Appendix to — Firm Productivity Growth and its Relationship to the Knowledge of New Workers

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Disclaimer

These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) and Longitudinal Business Database (LBD)] which are carefully managed by Stats NZ. For more information about the IDI and LBD please visit https://www.stats.govt.nz/integrated-data/.

The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the datas ability to support Inland Revenues core operational requirements.

A Additional regression specifications and robustness checks

This appendix presents additional results and robustness checks related to the analysis section of the main paper.

A.1 Average productivity differences between industries

A possible reason of why the estimation based on value-added per worker data supports the knowledge spillover channel while the results based on MFP measures do not is that between-industry productivity differences are important. As discussed in the paper, constructing the productivity gaps using MFP measures fails to account for any differences in the average productivity between industries. Therefore, the productivity gap measures could be misleading as measures of the true productivity differences.

To investigate whether the MFP estimates are biased as a result of using productivity gap measures that do not account for the between-industry productivity differences, the baseline model is re-estimated using value-added per worker data that is demeaned by the industry-year average. By demeaning in this manner, the between-industry productivity differences are removed from productivity gaps in the same manner as they are for the MFP measures of productivity. By comparing the results from the demeaned value-added labour productivity measure to the original value-added labour productivity results, we should be able to see if between-industry productivity differences significantly affect the estimated. The results of this comparison are presented in table 1.

All of the key coefficients in the two columns of table 1 are similar in magnitude and direction. This suggests that the difference in productivity gap coefficients between the value-added per worker and the MFP measures of firm productivity are not being driven by the fact that productivity gaps based on MFP measures fail to account for between-industry differences in average productivity. Instead the differences are likely the result of how MFP measures treat other inputs in the production process.

Table 1: Baseline model estimated using demeaned value-added data

	Value-added	**VA pw demeaned**
Productivity gap, hires from (β):		
More prod. firms	0.480***	0.488***
	(0.098)	(0.108)
Less prod. firms	0.153***	0.139***
	(0.030)	(0.028)
Hire intensity (λ):		
More prod. firms	-0.200***	-0.210***
	(0.057)	(0.061)
Less prod. firms	-0.117***	-0.116***
	(0.027)	(0.028)
$\Delta Q_{i,t}$ due to (γ):		
New hires	0.479***	0.468***
	(0.075)	(0.075)
Exiters	0.468***	0.457***
	(0.075)	(0.075)
Incumbents	0.494***	0.483***
	(0.075)	(0.074)
Parameter tests:		
$\Pr(\beta_M = \beta_L)$	0.001	0.001
$\Pr(\lambda_M = \lambda_L)$	0.237	0.221
$\Pr(\gamma_{new} = \gamma_{incmb})$	0.000	0.000
Obs.	37269	37269

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$, where the measure of productivity differs by column. Demeaned value-added per worker is demeaned using industry-year averages. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A.2 Results by industry

The benefit of the knowledge new workers bring to a firm may depend on many factors outside of the hiring firm's control, and specific to the industry in which it operates. For example, in industries in which firms have large capital outlays, knowledge from workers who have experience operating different vintages of capital may not be beneficial enough for the firm to change its current capital stock, limiting the benefit of the worker's knowledge to the firm. As a result, the effect of new worker's knowledge on hiring firms may vary across different industries in the economy.

One of the advantages of using data from the New Zealand LBD is that it contains information on firms in all measurable sectors of the economy. Table 2 reports results from estimating the benchmark model for a selection of the largest industry groups in the data. Because the classification of industry is rather granular in the data set (there are 39 industries), industries have been aggregated up to the one-digit level before estimating to improve the power of the regressions (for example, all manufacturing industries are grouped together).

It is difficult to draw general conclusions by comparing results across industry without collecting more detailed data on the properties and characteristics of each industry, However, the results in table 2 can still be used to assess if the results found so far are being driven by a subset of industries, or it they are generally applicable to all firms across the economy.

For the regressions using value-added per worker as the firm-level productivity measure, the majority of the industries show a larger coefficient on the productivity gap related to hires from more productive firms than the coefficient on the productivity gap related to hires from less productive firms. However, the statistical significance of this difference is mixed. For all industries, the average benefit from hire intensities are generally negative with a slightly larger coefficient related to the hire intensity from more productive firms.

The coefficients on the two productivity gaps for both MFP measures of productivity are, for the majority of cases, not statistically different from one another across all industries. In terms of economic magnitudes, only in the case of the professional services, construction, and agriculture and forestry industries for the Cobb-Douglas results are the coefficients related to the productivity gap from less productive firms somewhat larger than the coefficients related to the productivity gap from more productive firms (potentially explaining why we see this pattern in the baseline regression).

Overall, the results by industry suggest that the baseline results are broadly applicable across all the largest industries, and do not appear to be driven by any one industry in particular. Previous papers in the literature who have found support for a knowledge spillover channel in both labour productivity and MFP have typically used manufacturing data only (for example Stoyanov and Zubanov 2012). However, the results in table 2 show that even if we were to restrict the sample to only include firms in the manufacturing industries, the estimates found in this paper would still differ from those found in the previous papers for other countries.

Table 2: Benchmark regression by industry (1-digit level)

Value Added p.w.

	Baseline	**Industry:** **Manufac.**	**Prof. services**	**Constr.**	**Transport**	**Agri & Forest**	**Mining**
Prod. gap, hires from (β):							
More prod. firms	0.480***	0.148	1.342***	1.225***	0.716**	0.719***	0.361***
	(0.098)	(0.300)	(0.179)	(0.292)	(0.316)	(0.100)	(0.124)
Less prod. firms	0.153***	0.325***	0.022	0.249*	0.259***	0.063	0.351***
	(0.030)	(0.096)	(0.068)	(0.130)	(0.085)	(0.093)	(0.080)
Hire intensity (λ):							
More prod. firms	-0.200***	-0.023	-0.589***	-0.419***	-0.255	-0.297***	-0.253***
	(0.057)	(0.145)	(0.109)	(0.158)	(0.197)	(0.058)	(0.089)
Less prod. firms	-0.117***	-0.009	-0.299***	-0.164	-0.017	-0.096**	0.068
	(0.027)	(0.066)	(0.074)	(0.102)	(0.090)	(0.043)	(0.080)
Parameter tests:							
$\Pr(\beta_M = \beta_L)$	0.001	0.552	0.000	0.001	0.159	0.000	0.940
$\Pr(\lambda_M = \lambda_L)$	0.237	0.939	0.039	0.207	0.293	0.010	0.021
Obs.	37269	1695	9279	3600	3762	7506	5340

