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

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Disclaimer

The results in this paper are not official statistics, they have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Statistics New Zealand.

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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 section 3.3.1 of 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 labor productivity measure to the original value-added labor 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.

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

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 in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 2: Benchmark regression by industry (1-digit level)

	Value Added p.w.							**Cobb-Douglas**							**Trans-log**						
	Baseline	**Industry**						**Baseline**	**Industry**						**Baseline**	**Industry**					
		Manufac.	**Prof. services**	**Constr.**	**Transport**	**Agri & Forest**	**Mining**		**Manufac.**	**Prof. services**	**Constr.**	**Transport**	**Agri & Forest**	**Mining**		**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***	0.271***	0.114	0.085	0.160	0.779***	0.180**	0.280*	0.354***	0.306***	0.468***	0.366**	1.032***	0.281**	0.248***
	(0.098)	(0.300)	(0.179)	(0.292)	(0.316)	(0.100)	(0.124)	(0.065)	(0.154)	(0.081)	(0.137)	(0.276)	(0.073)	(0.149)	(0.068)	(0.112)	(0.120)	(0.170)	(0.342)	(0.136)	(0.090)
Less prod. firms	0.153***	0.325***	0.022	0.249*	0.259***	0.063	0.351***	0.374***	0.187**	0.231**	0.636**	0.855***	0.490***	0.396***	0.374***	0.272*	0.331***	0.679***	0.660***	0.258***	0.421***
	(0.030)	(0.096)	(0.068)	(0.130)	(0.085)	(0.093)	(0.080)	(0.054)	(0.088)	(0.105)	(0.284)	(0.327)	(0.144)	(0.079)	(0.056)	(0.140)	(0.101)	(0.227)	(0.216)	(0.073)	(0.098)
Hire intensity (λ):																					
More prod. firms	-0.200***	-0.023	-0.589***	-0.419***	-0.255	-0.297***	-0.253***	-0.012	0.107	0.073**	0.089	-0.177	0.028	-0.053	-0.037*	-0.029	-0.008	0.015	-0.253**	-0.007	-0.019
	(0.057)	(0.145)	(0.109)	(0.158)	(0.197)	(0.058)	(0.089)	(0.028)	(0.085)	(0.034)	(0.057)	(0.136)	(0.036)	(0.072)	(0.021)	(0.042)	(0.031)	(0.046)	(0.122)	(0.043)	(0.033)
Less prod. firms	-0.117***	-0.009	-0.299***	-0.164	-0.017	-0.096**	0.068	0.047*	0.021	-0.086**	0.066	0.164	0.065	0.166**	0.004	-0.003	-0.053*	0.030	0.019	-0.008	0.038
	(0.027)	(0.066)	(0.074)	(0.102)	(0.090)	(0.043)	(0.080)	(0.026)	(0.049)	(0.036)	(0.084)	(0.159)	(0.051)	(0.065)	(0.019)	(0.055)	(0.031)	(0.057)	(0.103)	(0.024)	(0.041)
Parameter tests:																					
$\Pr(\beta_M = \beta_L)$	0.001	0.552	0.000	0.001	0.159	0.000	0.940	0.217	0.671	0.244	0.092	0.853	0.055	0.475	0.808	0.840	0.360	0.228	0.338	0.874	0.173
$\Pr(\lambda_M = \lambda_L)$	0.237	0.939	0.039	0.207	0.293	0.010	0.021	0.145	0.391	0.004	0.849	0.108	0.583	0.037	0.174	0.720	0.321	0.848	0.063	0.985	0.340
Obs.	37269	1695	9279	3600	3762	7506	5340	28260	1257	7146	2700	2826	5565	3990	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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 labor 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.

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

Table 3: Benchmark regression by firm size

	Value-added			**Cobb-Douglas**			**Trans-log**		
	$\mathbf{FTE} \leq 20$	$20 < \mathbf{FTE} \leq 50$	$\mathbf{FTE} > 50$	$\mathbf{FTE} \leq 20$	$20 < \mathbf{FTE} \leq 50$	$\mathbf{FTE} > 50$	$\mathbf{FTE} \leq 20$	$20 < \mathbf{FTE} \leq 50$	$\mathbf{FTE} > 50$
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 in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 labor productivity data. However, the same cannot be said for the MFP measures of firm productivity.

A.3.1 Scale of the productivity gap

The productivity gap terms in equation 3 is constructed following the approach of Stoyanov and Zubanov (2012) and normalizes the sum of the productivity differentials by the size of the hiring firm's labor force.[1] This functional form implicitly assumes that to achieve the same percentage point increase in the hiring firm's productivity growth, a large firm need to absorb a larger amount of productive knowledge from new hires than a small firm would. While this is a reasonable assumption for knowledge that relates to specific roles/jobs within a firm, it is not necessarily true for all types of knowledge. Some knowledge may be equally applicable to firms, regardless of their size, such as firm restructuring.

