in different sectors of the economy.[17] They find that firms in manufacturing industries tend to have faster rates of convergence than firms in non-manufacturing industries.

The results of estimating Equation (3) at the broad sector level are reported in Table 5. In the OLS estimations, the speed of convergence is fastest in the goods-producing sector, followed by the primary sector and then much slower in the services sector. In the manufacturing sector, which is a sub-set of the goods-producing sector, the speed of convergence is estimated to be about the same as in the primary sector.[18]

There are also differences in the coefficients on the MFP growth of frontier firms across sectors. The productivity growth of firms in the primary sector is more responsive to growth in the frontier than firms in the goods-producing sector, and firms in the services sector are once again the least responsive. On average, a primary sector firm in an industry where the frontier is growing 5% a year will have MFP growth that is 1% faster than a primary sector firm in an industry with a stagnant frontier. In contrast, a services sector firm in an industry where the frontier is growing 5% will have MFP growth that is 0.004% faster than a firm in an industry with a stagnant frontier.

Estimates from the fixed-effects model give smaller variation in the speed of convergence and change in frontier coefficients. The services sector still has a slower rate of convergence than the primary and goods-producing sectors, but it has a faster rate of convergence than the manufacturing sector. Likewise, the coefficient on the change in the frontier for the services sector is lower than the coefficient for the primary and goods-producing sectors but higher than that of the manufacturing sector.

The differences between the OLS and fixed-effects estimates are perhaps unsurprising in light of the key methodological difference between the two estimation approaches. In the fixed-effects models, unobserved firm heterogeneity is removed. If the dispersion of this unobserved heterogeneity differs across sectors, then that may indicate differences in the extent to which firms in different sectors are influenced by spillover dynamics within their sector. Indeed, variation in firm-level fixed effects is larger across firms in the services sector than across firms in other parts of the economy (Figure 4). This is consistent with the OLS results showing smaller impacts of growth in the frontier and distance to frontier effects in the services sector.

[16] The primary sector consists of the following 1-digit ANZSIC industries: agriculture, forestry & fishing and mining. The goods-producing sector consists of: manufacturing; electricity, gas, water and waste services; and construction. The services sector consists of: wholesale trade; retail trade; accommodation & food services; transport, postal & warehousing; information media & telecommunications; financial & insurance services; rental, hiring & real estate services, professional, scientific & technical services; administrative and support services; arts & recreation services; and other services.

[17] Nishimura et al. (2005) use an industry dummy approach to assess the speed of convergence to the domestic productivity frontier for firms in the manufacturing and non-manufacturing sectors in Japan. We estimate the regressions separately for each sector to allow for heterogeneity in both the intercept and the distance-to-the-frontier coefficient.

[18] The manufacturing sector is the goods-producing sector excluding 1.) construction and 2.) electricity, gas, water & waste services.

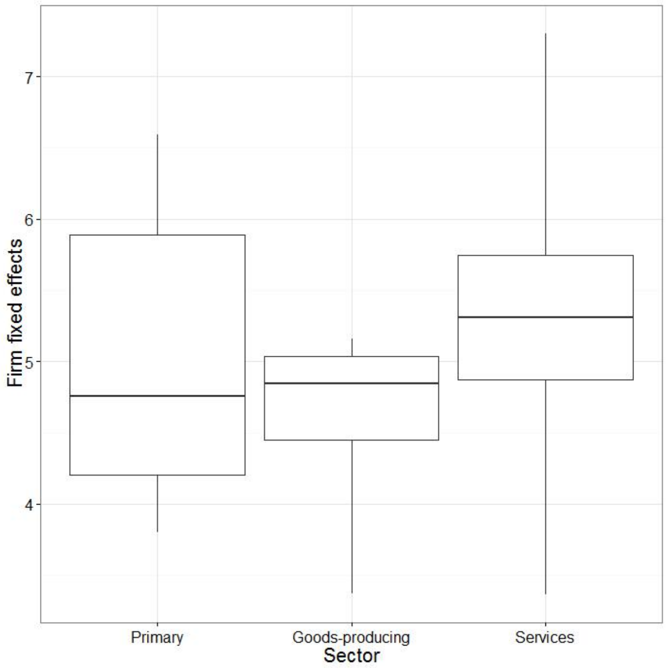
Table 5 Base convergence model by sector

Dep. Var: MFP growth ΔlnA_{it}	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Distance to frontier	0.2097*** (0.0033)	0.2367*** (0.0027)	0.158*** (0.0016)	0.2005*** (0.003)	0.7267*** (0.0092)	0.7298*** (0.0069)	0.6709*** (0.0043)	0.6002*** (0.0067)
Change in the frontier	0.2014*** (0.0326)	0.1444*** (0.0158)	0.0767*** (0.0177)	0.1579*** (0.0189)	0.4137*** (0.0326)	0.3827*** (0.0158)	0.3558*** (0.0177)	0.3319*** (0.0189)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies	No	No	No	No	Yes	Yes	Yes	Yes
Sector	Primary	Goods-producing	Services	Manufacturing[4]	Primary	Goods-producing	Services	Manufacturing[4]
Observations	63,780	114,558	277,554	54,342	63,780	114,558	277,554	54,342
R^2	0.1059	0.1127	0.0701	0.1186	0.1005	0.0993	0.0539	0.1109

Notes:

1. Regressions are estimated on laggard firms for 2001-2011. Outliers are excluded. Standard errors in brackets are clustered at the firm level.
2. Columns 10-13 are OLS estimates, columns 14-17 are fixed effects estimates. The R^2s in columns 10-13 are adjusted R^2, and for columns 14-17 are overall R^2 from Stata output.
3. * significant at 10% level, ** significant at 5% level, *** significant at 1% level
4. The 'Manufacturing' sector is a sub-set of the 'Goods-producing' sector that includes only manufacturing industries (ie, excludes electricity, gas, water & waste supply and construction industries).