Cobb-Douglas

	Baseline	**Industry:** **Manufac.**	**Prof. services**	**Constr.**	**Transport**	**Agri & Forest**	**Mining**
Prod. gap, hires from (β):							
More prod. firms	0.271***	0.114	0.085	0.160	0.779***	0.180**	0.280*
	(0.065)	(0.154)	(0.081)	(0.137)	(0.276)	(0.073)	(0.149)
Less prod. firms	0.374***	0.187**	0.231**	0.636**	0.855***	0.490***	0.396***
	(0.054)	(0.088)	(0.105)	(0.284)	(0.327)	(0.144)	(0.079)
Hire intensity (λ):							
More prod. firms	-0.012	0.107	0.073**	0.089	-0.177	0.028	-0.053
	(0.028)	(0.085)	(0.034)	(0.057)	(0.136)	(0.036)	(0.072)
Less prod. firms	0.047*	0.021	-0.086**	0.066	0.164	0.065	0.166**
	(0.026)	(0.049)	(0.036)	(0.084)	(0.159)	(0.051)	(0.065)
Parameter tests:							
$\Pr(\beta_M = \beta_L)$	0.217	0.671	0.244	0.092	0.853	0.055	0.475
$\Pr(\lambda_M = \lambda_L)$	0.145	0.391	0.004	0.849	0.108	0.583	0.037
Obs.	28260	1257	7146	2700	2826	5565	3990

Trans-log

	Baseline	**Industry:** **Manufac.**	**Prof. services**	**Constr.**	**Transport**	**Agri & Forest**	**Mining**
Prod. gap, hires from (β):							
More prod. firms	0.354***	0.306***	0.468***	0.366**	1.032***	0.281**	0.248***
	(0.068)	(0.112)	(0.120)	(0.170)	(0.342)	(0.136)	(0.090)
Less prod. firms	0.374***	0.272*	0.331***	0.679***	0.660***	0.258***	0.421***
	(0.056)	(0.140)	(0.101)	(0.227)	(0.216)	(0.073)	(0.098)
Hire intensity (λ):							
More prod. firms	-0.037*	-0.029	-0.008	0.015	-0.253**	-0.007	-0.019
	(0.021)	(0.042)	(0.031)	(0.046)	(0.122)	(0.043)	(0.033)
Less prod. firms	0.004	-0.003	-0.053*	0.030	0.019	-0.008	0.038
	(0.019)	(0.055)	(0.031)	(0.057)	(0.103)	(0.024)	(0.041)
Parameter tests:							
$\Pr(\beta_M = \beta_L)$	0.808	0.840	0.360	0.228	0.338	0.874	0.173
$\Pr(\lambda_M = \lambda_L)$	0.174	0.720	0.321	0.848	0.063	0.985	0.340
Obs.	38037	1752	9462	3693	3828	7566	5430

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), where the measure of productivity is either value-added per worker, Cobb-Douglas MFP, or Tans-log MFP. Industry classifications are based on the level 1 ANZSIC06 categories. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. The regression standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A.3 Results by firm size

The previous results have focused on the characteristics of the worker in relation to the productivity growth at the hiring firm. However, the characteristics of the hiring firm may also be an important factor for the productivity growth when hiring new workers. Stoyanov and Zubanov (2012) argue that firm size may be an important factor in the amount of productivity growth associated with hiring new workers since better managers facilitate larger firm sizes through their better management skill, and their better management skill may better facilitate the application of new knowledge within the firm.

Table 3 reports the results for estimating the baseline model separately for small firms (less than 20 full time equivalent workers), medium sized firms (20 to 50 full time equivalent workers), and larger firms (50 plus full time equivalent workers) for the main measures of productivity used in the analysis.

In the Cobb-Douglas based results, we can see that for small firms, the magnitude of the coefficient on the productivity gap associated with hires from more productive firms is around twice as large as the coefficient on the productivity gap associated with hires from less productive firms. However, for the medium and large sized firms, the relationship is flipped, with the magnitude of the coefficient on the productivity gap associated with hires from less productive firms being larger (in line with the pattern seen in the baseline results).

One concern with the Cobb-Douglas results by firm size is that the Cobb-Douglas production function imposes constant returns to scale for the input factors. And therefore, the differences in results by firm size could relate to different returns to scale for small and large firms. However, we can also see similar differences in the relative magnitudes of the productivity gap coefficients by firm size when using the productivity measured derived from the trans-log production function, which allows for non-constant returns to scale. This suggests that the difference seen between small and larger firms is not driven by the assumption of constant returns to scale.

The results using value-added per worker to measure firm productivity tell a different story from the MFP-based results. For all firm sizes, the coefficient associated with the productivity gap for hires from more productive firms is statistically larger than that associated with the productivity gap for hires from less productive firms. And when comparing coefficients across firm sizes, it is the magnitude of the productivity gap coefficients for large firms that stands out as being larger than for the other firm sizes. Overall, there is some tentative support for larger firms are better able to exploit knowledge spillovers for labour productivity data. However, the same cannot be said for the MFP measures of firm productivity.

A.4 Hiring margin

The process of advertising for, screening, and hiring new worker can often involve significant costs to a firm. As a result, some firms may choose not to seek out new employees, even when the expected payoff from doing so is positive. This creates a selection effect in the data among firms that may affect the estimate of how beneficial hiring new workers is to