To investigate this concern, the baseline model is modified to include terms for the average productivity difference between the sending and hiring firm so the change in the firm's productive knowledge stock now takes the form

$$\begin{aligned}
\beta \Delta know_{i,t} \quad = \quad & \beta_M \frac{\sum_{n \in \mathcal{N}_j, t-1} \mathbb{D}_n [\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& + \beta_{M,2} \frac{\sum_{n \in \mathcal{N}_j, t-1} \mathbb{D}_n [\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{H_{i,M,t-1}} \\
& + \beta_L \frac{\sum_{n \in \mathcal{N}_i, t-1} (1 - \mathbb{D}_n) [\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& + \beta_{L,2} \frac{\sum_{n \in \mathcal{N}_i, t-1} (1 - \mathbb{D}_n) [\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{H_{i,L,t-1}} \\
& + \sum_{s \in \mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}} \qquad (1)
\end{aligned}$$

where $H_{i,M,t-1} = \sum_{n \in \mathcal{N}_j, t-1} \mathbb{D}_n$ is the number of new hires from more productive firms, and $H_{i,L,t-1} = \sum_{n \in \mathcal{N}_j, t-1} (1 - \mathbb{D}_n)$ is the number of new hires from less productive firms. In this

[1] An alternative interpretation is that the productivity gap is the average productivity differential multiplied by the intensity of new hires.

new specification, β_M and β_L will relate to the benefit of new knowledge that scales with the size of the hiring firm, while $\beta_{M,2}$ and $\beta_{L,2}$ will related to the benefit of knowledge that is independent of the firm size.

Another potential issue with the scaling of the productivity gaps is there may be some economies, or dis-economies, of scale with regards to absorbing new knowledge. If there are limits on how quickly firms can adapt and implement new knowledge, then the marginal benefit of obtaining large amounts of new knowledge within a single year will be small. In such cases, the relationship between the productivity gap and productivity growth may not be linear.

Non-linearities in the ability to absorb new knowledge are also likely when a firm has a high staff turnover rate. A firm with a high turnover rate will tend to have a high productivity gap simply because of the number of hires they make each year. But despite the high number of hires, staff may not remain with the firm long enough for the firm to fully benefit from the new knowledge. To investigate if this is the case, the baseline model is augmented with the squared productivity gap to capture any non-linearities in the relationship between the productivity gap and the productivity growth in the hiring firm. Therefore the change in the hiring firm's productive knowledge would take the form

$$
\begin{aligned}
\beta \Delta know_{i,t} \;=\; & \beta_M \frac{\sum_{n\in\mathcal{N}_j,t-1} \mathbb{D}_n[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& +\beta_{M,3}\left(\frac{\sum_{n\in\mathcal{N}_j,t-1} \mathbb{D}_n[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}}\right)^2 \\
& +\beta_L \frac{\sum_{n\in\mathcal{N}_i,t-1}(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\
& +\beta_{L,3}\left(\frac{\sum_{n\in\mathcal{N}_i,t-1}(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}}\right)^2 \\
& + \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}}
\end{aligned} \tag{2}
$$

Table 4 presents the regression results found when augmenting the baseline model to include (i) the non-normalized productivity gap, and (ii) the squared productivity gap.

When using labor productivity (value-added per worker) to measure firm productivity, the inclusion of the non-normalized productivity gap (equation 1) does not seem to have a significant effect on estimated magnitudes of the original productivity gap terms. The coefficient on the productivity gap related to hires from more productive firms declines only slightly (from 0.48 to 0.388), while the coefficient on the productivity gap related to hires from less productive firms increases slightly from 0.153 to 0.242.

The coefficients related to the non-normalized productivity gaps (measuring the benefit of new knowledge not affected by the size of the hiring firm) are both estimated to be significant, but smaller in magnitude than the corresponding productivity gap coefficients. Surprisingly,