Figure 4 Dispersion of firm fixed effects by sector



Notes:

1. The line in the middle of the box plot is the median and the edges of the box are the lower and upper quartiles. The low and high points of the lines coming out of the boxes indicate the 10th and 90th percentiles.

Because the sector results may still mask industry-level heterogeneity, Equation (3) is run separately for each of the 50 industries in the sample.[19] The estimated convergence speeds are graphed in Figure 5 and Figure 6 for the OLS and fixed-effects models respectively. Consistent with the sector results reported above, the OLS results show that services-sector industries are clustered near the slow end of the industry speed of convergence distribution. However, a few service industries also have some of the fastest industry-convergence speeds in the economy. In broad terms, accommodation & food services; retail trade and wholesale trade have relatively fast convergence speeds, while administrative & support services; finance & insurance and professional, scientific & technical services have slow convergence speeds.

The fixed-effects results are different, with service industries spread throughout the speed of convergence distribution. As noted above, the differences between the OLS and fixed-effects estimates reflect industry differences in the distribution of firms' underlying innovative capabilities as captured by the firm-level fixed effects.

[19] Of course, these regressions exclude the industry-level variables for the change in the frontier, so Equation (3) becomes $\Delta lnA_{it} = \gamma_i + \lambda ln\left(\frac{A^F}{A_i}\right)_{t-1} + u_{it}$

Figure 5 OLS estimates of convergence speed by industry

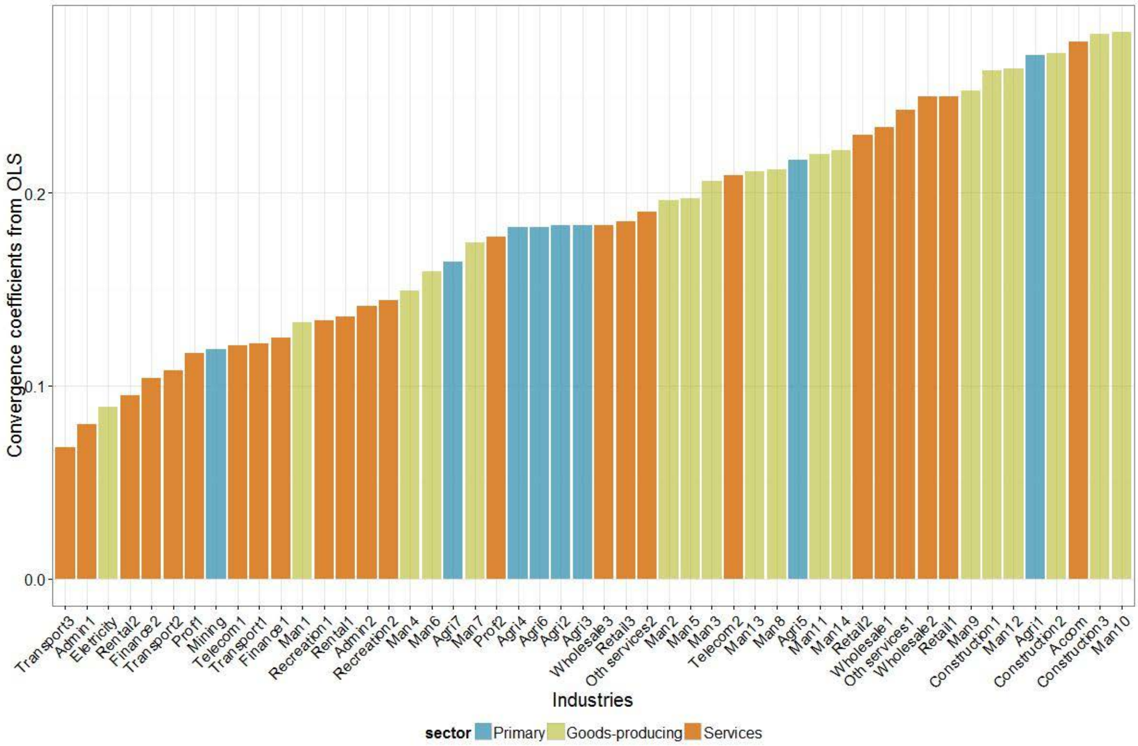
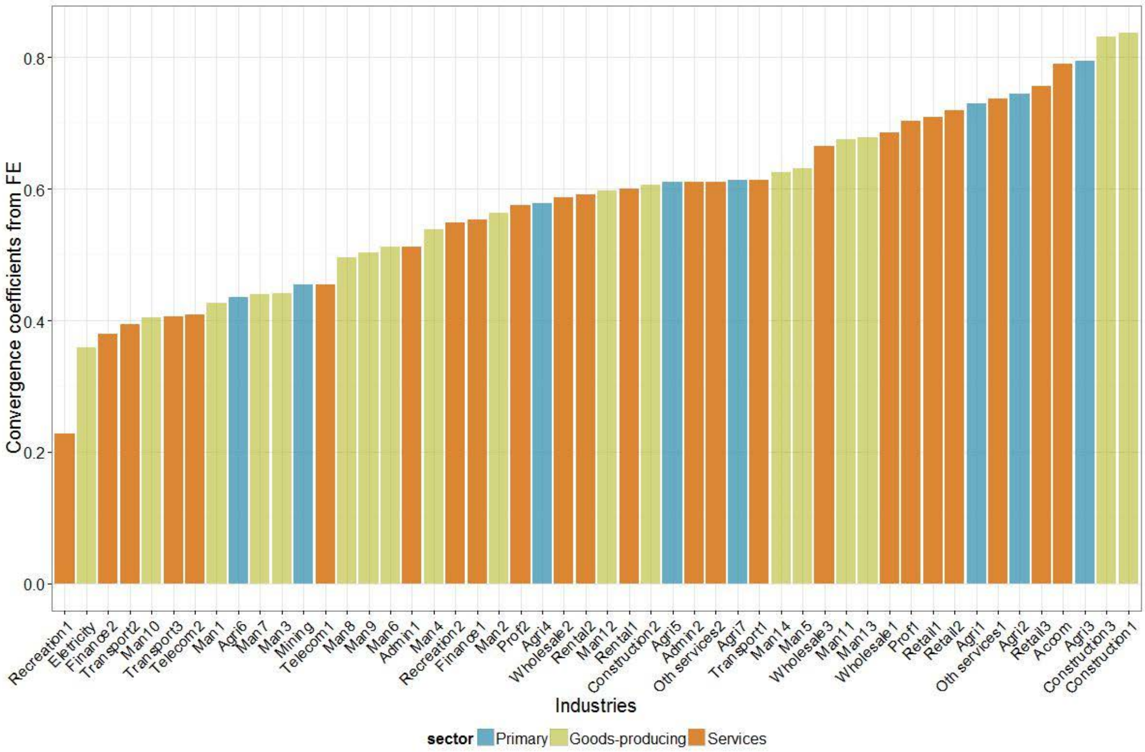