Table 3: Benchmark regression by firm size

	Value-added			Cobb-Douglas			Trans-log		
	FTE ≤ 20	$20 <$ **FTE** ≤ 50	**FTE** > 50	**FTE** ≤ 20	$20 <$ **FTE** ≤ 50	**FTE** > 50	**FTE** ≤ 20	$20 <$ **FTE** ≤ 50	**FTE** > 50
Prod. gap, hires from (β):									
More prod. firms	0.491***	0.366***	0.761***	0.372***	0.171*	0.297***	0.504***	0.320***	0.290***
	(0.124)	(0.140)	(0.134)	(0.127)	(0.096)	(0.109)	(0.109)	(0.107)	(0.109)
Less prod. firms	0.169***	0.109*	0.226***	0.188***	0.402***	0.473***	0.266***	0.542***	0.402***
	(0.026)	(0.057)	(0.075)	(0.058)	(0.087)	(0.116)	(0.074)	(0.104)	(0.109)
Hire intensity (λ):									
More prod. firms	-0.171***	-0.122	-0.456***	-0.019	0.010	-0.049	-0.066**	-0.043	-0.017
	(0.065)	(0.089)	(0.101)	(0.047)	(0.040)	(0.060)	(0.030)	(0.034)	(0.043)
Less prod. firms	-0.123***	-0.123**	-0.093	-0.038	0.065	0.084	-0.024	0.056*	-0.015
	(0.031)	(0.049)	(0.066)	(0.028)	(0.041)	(0.068)	(0.028)	(0.032)	(0.038)
Parameter tests:									
$\Pr(\beta_M = \beta_L)$	0.009	0.077	0.000	0.188	0.075	0.269	0.067	0.114	0.432
$\Pr(\lambda_M = \lambda_L)$	0.532	0.995	0.006	0.750	0.362	0.148	0.331	0.058	0.967
$\Pr(\gamma_{new} = \gamma_{incmb})$	0.017	0.007	0.004	0.924	0.257	0.029	0.353	0.659	0.055
Obs.	14214	12588	10437	9912	9660	8673	14457	12870	10686

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$. Firm size is determined by the average Full Time Equivalent (FTE) number of workers throughout the financial year. The baseline regression is run separately for small firms (FTE ≤ 20), medium sized firms ($20 <$ FTE ≤ 50), and large firms (FTE > 50). Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the firm. And this selection effect raises the question: are the estimated benefits of hiring new workers being driven by firms deciding at the margin whether to hire or not, or are the benefits being drive by firms deciding at the margin how many workers to hire?

To examine this issue, the baseline model is re-estimated on two subsets of firms. The first subset is those firms that hire from more productive firms in a given year. The second subset is those firms that choose to hire from less productive firms in a given year. By eliminating from the data firms that choose not to hire from sources with more and less productive knowledge respectively, we focus the estimation on the margin related to how many workers to hire, rather than the decision of whether to hire or not.[1] Table 4 presents the regression results.

All of the parameter estimates found for estimating on both sub-samples of data are similar in scale to those found in the estimation of the baseline model on the full data set. This suggests that the baseline estimates are being driven by the decision of how many workers to hire, rather than the decision of whether to hire or not.

A.5 Stoyanov and Zubanov (2012) estimation specification

While the baseline model used in this paper has similarities to the model used by Stoyanov and Zubanov (2012), an important difference is the equation in our paper relates the productivity gap to the change in productivity at the hiring firm, while the model of Stoyanov and Zubanov (2012) relates the productivity gap to the level of productivity at the hiring firm. The results from the analysis of this paper are also different to the results of the analysis by Stoyanov and Zubanov (2012) for Danish data. This paper finds support for the unmeasured worker quality channel in both labour productivity and MFP measures, and some support for the knowledge spillover channel only in the labour productivity data. Stoyanov and Zubanov (2012) on the other hand finds support for only the knowledge spillover channel, both in labour productivity and MFP data.

To eliminate the possibility that the differences in our findings and those of Stoyanov and Zubanov (2012) are the result of the choice of modelling approach, we transform the baseline model to a form that is closer to the structure the model used by Stoyanov and Zubanov (2012), and then re-estimate the model using the new form.

Substituting the identity $\Delta \ln A_{i,j,\tau(n)} = \ln A_{i,j,\tau(n)} - \ln A_{i,j,\tau(n)-1}$ into the model re-arranging yields the following expression which, like the model of Stoyanov and Zubanov (2012), relates the level of MFP to the change in firm knowledge:

$$\ln A_{i,j,t} \quad = \quad \beta_1 \Delta Q_{i,t} + \text{Exoposure}_{i,t} + \beta_3 \Delta ExTurn_{i,t} + \sum_{l=1}^{L} \beta_{A,l} \ln A_{i,j,t-l} + \Delta\theta_{j,t} + \varepsilon_{i,t} \qquad (1)$$

Following the approach of Stoyanov and Zubanov (2012), the dynamic panel model relationship above is estimated using a first-difference approach. Like for the baseline model

[1] The effects of imposing that the firm hires from both more and less productive firms are very similar.

Table 4: Scale effect from hiring margin

	Value-added			Cobb-Douglas			Trans-log		
	Baseline	**Firms that hire from**		**Baseline**	**Firms that hire from**		**Baseline**	**Firms that hire from**	
		More productive	**Less productive**		**More productive**	**Less productive**		**More productive**	**Less productive**
Prod. gap, hires from (β):									
More prod. firms	0.480***	0.483***	0.520***	0.271***	0.286***	0.179***	0.354***	0.353***	0.270***
	(0.098)	(0.099)	(0.085)	(0.065)	(0.064)	(0.061)	(0.068)	(0.069)	(0.079)
Less prod. firms	0.153***	0.168***	0.149***	0.374***	0.444***	0.368***	0.374***	0.330***	0.368***
	(0.030)	(0.040)	(0.031)	(0.054)	(0.067)	(0.053)	(0.056)	(0.057)	(0.054)
Hire intensity (λ):									
More prod. firms	-0.200***	-0.247***	-0.207***	-0.012	-0.043	0.031	-0.037*	-0.054**	-0.007
	(0.057)	(0.059)	(0.050)	(0.028)	(0.029)	(0.025)	(0.021)	(0.022)	(0.023)
Less prod. firms	-0.117***	-0.108***	-0.069**	0.047*	0.066**	0.060**	0.004	-0.012	0.019
	(0.027)	(0.030)	(0.027)	(0.026)	(0.028)	(0.026)	(0.019)	(0.019)	(0.019)
Parameter tests:									
$\Pr(\beta_M = \beta_L)$	0.001	0.002	0.000	0.217	0.081	0.017	0.808	0.791	0.292
$\Pr(\lambda_M = \lambda_L)$	0.237	0.060	0.027	0.145	0.011	0.437	0.174	0.166	0.423
Obs.	37269	27411	30219	28260	21420	23163	38037	28668	30420

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). Firms that hire from more (and less) productive firms is based on the flow of workers between PFP firms for which productivity can be measured. It ensures that the corresponding productivity gap and hiring intensities are non-zero. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

in the main part of the paper, the lagged level of productivity in period $t-2$ is used to instrument $\Delta \ln A_{i,j,t-1}$ as a control for potential Nickell bias in the regression. The results of the regression using all three firm productivity measures are presented in table 5.