Table 4: Additional productivity gap dynamics

	Value-added			Cobb-Douglas			Trans-log		
	Baseline	**+ non-norm gap**	**+ sqrd prod gap**	**Baseline**	**+ non-norm gap**	**+ sqrd prod gap**	**Baseline**	**+ non-norm gap**	**+ sqrd prod gap**
Productivity gap, hires from (β):									
More prod. firms	0.480***	0.388***	0.959***	0.271***	0.219**	0.401***	0.354***	0.082	0.616***
	(0.098)	(0.097)	(0.087)	(0.065)	(0.087)	(0.068)	(0.068)	(0.073)	(0.084)
Less prod. firms	0.153***	0.243***	0.176***	0.374***	0.400***	0.519***	0.374***	0.310***	0.519***
	(0.030)	(0.063)	(0.042)	(0.054)	(0.077)	(0.076)	(0.056)	(0.073)	(0.063)
Non-normalized prod. gap									
More prod. firms		0.067***			-0.005			0.076***	
		(0.014)			(0.013)			(0.016)	
Less prod. firms		-0.021**			0.023			0.005	
		(0.010)			(0.015)			(0.011)	
Squared productivity gap									
More prod. firms			-0.188***			-0.150**			-0.192***
			(0.024)			(0.073)			(0.041)
Less prod. firms			0.005			0.107***			0.147***
			(0.004)			(0.038)			(0.052)
Hire intensity (λ):									
More prod. firms	-0.200***	-0.171***	-0.392***	-0.012	-0.006	-0.046*	-0.037*	0.033	-0.097***
	(0.057)	(0.058)	(0.050)	(0.028)	(0.035)	(0.026)	(0.021)	(0.021)	(0.024)
Less prod. firms	-0.117***	-0.012	-0.075**	0.047*	0.062**	0.086***	0.004	-0.005	0.042**
	(0.027)	(0.036)	(0.030)	(0.026)	(0.031)	(0.028)	(0.019)	(0.022)	(0.018)
Parameter tests:									
$\Pr(\beta_M = \beta_L)$	0.001	0.208	0.000	0.217	0.113	0.228	0.808	0.025	0.327
$\Pr(\lambda_M = \lambda_L)$	0.237	0.028	0.000	0.145	0.159	0.001	0.174	0.240	0.000
Obs.	37269	23199	37269	28260	18423	28260	38037	23877	38037

Notes: The dependent variable in the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). The second and third column of each productivity measures adds to the baseline model the average productivity difference, and the squared productivity gap respectively. 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the coefficient on the non-normalized productivity gap from less productive firms is negative. Because the productivity difference with less productive firms is negative, the negative coefficient implies that sourcing the average worker from even less productive firms raises productivity growth in the hiring firm. While this result in isolation is unexpected, it should also be noted that the coefficient on the standard (normalized) productivity gap for hires from less productive firms grew in magnitude. This will offset the supposed productivity gains through the non-normalized productivity gap when hiring from less productive firms.

For the Cobb-Douglas measure of firm productivity, the coefficients on the non-normalized productivity gaps are generally smaller. In addition, the other parameters in the model are generally unaffected by the inclusion of the non-normalized productivity gaps. However, for the trans-log measure of productivity, the results show that the productivity gains associated with hiring from more productive firms are more closely associated with the average productivity difference from new hires (the non-normalized productivity gap) rather than the (normalized) productivity gap adjusted for firm size. The estimated coefficient on the productivity gap related to hires from more productive firms declines significantly (from 0.354 to 0.082), and the coefficient for the non-normalized productivity gap (0.076) is significant. This suggests that when using trans-log productivity, the gains associated with the exposure to new and better productive knowledge tends to be independent of the hiring firm's size. Because the trans-log productivity measure is more flexible to changes in the firm's production structure than the Cobb-Douglas measure, this suggests that firms adapt their production technology in response to new and better knowledge.

When the squared productivity gap term is added to the baseline model we see two main patterns emerge in the parameter values across all the productivity measures. First, the magnitude of the coefficients on the original productivity gaps increase. Second, the coefficient on the squared productivity gaps are negative for hires from more productive firms, and positive for hires from less productive firms.

The negative coefficient on the squared productivity gap for hires from more productive firms is similar in magnitude to across all productivity measures, and implies a concave function for the correlation with productivity growth at the hiring firm. Therefore the marginal gain from a larger productivity gap is decreasing, and for very large values of the productivity gap, the expected gains in productivity growth can even be negative.

With regards to hires from less productive firms, the coefficients related to the squared productivity gaps are positive, and significant in the cases of the MFP measures. This implies that the marginal productivity loss associated with hiring from less productive firms is increase with the size of the productivity gap.

Overall, these results show some support for non-linearities in relation to the benefit of new knowledge for the hiring firm. However, even when accounting for these non-linearities, the coefficients related to the original productivity gaps are not dramatically affected.

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 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.[2] 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 that equation 5 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 labor productivity and MFP measures, and some support for the knowledge spillover channel only in the labor productivity data. Stoyanov and Zubanov (2012) on the other hand finds support for only the knowledge spillover channel, both in labor 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 given equation 5 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 $\Delta \ln A_{i,j,\tau} = \ln A_{i,j,\tau} - \ln A_{i,j,\tau-1}$ into equation 5 and re-arranging yields the following expression which, like the model of Stoyanov and Zubanov (2012), relates

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

Table 5: 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the level of MFP to the change in firm knowledge:

$$\ln A_{i,j,t} = \beta_1 \Delta Q_{i,t} + \text{Exoposure}_{i,t} + \beta_3 \Delta ExTurn_{i,t} + \sum_{l=1}^{L} \beta_{A,l} \ln A_{i,j,t-l} + \Delta\theta_{j,t} + \varepsilon_{i,t} \quad (3)$$

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 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 6.