Figure 6 Fixed-effects estimates of convergence speed by industry



Notes:

1. Regressions are estimated on laggard firms for 2001-2011. Outliers are excluded.
2. Separate regressions are estimated for each industry.
3. Industries are categorised according to their ANZSIC 1-digit codes, with sequential numbering for each sub-industry. Some of the 1-digit industries have been abbreviated as follows: 'Agriculture' is Agriculture, forestry & fishing; 'Electricity' is Electricity, gas, water and waste services; 'Wholesale' is Wholesale trade; 'Retail' is Retail trade; 'Accommodation' is Accommodation & food services; 'Transport' is Transport, postal & warehousing; 'Telecom' is Information media & telecommunications; 'Finance' is Financial & insurance services; 'Rental' is 'Rental, hiring & real estate services'; 'Profession' is Professional, scientific & technical services; 'Admin' is Administrative & support services; 'Recreation' is 'Arts & recreation services'.

4.2 The extended convergence model

We now use the extended convergence model specified in Equation (4) to explore the influence of exporting and foreign ownership on the speed of convergence. These two measures of international openness are assessed at both the firm and industry level. Further, the direct effect on firm MFP growth and the indirect effect via the speed of convergence are both assessed.

Firm-level exporting and FDI

Does productivity growth and the speed of convergence differ for firms with different degrees of exposure to international markets? To examine this question, time-invariant FDI dummies and export intensity dummies are incorporated into Equation (4) to differentiate between foreign-owned and domestically-owned firms, as well as non-exporters, occasional exporters and frequent exporters.[20] In addition, other firm characteristics (specifically firm age and size) are also included in the model.

Why might foreign-owned firms have, on average, different productivity growth rates or convergence speeds than domestically-owned firms? It may take time for firms entering a foreign market to learn about local market conditions, consumer preferences and business practices. This makes it more costly for firms to operate abroad than domestically. As such, foreign-owned firms must have some advantage over domestic firms that offsets these additional costs. For example, this could be in the form of superior technology, scale economies, greater market power, or through owning a patent.

This suggests that foreign firms may undergo a learning-by-doing process when they enter a foreign market. Once this learning process is complete, however, these firms are likely to have greater productivity potential relative to domestic firms. As such, foreign-owned firms are likely to have higher productivity growth and higher speeds of convergence than domestically-owned firms. In the context of Equation (4), this would show up as positive coefficients on both the direct and indirect effects of foreign ownership.

In a similar way, there are likely to be learning and selection effects for exporting firms. Given the high fixed costs associated with entering export markets, only the most productive firms are likely to export. However, exporting can also enhance productivity growth via learning – for example, about new technologies – and increased scale effects. As such, exporting firms may have higher productivity growth and speeds of convergence relative to non-exporting firms. Therefore, the coefficients on both the direct and indirect effects from exporting in Equation (4) are also likely to be positive. Moreover, firms that export on a consistent basis are likely to reap greater productivity benefits. This suggests that firms that export frequently will convergence more quickly than firms that export occasionally.

Using firm-level variables in Equation (4) to capture foreign ownership and exporting raises the possibility of endogeneity. For example, if firms with higher productivity growth are targeted for foreign acquisition, then productivity growth may be driving foreign-ownership rather than the other ways around.[21] However, the use of time-invariable measures of firm exporting and FDI mitigates this potential issue (see Section 3).

We apply both a standard OLS specification and an OLS specification with additional lags of the dependent and some of the explanatory variables to account for serial correlation (Kao & Chiang, 1999). The use of time-invariant variables precludes the use of the fixed-effects specifications.

Firm age and size both have a positive direct effect on MFP growth at the firm level, although the coefficient on the direct effect of firm age is quite small (Table 6). The indirect effect of firm age on the

[20] To our knowledge, the only existing paper that examines the impact of *firm-level* characteristics on the speed of convergence is Iacovone and Crespi (2010), which examines the impact of technology efforts and trade integration on the speed of *labour* productivity convergence towards the domestic and international frontiers (using the international frontier data of Bartelsman et al., 2008). It finds that technology effects rather than trade exposure are key to speeding up convergence toward the international frontier. Trade exposure does play a role in enhancing productivity growth, but only for firms that are already close to the international frontier.

[21] Fabling and Sanderson (2014) suggests that high-performing New Zealand firms are targeted for foreign acquisition, based on a number of performance measures including labour productivity levels, capital intensity, size and average wages. However, the relationship between foreign acquisition and MFP levels is less clear, with foreign-acquisition targets concentrated in both extremes of the MFP distribution. In addition, the argument of a selection effect is likely to be weaker in the case of MFP *growth*.

speed of convergence is negative, suggesting that young firms converge more quickly towards the domestic productivity frontier. However, the coefficient on the indirect effect is small and therefore not economically significant. The indirect effect of firm size is positive, suggesting that relatively large firms are likely to converge more quickly towards the domestic productivity frontier.