Table 5: Regressions using a functional form similar to Stoyanov and Zubanov (2012)

	Value-added		**Cobb-Douglas**		**Trans-log**	
	Baseline	**S-Z like**	**Baseline**	**S-Z like**	**Baseline**	**S-Z like**
Prod. gap, hires from (β):						
More prod. firms	0.480***	0.909***	0.271***	0.459***	0.354***	0.654***
	(0.098)	(0.092)	(0.065)	(0.070)	(0.068)	(0.090)
Less prod. firms	0.153***	0.147***	0.374***	0.673***	0.374***	0.397***
	(0.030)	(0.026)	(0.054)	(0.077)	(0.056)	(0.065)
Hire intensity (λ):						
More prod. firms	-0.200***	-0.319***	-0.012	0.042	-0.037*	-0.053*
	(0.057)	(0.045)	(0.028)	(0.026)	(0.021)	(0.025)
Less prod. firms	-0.117***	-0.190***	0.047*	0.073**	0.004	-0.049*
	(0.027)	(0.024)	(0.026)	(0.026)	(0.019)	(0.019)
Parameter tests:						
$\Pr(\beta_M = \beta_L)$	0.001	0.000	0.217	0.026	0.808	0.014
$\Pr(\lambda_M = \lambda_L)$	0.237	0.009	0.145	0.382	0.174	0.900
Obs.	37269	49905	28260	50859	38037	50859

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). "S-Z like" refers to the model estimated by first differencing equations equation 1 based on the model used by Stoyanov and Zubanov (2012). Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The coefficients in table 5 for the Stoyanov and Zubanov (2012) like model differ in magnitude from those of the baseline model presented earlier in the paper. However, the relative size and direction of the parameters are broadly similar.[2] Therefore, the findings in this paper are robust to the change in model specification considered by Stoyanov and Zubanov (2012). And the modelling choice approach does not seem to be the driver of the differences in results from our analysis and that of Stoyanov and Zubanov (2012).

A.6 Additional instruments for $\Delta \ln A_{i,j,t-1}$

Lagged productivity is an important control in the model. Today's productivity growth as well as the firm's hiring decisions are likely to be correlated with lagged productivity. However, as mentioned in the paper, including $\Delta \ln A_{i,j,t-1}$ in the regression is problematic due

[2] The most significant difference is in the last column where the coefficient on the productivity gap from hires from more productive firms is now larger than the coefficient on the productivity gap from hires from less productive firms.

to the presence of large Nickell bias in the data. Therefore, in the baseline model $\ln A_{i,j,t-2}$ is used as an instrument for $\Delta \ln A_{i,j,t-1}$. However, $\ln A_{i,j,t-2}$ is not the only instrument that can be used for $\Delta \ln A_{i,j,t-1}$. Blundell and Bond (1998) developed a technique that extends the Arellano-Bond estimation to include both the lagged levels and lagged differences of productivity as suitable instrumental variables in the estimation of dynamic panel models.

Table 6 reports the results of estimating the model using the Blundell and Bond (1998) approach with extra instruments for the change in lagged productivity ($\Delta \ln A_{i,j,t-1}$) against the baseline regressions. For all three productivity measured considered, the coefficients in the model do not change dramatically with the inclusion of additional instruments for past productivity. From these results, we can conclude that the results of our analysis are not sensitive to the inclusion of additional instruments.

A.7 More worker quality controls

Stockinger and Wolf (2016) found that for German firms, hiring from more productive firms was not correlated with productivity gains at the hiring firm, but hiring from less productive firms was. Their analysis reveals that there is a strong selection effect occurring, where the workers who move from more to less productive firms tend to be the workers who are among the lowest paid in their firm, and the workers who move from less to more productive firms tend to be the from the highest paid in the firm. To explore whether such a selection effect is influencing the estimates of the productivity gap and hire intensity coefficients in this paper's analysis, the approach of Stockinger and Wolf (2016) is adapted to the baseline model.

Since we are unable to observe the reason for the hiring firm's recruitment choices, it is possible that the types of workers the firms recruit are correlated with the productivity level of the worker's previous firm (e.g. hire only managers from productive firms, and production line workers from less productive firms). As a result, the coefficient on the productivity gap variables will be biased as it is measuring two factors, the productivity knowledge from new workers, and the job-type of these new workers.

As an attempt to control for this, two different measures of the worker's rank within the sending firm are used. The average ranking of new workers' pay, and the average ranking of new workers' previous human capital. Recall that the human capital measure is constructed from a log-wage regression so both rankings used as controls are correlated with one another, so one should expect that the results should not be too dis-similar. Table 7 presents the results of estimating the baseline model with these additional controls.

The results show that the key coefficients in the regression are unaffected by the inclusion of the additional controls. Therefore, it does not appear that the knowledge gap variables is proxying for the (measurable) quality of workers within their previous firm. So unlike the German data, there does not seem to be a significant selection effect in the types of workers hired from more and less productive firms within the New Zealand data.

Table 6: Effect of additional instruments for lagged productivity

	Value-added		**Cobb-Douglas**		**Trans-log**	
	Baseline	**Blundell-Bond**	**Baseline**	**Blundell-Bond**	**Baseline**	**Blundell-Bond**
Productivity gap, hires from (β):						
More prod. firms	0.480***	0.515***	0.271***	0.257**	0.354***	0.250***
	(0.098)	(0.124)	(0.065)	(0.112)	(0.068)	(0.093)
Less prod. firms	0.153***	0.172***	0.374***	0.363***	0.374***	0.296***
	(0.030)	(0.043)	(0.054)	(0.086)	(0.056)	(0.075)
Hire intensity (λ):						
More prod. firms	-0.200***	-0.193***	-0.012	-0.018	-0.037*	-0.027
	(0.057)	(0.063)	(0.028)	(0.030)	(0.021)	(0.021)
Less prod. firms	-0.117***	-0.108***	0.047*	0.044	0.004	0.007
	(0.027)	(0.027)	(0.026)	(0.027)	(0.019)	(0.018)
Obs.	37269	49920	28260	38049	38037	50874