Foreign ownership is estimated to have a positive direct and indirect effect in the OLS estimation (Column (18)), indicating that foreign-owned firms tend to have faster MFP growth and speeds of convergence. To give some indication of the magnitude, for a firm that is the median distance behind the domestic productivity frontier (0.36), foreign ownership increases its speed of convergence by 0.9 percentage points from 7.2% to 8.1%. However, in the OLS specification with additional lags (Column (19)), both the direct and indirect effects of foreign ownership are statistically insignificant. Thus, there is some evidence that foreign ownership increases the speed of convergence.

The direct effect of being an occasional exporter is not significant, while the direct effect of being a frequent exporter is positive and significant in both specifications. The indirect effect for occasional exporters is positive and significant in both estimations. For a firm at the median distance to the frontier (0.36), the speed of convergence is estimated to be 6.8% a year for non-exporters and 7.3% for occasional exporters. The interaction term for frequent exporters is positive for both OLS specifications but not statistically significant. While the speed of convergence estimate for occasional exporters is higher than for frequent exporters, because the direct effect is larger for frequent exporters, the predicted value of MFP growth is higher for frequent exporters than for occasional exporters (holding other variables at their mean values).

As an aside, the OLS and OLS with additional lags give consistent results in terms of the direction of the effects, although the magnitude of some of the coefficients differ. For example, OLS gives a higher estimate for the speed of convergence (0.19) than the OLS specification with additional lags (0.14), suggesting that some of the measured speed of convergence in the OLS estimation is mean reversion.

Table 6 Extended convergence model results: firm-level variables

Dep. Var: MFP growth ΔlnA_{it}	(18)	(19)
Distance to frontier	0.1902*** (0.0026)	0.1362*** (0.0032)
Change in frontier	0.1218*** (0.0121)	0.0971*** (0.048)
Lag of MFP growth		-0.1817*** (0.0025)
Lag of change in frontier		-0.0634*** (0.0146)
Age	0.0004*** (0.00)	0.0001*** (0.00)
Size	0.0135*** (0.0006)	0.0095*** (0.0006)
Occasional exporter (base: non-exporter)	-0.0003 (0.0014)	-0.0014 (0.0014)
Frequent exporter (base: non-exporter)	0.0088*** (0.0016)	0.0056** (0.0017)
Foreign-owned	0.0103*** (0.0036)	0.0054 (0.0036)
Age x distance to frontier	-0.0014*** (0.0001)	-0.0008*** (0.0001)
Size x distance to frontier	0.0102*** (0.0015)	0.0096 (0.0016)
Occasional exporter x distance to frontier	0.0172** (0.0034)	0.0141*** (0.0035)
Frequent exporter x distance to frontier	0.0096 (0.0036)	0.0071 (0.0041)
Foreign-owned x distance to frontier	0.0165*** (0.0093)	0.0173 (0.01)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Firm dummies	No	No
Observations	455,829	326,403
Adjusted R^2	0.0909	0.1206

Notes:

1. Column 18 is OLS, column 19 is OLS with additional lags to account for serial correlation. Fixed effects and FE-GMM are not included due to presence of time-invariant variables.
2. Regressions are estimated on laggard firms for 2001-2011. Outliers are excluded. Standard errors in brackets are clustered at the firm level.
3. * significant at 10% level, ** significant at 5% level, *** significant at 1% level

Industry-level exporting and FDI

The extent of industry integration into the global economy via exporting and foreign ownership may influence productivity growth in firms within the industry in ways that differ from firm-level openness. We incorporate industry-level variables of exporting and foreign ownership into Equation (4) to explore additional transmission channels through which international integration might influence firm productivity growth and convergence. For example, a foreign-owned firm operating in New Zealand may introduce new technologies that domestic firms in the same market can then adopt more easily. Exporting may have a similar effect if exporting firms introduce new technologies that are then adopted more easily by other firms in the local market. A greater prevalence of foreign-owned or exporting firms may also improve productivity growth by increasing competitive pressure in the domestic product market in their industry.

The expected indirect effects of greater industry-level international openness on the speed of convergence are less clear than the indirect effects of firm-level openness. Increased industry openness may slow the speed of convergence if firms that are closer to the domestic productivity frontier benefit disproportionately from greater global integration, as these firms pull away from lower-productivity firms in the same industry. Existing empirical results on the effect of international integration on the speed of convergence are mixed. Griffith et al. (2006) find that a higher share of industry employment in US multinationals increases the speed of convergence for UK manufacturing firms. Peri and Urban (2006) find a similar result for Italian and German manufacturing firms. In addition, using data for Chile, Alvarez and Crespi (2007) find that a higher share of foreign firms in an industry has a positive effect on the speed of convergence. In contrast, Chevalier et al. (2012) find that the share of exports in value add slows the speed of convergence among French firms because exporting largely benefits firms that already have higher-than-average productivity levels.

The results of estimating Equation (4) using industry-level measures of exporting and foreign ownership are reported in Table 8. These indicate that the industry share of employment in foreign-owned firms has a positive and significant direct effect on MFP growth, but slows the speed of convergence.[22] To give an idea of magnitude, if the employment share in foreign-owned firms in an industry increases from 20% to 30%, the speed of convergence for a firm at the median distance to the frontier (0.36) slows from 7.3% a year to about 6.6% in the OLS model and from 24.8% to 22.1% in the fixed-effects model.

The results for exporting show a similar pattern to the FDI results. The direct effect of the employment share in exporting firms in an industry is positive, albeit insignificant in some specifications. As with the results for FDI, the effect of exporting on the speed of convergence is negative. If the employment share in exporting firms increases from its mean value of 32% to 42% in an industry, then the speed of convergence for a firm that is the median distance behind the frontier (0.36) falls from 7.3% a year to 6.8% in the OLS model and from 26.6% to 25.5% in the fixed-effects model.

[22] An alternative approach is to use the industry share of value-added in foreign-owned or exporting firms. We find that using this measure does not substantially change the results. Detailed results are available on request.