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$, where the measure of productivity differs by column. The Blundell-Bond columns report regression results using lags of productivity ($\ln(A_{i,t-x})$) and change in productivity $\ln(A_{i,t-x})$ as instruments for past productivity. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. Productivity gaps are constructed using the subset of new hires from other private for profit firms for which productivity can be observed. The regression standard errors are clustered at the firm level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Additional controls for the types on new workers hired

	Value-added			Cobb-Douglas			Trans-log		
	Baseline	**Additional controls:**		**Baseline**	**Additional controls:**		**Baseline**	**Additional controls:**	
		real earn. ranking	**quality ranking**		**real earn. ranking**	**quality ranking**		**real earn. ranking**	**quality ranking**
Productivity gap, hires from (β):									
More prod. firms	0.480***	0.478***	0.530***	0.271***	0.269***	0.199***	0.354***	0.352***	0.266***
	(0.098)	(0.098)	(0.082)	(0.065)	(0.064)	(0.060)	(0.068)	(0.068)	(0.078)
Less prod. firms	0.153***	0.144***	0.131**	0.374***	0.374***	0.448***	0.374***	0.370***	0.324***
	(0.030)	(0.030)	(0.041)	(0.054)	(0.054)	(0.066)	(0.056)	(0.055)	(0.056)
Earnings pctile rank within:									
More prod. firms		0.043***			0.005			0.010**	
		(0.007)			(0.006)			(0.004)	
Less prod. firms		-0.034***			-0.015*			-0.010**	
		(0.009)			(0.007)			(0.005)	
Worker qual. pctile rank within:									
More prod. firms			-0.125***			0.003			0.001
			(0.019)			(0.013)			(0.009)
Less prod. firms			-0.015			-0.040***			-0.008
			(0.020)			(0.015)			(0.012)
Parameter tests:									
$\Pr(\beta_M = \beta_L)$	0.001	0.001	0.000	0.217	0.206	0.004	0.808	0.834	0.533
$\Pr(\lambda_M = \lambda_L)$	0.237	0.131	0.001	0.145	0.107	0.047	0.174	0.116	0.537
Obs.	37269	37269	23199	28260	28260	18423	38037	38037	23877

Notes: The dependent variable is $\Delta \ln A_{i,j,t}$.The average rank at the previous firm is measured as the average percentile ranking of the worker's who leave to be hired by the hiring firm. Standard errors are reported in parentheses. Each regression includes industry-year fixed effects, lagged productivity changes, hiring intensities from other sources, and excess turnover as additional regressors. The regressor $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$. Productivity lag length is chosen to minimize autocorrelation in the residual. Productivity gaps are constructed using the subset of new hires from other private for profit firms for which productivity can be observed. The regression standard errors are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B Results for other productivity measures

The analysis of this paper considers a range of firm productivity. These include labour productivity, measures as value-added per worker, and various measures of multi-factor (or total-factor) productivity estimated by Fabling and Maré (2015) that are derived from a (i) Cobb-Douglas production function; (ii) Cobb-Douglas production function featuring firm fixed effects; and (iii) trans-log production function. This appendix replicates the main summary statistics and regression tables from the body of the paper using for the productivity measures that were not presented.

B.1 Summary statistics tables

Table 9 reproduces the summary statistics based on the trans-log productivity measure.

Table 8 replicate the transition matrix of worker movements between PFP productivity deciles for the various MFP measures of firm productivity. In general, firms appear to have equal access to workers in other productivity deciles, irrespective of the productivity decile of the hiring firm.

Table 8: Worker transitions

(a) Cobb-Douglas

Hiring firm's	Source of new employee hires													
	PFP productivity decile										New	Non	Firms with	PFP miss.
prod. decile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Arrivals**	**Market**	**L<5**	**data**
1	0.12	0.06	0.04	0.04	0.03	0.03	0.03	0.03	0.04	0.04	0.00	0.15	0.31	0.08
2	0.10	0.07	0.04	0.04	0.03	0.03	0.03	0.03	0.04	0.04	0.00	0.14	0.33	0.08
3	0.10	0.07	0.04	0.04	0.04	0.04	0.03	0.03	0.04	0.04	0.00	0.14	0.31	0.08
4	0.09	0.07	0.04	0.04	0.04	0.04	0.03	0.03	0.04	0.04	0.00	0.14	0.32	0.08
5	0.09	0.06	0.04	0.04	0.04	0.04	0.03	0.03	0.04	0.04	0.00	0.14	0.31	0.08
6	0.09	0.06	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.00	0.14	0.32	0.08
7	0.08	0.06	0.04	0.04	0.03	0.05	0.04	0.04	0.05	0.04	0.00	0.14	0.30	0.08
8	0.09	0.06	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.04	0.00	0.15	0.30	0.08
9	0.09	0.06	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.00	0.15	0.29	0.09
10	0.09	0.05	0.04	0.03	0.03	0.03	0.04	0.03	0.05	0.05	0.00	0.15	0.31	0.09

(b) Trans-log

Hiring firm's	Source of new employee hires													
	PFP productivity decile										New	Non	Firms with	PFP miss.
prod. decile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Arrivals**	**Market**	**L<5**	**data**
1	0.05	0.06	0.06	0.05	0.04	0.04	0.03	0.03	0.03	0.05	0.00	0.16	0.31	0.08
2	0.05	0.06	0.06	0.05	0.05	0.04	0.03	0.03	0.03	0.05	0.00	0.15	0.31	0.09
3	0.05	0.06	0.06	0.05	0.05	0.04	0.03	0.04	0.03	0.05	0.00	0.14	0.31	0.08
4	0.05	0.06	0.06	0.05	0.05	0.04	0.04	0.04	0.03	0.05	0.00	0.14	0.30	0.08
5	0.05	0.06	0.06	0.05	0.05	0.04	0.04	0.03	0.03	0.05	0.00	0.14	0.32	0.08
6	0.06	0.06	0.06	0.05	0.05	0.04	0.04	0.04	0.03	0.05	0.00	0.14	0.30	0.08
7	0.05	0.05	0.06	0.05	0.05	0.04	0.04	0.04	0.04	0.05	0.00	0.14	0.32	0.08
8	0.05	0.05	0.06	0.05	0.05	0.04	0.04	0.04	0.04	0.05	0.00	0.14	0.32	0.08
9	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.06	0.00	0.14	0.31	0.08
10	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.04	0.08	0.00	0.14	0.31	0.08

Notes: Each cell shows the fraction of total hires made by all firms in each productivity decile (row) from each source (column). Each row sums to one. Cells are shaded based upon the fraction of hires, with darker shades corresponding to a higher fraction of total hires. Deciles correspond to the firm's productivity ranking within each year, with decile 10 referring to the most productive firms.

Table 9: Summary statistics at the firm-year level (Trans-log)

	Firms in sample ($FTE \geq 10$)			Firms that hire new workers			Firms that hire from more productive firms			Firms that do not hire		
Variable	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**
Labor productivity												
log V.A. per worker	11.102	11.094	N.A.	11.101	11.093	N.A.	11.018	11.030	N.A.	11.176	11.165	N.A.
Growth rate V.A. per worker (%)	-0.004	0.000	0.432	-0.003	0.001	0.432	-0.002	0.002	0.456	-0.040	-0.019	0.388
Productivity gap												
Aggregate gap	-0.001	0	0.113	-0.001	0	0.114	0.018	0.009	0.118	0	0	0
More prod. firms gap	0.032	0.008	0.084	0.033	0.009	0.084	0.050	0.024	0.100	0	0	0
Less prod. firms gap	-0.033	-0.010	0.075	-0.033	-0.011	0.076	-0.031	-0.012	0.062	0	0	0
Labor force												
Total FTE units of labor	56.230	17.961	255.994	56.953	18.166	258.128	75.567	22.298	312.738	14.248	12.181	8.657
Share of FTE from new hires	0.194	0.155	0.169	0.198	0.157	0.169	0.216	0.178	0.162	0	0	0
Share of FTE from exiting workers	0.172	0.136	0.150	0.174	0.138	0.150	0.189	0.154	0.147	0.086	0.042	0.165
Excess (annual) turnover	0.514	0.457	0.329	0.522	0.462	0.325	0.586	0.529	0.328	0.019	0	0.054
New Hires												
No. of new employees	22.070	7	101.667	22.448	7	102.498	31.525	11	124.889	0	0	0
Share of hires from brand new workers	0.001	0	0.018	0.001	0	0.018	0.001	0	0.010	0	0	0
Share of hires from non-market	0.116	0.062	0.166	0.116	0.062	0.165	0.104	0.078	0.120	0	0	0
Share of hires from small firms (L<5)	0.288	0.250	0.232	0.288	0.250	0.231	0.260	0.250	0.172	0	0	0
Share of hires from missing prod. data	0.102	0.051	0.154	0.102	0.053	0.154	0.091	0.069	0.108	0	0	0
Share of hires from PFP	0.494	0.500	0.257	0.494	0.500	0.257	0.543	0.527	0.199	0	0	0
within same industry	0.131	0.061	0.180	0.131	0.062	0.180	0.144	0.100	0.168	0	0	0
More productive sources	0.215	0.167	0.224	0.215	0.167	0.224	0.317	0.273	0.205	0	0	0
Obs.	126048			124146			81693			1902		

Notes: Summary statistics based on the sample of firm-year observations in the data set. FTE refers to Full Time Equivalent units of labour (1 FTE = 1 worker per year). Shares of hires are computed as the number of hires from the subgroup relative to the total number of new hires for that firm-year. N.A. denotes values that have been censored in accordance with Statistics New Zealand's confidentiality guidelines. PFP denotes Private For Profit firms (those for which we have productivity data). 'Firms that hire from more productive firms' denotes any firm that hires at least one worker from a more productive firm during that year.

C Further summary statistics regarding the firms

Examining the relationship between new hires and productivity growth at the hiring firm is only a worthwhile exercise if: (i) there is cross-sectional variation in firm productivity so that firm have exposure to different productive ideas when hiring, and (ii) there is dynamic variation in firm productivity so that we may try to relate changes in productivity to changes in hiring rates of new workers. This appendix explores these issues and provides more detail on the productivity of firms within New Zealand.

C.1 Distribution of firm productivity

Figure 1 plots the kernel density estimates of the various productivity distributions, aggregated up to the 1-digit industry group classifications for the firms in the sub-sample (firms with an average labour force size of at least 10 full time employees over the year), and averaged over the entire sample period 2001-2012.

The measures of MFP in most industries is distributed fairly symmetrically around the industry averages, with the Trans-log (the most flexible production function specification) showing the greatest symmetry. The notable exception to this symmetry is the Finance industry in which the productivity distribution is skewed to the right in all the productivity measures.

In terms of value-added per worker (labour productivity), subplot 1a shows, unsurprisingly, that firms in capital intensive industries such as Mining, Electrical and Water supply, and Financing tend to have higher levels of labour productivity than more labour intensive firms such as Retail, and the various service industries. The log-productivity differences between these industries indicates that there is significant differences between the levels of value-added per worker across the different industries.

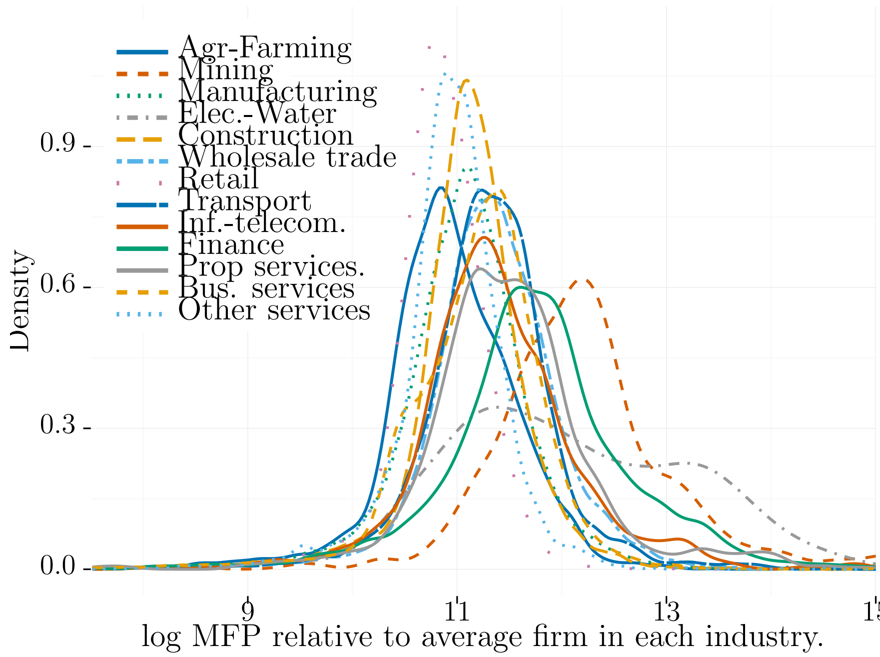
C.2 Productivity dynamics

Table 10 presents a summary of the productivity transition dynamics within the sample. For each productivity decile in a given year (row), table 10 shows the fraction of firms within that productivity decile that where in each source (column) during the previous year. There are 12 possible sources for firms, 10 productivity deciles, and two reasons for being out of scope, either missing productivity data during the previous year, or being too small (less than 10 full time workers on average over the year).