Table 7 Extended convergence model results: Industry-level variables

Dep. Var: MFP growth ΔlnA_{it}	(20)	(21)	(22)	(23)
Distance to frontier	0.2151*** (0.0025)	0.7684*** (0.0061)	0.1646 (0.0029)	0.8297*** (0.0115)
Change in frontier	0.1172*** (0.0124)	0.3667*** (0.0117)	0.0984 (0.0153)	0.3233*** (0.0162)
Lag of MFP growth			-0.1822 (0.0025)	-0.0172*** (0.0027)
Lag of change in frontier			-0.0566 (0.015)	-0.2406*** (0.0158)
Age	-0.0002*** (0.000)	-0.0036*** (0.0001)	-0.0002 (0.00)	-0.0034*** (0.0002)
Size	0.0186*** (0.0003)	0.0131*** (0.0011)	0.0137 (0.0003)	0.0103*** (0.0016)
Share of employment in exporting firms	0.0177 (0.0068)	0.0787*** (0.0101)	0.0219 (0.008)	0.0853*** (0.0196)
Share of employment in foreign-owned firms	0.0328** (0.0076)	0.0916** (0.0134)	0.0222 (0.0089)	0.0346* (0.0205)
Exporting x distance to frontier	-0.0182*** (0.0064)	-0.0884*** (0.0162)	-0.0139 (0.0068)	-0.1295*** (0.0216)
FDI x distance to frontier	-0.0941*** (0.0092)	-0.282*** (0.0274)	-0.0887 (0.0029)	-0.2531*** (0.0375)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Firm dummies	No	Yes	No	Yes
Observations	450,129	450,129	325,086	322,671
R^2	0.0899	0.0642	0.1203	0.0558

Notes:

1. Column 20 is OLS, column 21 is fixed effects, column 22 is fixed effects with additional lags to account for serial correlation.
2. FE-GMM is not included. The appearance of multiple A_{ijt-1} terms in the model that would each need to be instrumented by A_{ijt-2} presents issues as we cannot test for weak instruments in this multiple-instrument setting. The use of Arellano-Bover via the xtabond2 ado for Stata (Roodman, 2009a) would allow testing of weak instruments in such a setting, however, as noted in Section 2.2, our dataset does not meet the assumptions of Arellano-Bover.
3. Regressions are estimated on laggard firms for 2001-2011. Outliers are excluded. Standard errors in brackets are clustered at the firm level.
4. * significant at 10% level, ** significant at 5% level, *** significant at 1% level

The results reported in Table 3 show that foreign-owned and exporting firms tend to have higher productivity levels and growth rates than non-exporting or domestically-owned firms. As such, it may be that the negative impact of exporting and foreign ownership on the speed of convergence is being driven by a similar mechanism as found by Chevalier et al. (2012) for French firms. That is, globalisation has a greater positive impact on the productivity growth of leading firms than of the less productive firms, thereby leading to a reduction in the speed of convergence across the distribution as a whole.

To test this idea, we regress firm MFP growth against firm productivity levels at time *t-1* with the addition of coefficients to capture the direct effects of firm-level FDI and exporting on firms in each decile of the productivity distribution. The results, show that exporting and foreign ownership have a positive and statistically significant impact on MFP growth for firms in every decile of the productivity distribution (Table 8).

Broadly speaking, the coefficients on exporting and foreign ownership display a U-shaped pattern across productivity deciles. That is, the positive impacts of exposure to international markets are particularly strong for firms in the upper and lower deciles of the productivity distribution and comparatively weaker for firms in the middle of the distribution. However, because exporting and foreign-owned firms tend to be clustered towards the top of the productivity distribution, the beneficial impact of international exposure is spread across a larger number of firms in the high-productivity deciles than in the low-productivity deciles.

To illustrate, Figure 7 graphs the estimated coefficients of frequent exporting, occasional exporting and foreign ownership on MFP growth by productivity decile. The width of the bars in these graphs is proportionate to the share of firms in each of these categories. Consistent with the characteristics of frontier firms, foreign-owned and frequent exporting firms are clustered in high-productivity deciles. This may be why the speed of convergence is lower in FDI-intensive and exporting-intensive industries. That is, firms closer to the domestic productivity frontier benefit disproportionately from greater global integration.

Table 8 Coefficients on exporting and FDI variables by decile

Exporting	Deciles									
	1	2	3	4	5	6	7	8	9	10
Lagged MFP	-0.264*** (0.003)	-0.175*** (0.0148)	-0.185*** (0.019)	-0.107*** (0.020)	-0.115*** (0.021)	-0.132*** (0.020)	-0.175*** (0.018)	-0.150*** (0.016)	-0.089*** (0.012)	-0.077*** (0.002)
Frequent exporter	0.039*** (0.004)	0.023*** (0.002)	0.017*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.016*** (0.002)	0.017*** (0.002)	0.019*** (0.002)	0.017*** (0.002)	0.023*** (0.002)
Occasional exporter	0.047*** (0.004)	0.019*** (0.002)	0.013*** (0.002)	0.007*** (0.002)	0.006*** (0.002)	0.004** (0.002)	0.005*** (0.001)	0.006*** (0.002)	0.006*** (0.002)	0.011*** (0.002)
Observations	42573	48894	51669	53691	54702	55761	56373	56802	57165	55782
R^2	0.162	0.010	0.006	0.004	0.005	0.004	0.006	0.006	0.006	0.03