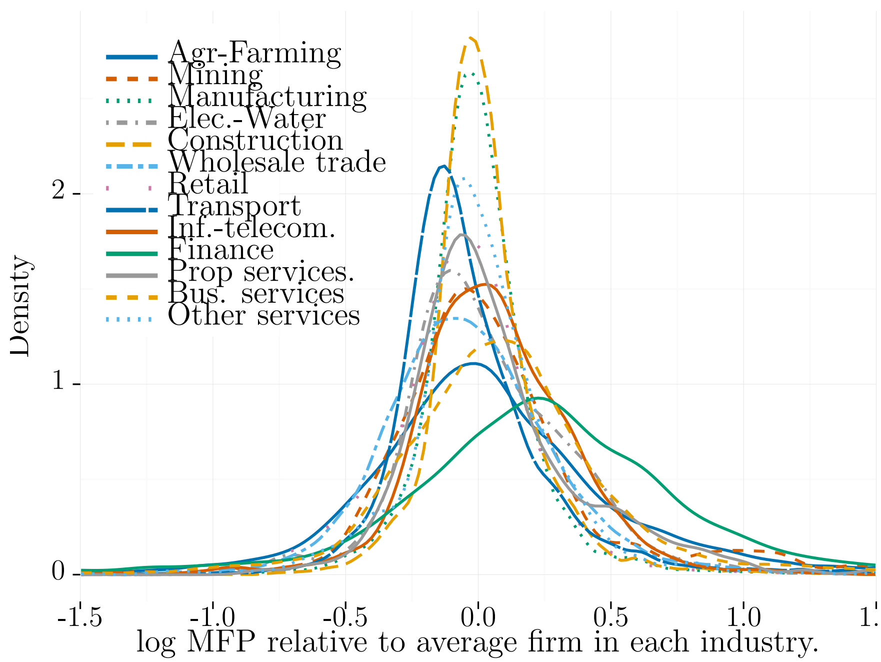
The transition matrices in table 10 show that there is some persistence in the firm's productivity ranking. Depending upon the productivity measure and productivity decile, a firm has around a 20 to 50 percent chance of been in the same productivity decile in the previous year. If firms do transition between productivity deciles, they tend not to make large jumps between very different deciles. And this pattern holds for all of the productivity deciles considered.

Figure 1: Kernel density estimates of the productivity distributions

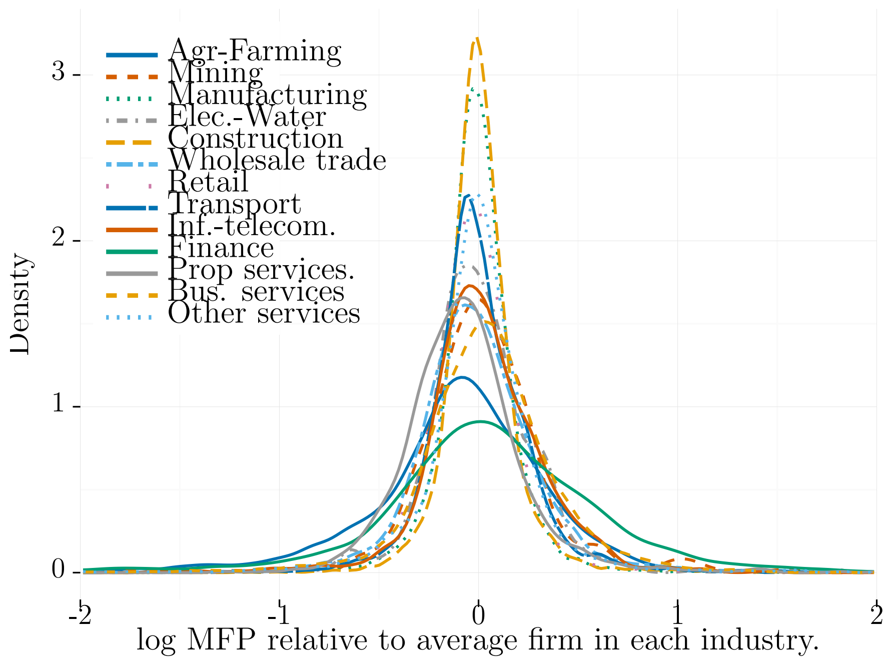
(a) Value-added per worker



(b) Cobb-Douglas



(c) Trans-log



Notes: Each subplot shows the kernel density estimate of productivity in each of the 13 1-digit industry groups for all the firms in the sample (those with an average annual employment of more than 10 full time equivalent workers) aggregated over the entire sample period. All measures of firm-level productivity are computed at the 4-digit industry level before aggregation. For the measures of MFP (Cobb-Douglas, Fixed effects, and Trans-log), firm-level productivity is computed relative to the average in the industry-year using all firms (even those with FTE<10). For the measure of value-added per worker, results from each year are converted to real values.