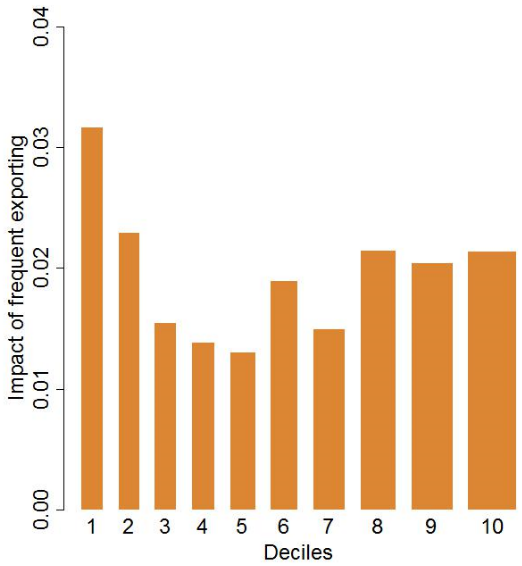
FDI	Deciles									
	1	2	3	4	5	6	7	8	9	10
Lagged MFP	-0.258*** (0.003)	-0.172*** (0.015)	-0.184*** (0.019)	-0.104*** (0.021)	-0.115*** (0.021)	-0.13*** (0.021)	-0.173*** (0.019)	-0.145*** (0.016)	-0.088*** (0.012)	-0.079*** (0.003)
Foreign-owned	0.052*** (0.01)	0.056*** (0.008)	0.033*** (0.006)	0.021*** (0.006)	0.05*** (0.005)	0.031*** (0.004)	0.029*** (0.004)	0.023*** (0.003)	0.025*** (0.003)	0.029*** (0.003)
Observations	42573	48894	51669	53691	54702	55761	56373	56802	57165	55782
R^2	0.154	0.009	0.005	0.003	0.004	0.004	0.005	0.004	0.006	0.024

Notes:

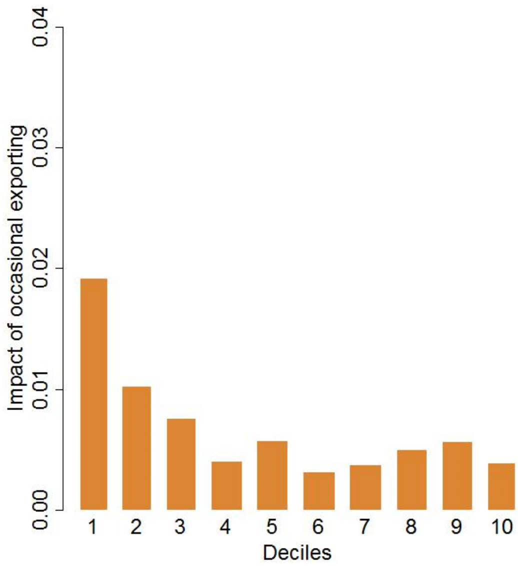
1. Deciles 1-9 are laggard firms and decile 10 are frontier firms.
2. Coefficient on FDI and exporting are estimated for each decile from the equations $\Delta ln A_{ijt} = \alpha + \beta ln A_{ijt-1} + \delta FDI_i + u_{ijt}$ and $\Delta ln A_{ijt} = \alpha + \beta ln A_{ijt-1} + \delta_1 OccasionalExporter_i + \delta_2 FrequentExporter_i + u_{ijt}$.

Figure 7 Coefficients on exporting and FDI variables by deciles

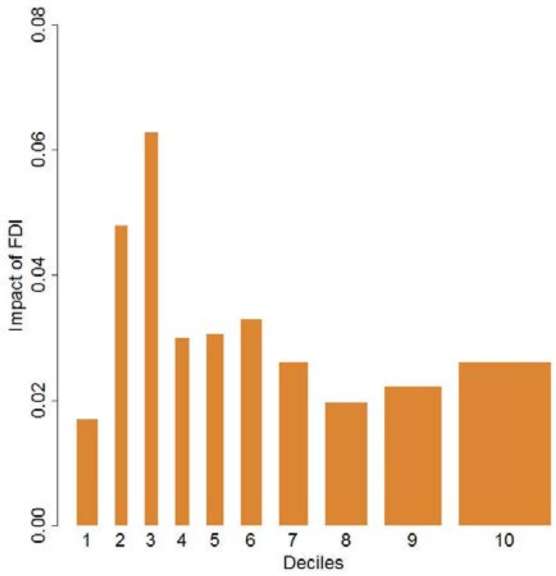
A. Frequent exporting



B. Occasional exporting



C. FDI



Notes:

1. The height of the bars corresponds to estimated coefficients from Table 8.
2. The width of the bars represents shares of exporting or FDI firms. The wider the bar, the larger the concentration of exporting or FDI firms.

5 Discussion and conclusions

New Zealand has a poor productivity track record and there is little evidence of convergence towards more productive OECD countries. At the same time, the distribution of MFP across firms in the same industry is wide and it is at least possible that some New Zealand firms operate at, or close to, the international technological frontier. This raises questions about the extent to which new technologies and production techniques diffuse from high- to low-productivity firms within the New Zealand economy.

This paper investigates the extent to which low-productivity firms in New Zealand converge towards high-productivity firms operating at the domestic technological frontier in the same industry. The theoretical idea underlying this convergence process is that knowledge spillovers between firms are to some extent non-rival and not fully appropriable. As such, firms below the domestic productivity frontier can potentially improve their productivity by learning from better-performing firms in their industry.

Estimating the model across New Zealand firms shows that convergence to the domestic productivity frontier is significant and economically important. However, the extent of technology spillovers is considerably different across sectors and industries. In particular, firms in some parts of the services sector have slower convergence speeds relative to firms in other parts of the economy. This raises questions about the incentives for technological diffusion in some service industries. This result for the domestic economy is analogous to international evidence on stronger convergence across countries in manufacturing sectors than in services sectors (Rodrik, 2012). The international literature on resource allocation across firms also indicates that employment allocation is less likely to be productivity enhancing in services sectors (Andrews & Cingano, 2014).

The basic convergence model is extended to assess the influence of international openness – exporting and foreign ownership – on technology transfer. This yields some evidence that exporting and foreign ownership hastens firm MFP growth and the speed of convergence to the technological frontier. However, at the industry level, greater exporting and foreign-ownership intensity can slow the convergence process. This may reflect the fact that exporting and foreign-owned firms tend to already have high productivity. So as productivity growth improves in these firms due to enhanced international engagement, the productivity distribution at the industry level tends to widen.

As well as advancing our understanding of convergence forces within New Zealand, the model developed in this paper can also be extended in a number of directions. For example, it may be possible to include measures of the international productivity frontier in the model (for example see Bartelsman et al., 2008; Iacovone & Crespi, 2010). This would allow an assessment of the relative importance of the international and domestic productivity frontiers for firms at different points of the productivity distribution to be made.

The model could also be extended to assess the impact of regional productivity frontiers at the level of New Zealand's local labour markets. This would be useful in assessing the impact of small local markets on the productivity performance of New Zealand firms. The impact of geographic proximity and competition on MFP growth could also be assessed within this framework. OECD indicators of product market regulation at the industry level could also be included to look at the impact of broad regulatory settings on the diffusion of productivity shocks from the productivity leader.

The model could also be extended to look at the effect of R&D spending and other measures of innovation intensity on MFP growth directly and indirectly through increased absorptive capacity and therefore faster technological diffusion (see Iacovone & Crespi, 2010). If the model is estimated across firms with six or more employees that are included in the Business Operations Survey, this work could be extended further to look at impact on productivity growth of a range of other factors, including investment in ICT, management quality, and so forth.

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Appendix A Characteristics of outliers

As described in Section 2, about 4% of firms are identified as outliers. Table A.1 shows the results of a logistic regression of the likelihood of a firm being an outlier. Firms in all productivity deciles are less likely to be outliers than firms in the lowest productivity decile. Outlier firms are more likely to be small and young. They are also more likely to be foreign owned and exporters.

Table A.1 Logistic regression on the characteristics of outliers

Dep. Var: Outlier=1; non-outlier=0	
Log MFP decile at t-1 (base: decile 1)	
Decile 2	-1.482*** (0.0285)
Decile 3	-1.866*** (0.0306)
Decile 4	-2.056*** (0.0322)
Decile 5	-2.178*** (0.0333)
Decile 6	-2.172*** (0.0332)
Decile 7	-2.121*** (0.0331)
Decile 8	-2.034*** (0.0329)
Decile 9	-1.745*** (0.0311)
Firm size (base: <6 employees)	
6-9 employees	-0.339*** (0.0247)
10-19 employees	-0.3885*** (0.0306)
20-49 employees	-0.359*** (0.0403)
50-99 employees	-0.271*** (0.0684)
100+ employees	-0.909*** (0.0855)
Firm age (base: <5 years)	
5-9 years	-0.235*** (0.0233)
10-19 years	-0.392*** (0.0244)
20+ years	-0.353*** (0.0284)
Export intensity (base: non-exporter)	
Occasional exporter	0.0832*** (0.0260)
Frequent exporter	0.238*** (0.0241)
Foreign ownership (0=domestic ownership)	0.489*** (0.0513)
Observations	477,621
R^2	0.227

Notes:

1. Decile 10 are frontier firms.

Appendix B Measurement error robustness test

Despite the removal of outliers, spurious correlation may still be an issue. As a robustness check, we test the relationship between MFP growth and MFP levels using a categorical measure of productivity rather than a continuous one, following Griffith et al. (2009). While it may be difficult to measure a firm's precise level of MFP, we can be more confident in identifying which productivity decile the firm belongs to. Indeed, annual transition matrices show a high degree of persistence, with about 70-80% of firms remaining in the same decile or moving to an adjacent decile (Table B.1).

Table B.1 Transition matrix of annual firm productivity

		Period t									
	Deciles	1	2	3	4	5	6	7	8	9	10
Period t-1	1	0.575	0.201	0.082	0.046	0.031	0.022	0.016	0.012	0.009	0.006
	2	0.191	0.349	0.201	0.104	0.060	0.037	0.023	0.017	0.012	0.007
	3	0.076	0.201	0.275	0.191	0.106	0.066	0.038	0.024	0.015	0.008
	4	0.041	0.101	0.195	0.245	0.182	0.109	0.062	0.034	0.020	0.010
	5	0.027	0.057	0.107	0.185	0.232	0.183	0.108	0.058	0.029	0.013
	6	0.018	0.035	0.062	0.109	0.184	0.234	0.185	0.103	0.051	0.019
	7	0.014	0.022	0.037	0.062	0.109	0.186	0.257	0.192	0.090	0.031
	8	0.010	0.015	0.023	0.035	0.060	0.104	0.193	0.294	0.204	0.062
	9	0.008	0.011	0.014	0.020	0.031	0.051	0.096	0.206	0.381	0.184
	10	0.006	0.007	0.008	0.010	0.014	0.021	0.034	0.066	0.194	0.640

We find that firms in the lowest decile (those furthest away from the frontier) experience faster convergence speeds, and that the convergence speeds decrease monotonically with the deciles, with those nearest to the frontier experiencing the slowest growth rates (Table B.2). In addition, the difference between the respective deciles decreases with the deciles, which is consistent with the finding that the speed of convergence increases as the distance to the frontier increases.

Table B.2 Robustness test: Decile model

Dep. Var: MFP growth ΔlnA_{it}	(23)	(24)
Change in frontier	0.0377*** (0.0121)	0.0735*** (0.0116)
Decile 1	0.1803*** (0.0015)	0.5725*** (0.0025)
Decile 2	0.1097*** (0.0011)	0.4196*** (0.0018)
Decile 3	0.0819*** (0.0011)	0.3342*** (0.0016)
Decile 4	0.0631*** (0.001)	0.2712*** (0.0015)
Decile 5	0.0502*** (0.001)	0.2195*** (0.0014)
Decile 6	0.0398*** (0.001)	0.1729*** (0.0013)
Decile 7	0.0279*** (0.001)	0.1239*** (0.0012)
Decile 8	0.017*** (0.009)	0.0701*** (0.0011)
Year dummies	Yes	Yes
Industry dummies	-	-
Firm dummies	No	Yes
Observations	455,892	455,892
Adjusted R^2	0.0795	0.0766

Notes:

1. Decile 9 is the excluded category. Decile 10 firms are defined to be frontier firms.
2. Regressions are estimated on laggard firms for 2001-2011. Outliers are excluded. Standard errors in brackets are clustered at the firm level.
3. * significant at 10% level, ** significant at 5% level, *** significant at 1% level

Appendix C Production function estimation[23]