Table 10: Firm productivity transition matrices

(a) Value-added per worker

Firm's current prod. decile	**Firm's previous productivity decile**										**Missing prod data**	**L<10**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**		
1	0.32	0.13	0.05	0.04	0.03	0.02	0.02	0.01	0.01	0.01	0.27	0.1
2	0.11	0.31	0.14	0.05	0.02	0.02	0.01	0.01	0.01	0	0.22	0.1
3	0.05	0.13	0.26	0.15	0.06	0.03	0.02	0.01	0	0	0.2	0.09
4	0.04	0.05	0.14	0.22	0.15	0.07	0.03	0.02	0.01	0	0.2	0.09
5	0.03	0.02	0.05	0.14	0.23	0.14	0.06	0.03	0.01	0.01	0.18	0.09
6	0.02	0.02	0.03	0.06	0.14	0.22	0.16	0.06	0.02	0.01	0.18	0.07
7	0.01	0.01	0.01	0.03	0.06	0.14	0.24	0.16	0.05	0.01	0.19	0.07
8	0.01	0.01	0.01	0.01	0.03	0.06	0.15	0.27	0.17	0.03	0.18	0.07
9	0.01	0	0	0.01	0.01	0.02	0.05	0.15	0.35	0.13	0.19	0.07
10	0.01	0	0	0	0	0.01	0.01	0.03	0.12	0.57	0.19	0.06

(b) Cobb-Douglas

Firm's current prod. decile	**Firm's previous productivity decile**										**Missing prod data**	**L<10**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**		
1	0.33	0.12	0.06	0.03	0.03	0.02	0.02	0.02	0.01	0.02	0.25	0.09
2	0.12	0.25	0.15	0.07	0.04	0.03	0.02	0.02	0.01	0.01	0.21	0.08
3	0.05	0.13	0.2	0.15	0.08	0.04	0.03	0.02	0.01	0.01	0.2	0.08
4	0.04	0.07	0.13	0.18	0.13	0.08	0.04	0.03	0.02	0.01	0.2	0.08
5	0.03	0.04	0.07	0.13	0.18	0.14	0.08	0.05	0.02	0.01	0.18	0.08
6	0.02	0.03	0.04	0.07	0.13	0.17	0.14	0.07	0.03	0.02	0.19	0.09
7	0.02	0.02	0.02	0.04	0.07	0.14	0.18	0.14	0.07	0.02	0.19	0.08
8	0.01	0.01	0.02	0.02	0.04	0.07	0.13	0.22	0.16	0.04	0.18	0.09
9	0.01	0.01	0.01	0.01	0.02	0.03	0.06	0.14	0.28	0.14	0.18	0.09
10	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.13	0.44	0.2	0.09

(c) Trans-log

Firm's current prod. decile	Firm's previous productivity decile 1	2	3	4	5	6	7	8	9	10	Missing prod data	L<10
1	0.32	0.13	0.06	0.04	0.03	0.02	0.02	0.02	0.01	0.01	0.26	0.09
2	0.12	0.24	0.15	0.07	0.05	0.03	0.02	0.02	0.01	0.01	0.21	0.08
3	0.06	0.14	0.19	0.13	0.08	0.05	0.03	0.02	0.01	0.01	0.2	0.08
4	0.04	0.07	0.13	0.18	0.13	0.08	0.05	0.03	0.02	0.01	0.19	0.08
5	0.03	0.04	0.08	0.13	0.17	0.13	0.08	0.05	0.03	0.01	0.19	0.07
6	0.02	0.03	0.05	0.08	0.13	0.16	0.13	0.08	0.04	0.02	0.2	0.08
7	0.02	0.02	0.02	0.04	0.07	0.13	0.18	0.15	0.07	0.03	0.18	0.09
8	0.01	0.01	0.02	0.02	0.04	0.07	0.14	0.21	0.16	0.05	0.18	0.09
9	0.01	0.01	0.01	0.01	0.02	0.04	0.06	0.14	0.28	0.14	0.19	0.08
10	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.05	0.14	0.43	0.2	0.09

Notes: Each cell shows the fraction firms in the productivity decile for the current year (row) that were in each productivity decile, or out of scope in the previous year (column). For example, cell (1,1) refers to the fraction of firms in productivity decile one, that were also in productivity decile one last year. And cell (1,2) refers to the fraction of firms in productivity decile one that were in productivity decile two last year. Cells are shaded based upon the fraction of firms that were in that previous source last year, with darker shades corresponding to a higher fraction. Deciles correspond to the firm's productivity ranking within each year, with decile 10 referring to the most productive firms.

C.3 Distribution of firm size (Zipf's law)

For many countries around the world, the distribution of firm sizes (measured in labour units) in the economy has been shown to be well approximated by a Pareto distribution where the tail parameter is close to unity. This implies that the share of firms whose size is above a given value is inversely proportional to that value. More formally, The share of firms with a size larger than s is given by

$$\Pr[S \geq s] = \left(\frac{\lambda}{s}\right)^{\alpha} \tag{2}$$

where s is the size of the firm (measured in labour units), λ is a scale parameter, and α is the tail parameter. Zipf's law implies $\alpha = 1$.

To test whether the Zipf's law holds for the distribution of firm size in New Zealand, the log of the firm's size percentile is regressed on the log of the firm size and a constant. The coefficient on the log of the firm size corresponds to $-\alpha$. The results of this regression are presented in Table 11. Because there are a significant number of very small sized firms (and firms without employees) in the economy, the regression is run on several different sub samples where firm's below a certain minimum size have been dropped.

The point estimates of $-\alpha$ for all the sub-sample regressions are close in magnitude to negative one, the value implied by Zipf's law, although given the large number of observations in the sample their values are statistically different from minus one at the one percent level of significance. A large number of firms in the data set employ one or fewer full time employees on average through the year (e.g. some sole proprietors). Increasing the minimum firm size for the regression from one to two FTEs halves the number of observations, and has a

Table 11: Estimates of Zipf's law for the distribution of firm size

	Minimum firm size (FTE =)			
	1	**2**	**5**	**10**
log(FTE) ($-\alpha$)	-0.963***	-1.044***	-1.089***	-1.084***
	(0.000)	(0.000)	(0.000)	(0.000)
constant	-0.128***	0.803***	1.761***	2.486***
	(0.000)	(0.000)	(0.000)	(0.000)
Pr($\alpha = 1$)	0	0	0	0
R^2	0.993	0.997	0.999	0.997
Obs.	1284588	608814	265680	126288

Notes: Dependent variable is the log of the firm size percentile. Each column represents a separate regression for sub-samples using different minimum firm sizes, where firm size is measured in average Full Time Equivalent workers (FTE) over the year. A coefficient of $\alpha = -1$ is consistent with Zipf's law. Standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.02$, *** $p < 0.01$

noticeable impact on the point estimate of α, increasing it form 0.963 to 1.044. However, the estimate of α is relatively robust to further increases in the minimum firm size used for the sample and remains marginally greater than unity. As a result, the distribution of firm sizes in the New Zealand economy is consistent with Zipf's law.

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