We assume that each firm's gross output (Y) follows the Cobb-Douglas production mechanism and is produced with labour (L), physical capital (K) and intermediate (M) inputs.[24] Specifically the production function is:

$$Y_{ijt} = A_{ijt} L_{ijt}^{\beta_{1j}} K_{ijt}^{\beta_{2j}} M_{ijt}^{\beta_{3j}} \tag{C.1}$$

Or, in logs:

$$lnY_{ijt} = \beta_{1j}\, ln\, L_{ijt} + \beta_{2j}\, ln\, K_{ijt} + \beta_{3j}\, ln\, M_{ijt} + ln\, A_{ijt} \tag{C.2}$$

where *i, j* and *t* index firms, industries and time respectively. β_{1j}, β_{2j} and β_{3j} are industry-specific output elasticities with respect to labour, capital and intermediate inputs respectively and A_{ijt} is MFP.[25]

There are several ways to estimate this production function, such as ordinary least square (OLS), fixed effects, generalised method of moments (GMM), semi-parametric estimators such as Olley and Pakes (1996) and Levinsohn and Petrin (2003) and structural estimator such as Ackerberg, Caves, and Frazer (2006). Van Beveren (2012) found that MFP productivity estimates are similar among different estimators.[26] We also tested the robustness of our MFP calculations to the estimation methods, including Olley and Pakes (1996) and Levinsohn and Petrin (2003) and found that they made little difference to measured MFP. This result is also confirmed by Fabling and Maré (forthcoming).

In this paper, firm-level MFP is estimated by fixed effects. Under this framework, production inputs (labour, capital and intermediate) are assumed to be strictly exogenous to output and unobserved and time-invariant firm productivity, ω_{ij}.[27] Time dummies are included in the regression to control macro-economic shocks to production. This results in the following equation:

$$lnY_{ijt} = \beta_{1j}\, ln\, L_{ijt} + \beta_{2j}\, ln\, K_{ijt} + \beta_{3j}\, ln\, M_{ijt} + \sum_{t=2001}^{2011} \pi_t T_t + \omega_{ij} + \beta_{0j} + \varepsilon_{ijt} \tag{C.3}$$

where $ln\, A_{ijt} = \beta_{0j} + \omega_{ij} + \varepsilon_{ijt}$

T_t are year dummies with the year 2000 set as the base year. Firm-level productivity consists of three components β_{0j}, ω_{ij} and ε_{ijt}. β_{0j} is the intercept and measures the average MFP across firms and over time. ω_{ij} measures firm-specific deviation from that average. ε_{ijt} is the deviation from firm-specific productivity due to measure error.

In applying this estimation to LBD, gross output is measured as total income adjusted for change in stocks and excluding income from interest and dividends. Labour input is the sum of working proprietors and rolling mean employee count from the Linked Employer-Employee Database (LEED). Capital is the sum of depreciation, leasing and rates and the cost of borrowing times total fixed assets. The cost of borrowing is set at a constant 10%. Intermediate consumption is measured as the value of

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[23] We are grateful to Richard Fabling and Dave Maré for providing us with their SQL and Stata code for extracting the necessary data from LBD and undertaking these production function calculations.

[24] Alternatively, a firm's production can be estimated by the value-add method - $lnVA_{ijt} = \beta_{1j}\, ln\, L_{ijt} + \beta_{2j}\, ln\, K_{ijt} + ln\, A_{ijt}$. Under the value-add method, a firm's VA is only dependent on labour and capital inputs. One potential issue with this method is that firms with negative VA will be dropped in the log-transformation, creating some selection bias.

[25] Hilary, Tinh, and Philip (2012) shows that there are large differences in output elasticities across industries in New Zealand.

[26] Although there are little differences in the measured MFP from these different estimators, Van Beveren (2012) and Ornaghi and Van Beveren (2012) point out that the semi-parametric method and structural estimator are reasonable estimators as other estimators suffer from several biases.

[27] Under the assumption of exogeneity, firms do not choose inputs in reaction to productivity shocks. In practice, this assumption may not be valid as the input choice is dynamic and evolves with productivity (Ackerberg, Benkard, Berry, & Pakes, 2007).

other inputs to the production process adjusted for changes in stocks of raw material. All these numbers except labour input are deflated by industry Producer Price Indexes. As such, like other countries' firm microdata, the lack of firm information on quantities and prices is a limitation.

Appendix D Characteristics of frontier firms

Table D.1 shows the results of a logistic regression of frontier versus laggard firms. Firms that have higher past productivity are more likely to be on the frontier the next year. Compared to firms with less than 6 employees, frontier firms are more likely to have 6-49 employees but less likely to have 50-99 employees. Frontier firms are more likely to be young, exporters and foreign owned.

Table D.1 Logistic regression of the characteristics of frontier firms

Dep. Var: Frontier=1; Laggard=0	
Log MFP decile at t-1 (base: decile 1)	
Decile 2	1.033*** (0.1890)
Decile 3	1.495*** (0.1797)
Decile 4	1.803*** (0.1769)
Decile 5	2.246*** (0.1733)
Decile 6	2.739*** (0.1709)
Decile 7	3.3006*** (0.1692)
Decile 8	4.112*** (0.1681)
Decile 9	5.422*** (0.1675)
Firm size (base: <6 employees)	
6-9 employees	-0.1933*** (0.0246)
10-19 employees	-0.234*** (0.0280)
20-49 employees	-0.086** (0.0364)
50-99 employees	0.149*** (0.0569)
100+ employees	0.056 (0.0639)
Firm age (base: <5 years)	
5-9 years	-0.099*** (0.0272)
10-19 years	-0.157*** (0.0271)
20+ years	-0.217*** (0.0312)
Export intensity (base: non-exporter)	
Occasional exporter	0.053*** (0.0263)
Frequent exporter	0.266*** (0.0268)
Foreign ownership (0=domestic ownership)	0.454*** (0.0527)
Observations	477,621
R^2	0.225

Notes:

1. Decile 10 are frontier firms.