Table 6: 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 4 and 3, 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The coefficients in table 6 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.[3] Therefore, the findings in this paper are robust to the change in model specification considered by Stoyanov and Zubanov (2012).

[3]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.

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 Alternative measures of worker quality

The measure of worker quality used so far is based solely on the characteristics of the worker that are applicable to all firms (the worker fixed effect and other demographic type variables). It does not account for how productive the worker is in a specific job. As a result, the measure of worker quality could be misleading for the measure of quality applicable to the specific hiring firm.

To address this concern, the baseline model is re-estimated using two alternative measures of worker quality. The first alternative is to only use the worker fixed effect from the wage regression (dropping the characteristics such as age and gender). The second alternative is to construct a measure of worker quality by subtracting the firm fixed effect from the worker's wage (effectively adding the regression residual back into the baseline measure of quality). This second measure of worker quality should capture any worker-firm match quality at the hiring firm. Our main interest lies in seeing if the estimates of the coefficients for the productivity gaps and hire intensities vary with the changes in the choice of worker quality measure. If they do vary significantly, it would suggest that the support found so far for the knowledge spillover and unmeasured worker quality channel could be related to the lack of control within the model for the worker-firm match quality. The results of the regressions using the alternate measures of worker quality are presented in table 7.

The regression results in table 7 show that the coefficients related to the productivity gaps and hire intensities are not significantly affected when the measure of worker quality is changed to either of the alternatives. This set of results suggests that the productivity gap and hiring intensities are not proxying for worker-firm match quality that can be measured through the observation of the worker's wage.[4]

B Results for other productivity measures

The analysis of this paper considers a range of firm productivity. These include labor 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.

[4]Technically it is still possible that the firms may have significant bargaining power in the wage negotiations that they are able to fully capture the benefit of worker skill without paying the workers a higher wage. However, with the regulatory environment in New Zealand, it is unlikely firms have this much power.

Table 7: Alternative measures of worker quality

	Value-added			**Cobb-Douglas**			**Trans-log**		
Measure of worker quality:	**Baseline**	**WFE**	**Wages-FFE**	**Baseline**	**WFE**	**Wages-FFE**	**Baseline**	**WFE**	**Wages-FFE**
Productivity gap, hires from (β):									
More prod. firms	0.480***	0.485***	0.482***	0.271***	0.272***	0.271***	0.354***	0.356***	0.353***
	(0.098)	(0.099)	(0.098)	(0.065)	(0.065)	(0.064)	(0.068)	(0.069)	(0.068)
Less prod. firms	0.153***	0.156***	0.151***	0.374***	0.375***	0.375***	0.374***	0.380***	0.373***
	(0.030)	(0.031)	(0.030)	(0.054)	(0.054)	(0.054)	(0.056)	(0.056)	(0.056)
Hire intensity (λ):									
More prod. firms	-0.200***	-0.180***	-0.201***	-0.012	-0.008	-0.011	-0.037*	-0.028	-0.037*
	(0.057)	(0.058)	(0.057)	(0.028)	(0.027)	(0.028)	(0.021)	(0.021)	(0.021)
Less prod. firms	-0.117***	-0.106***	-0.110***	0.047*	0.050*	0.048*	0.004	0.011	0.005
	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.019)	(0.018)	(0.019)
Parameter tests:									
$\Pr(\beta_M = \beta_L)$	0.001	0.001	0.001	0.217	0.221	0.211	0.808	0.785	0.811
$\Pr(\lambda_M = \lambda_L)$	0.237	0.293	0.196	0.145	0.147	0.137	0.174	0.208	0.164
Obs.	37269	37269	37269	28260	28260	28260	38037	38037	38037

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). Each column denotes a different measure of worker quality ($Q_{i,t}$). WFE denotes worker quality measured by the Worker Fixed Effect. Wages-FFE denotes worker quality measured as the log of wages less the Firm Fixed Effect. 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 8: 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 labor (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.

B.1 Summary statistics tables

Table 8 reproduces the summary statistics based on the trans-log productivity measure.

Table 9 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 9: Worker transitions

(a) Cobb-Douglas

Hiring firm's prod. decile	Source of new employee hires: PFP productivity decile 1	2	3	4	5	6	7	8	9	10	New Arrivals	Non Market	Firms with L<5	PFP miss. 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) Cobb-Douglas with Fixed Effects

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

(c) Trans-log

Hiring firm's prod. decile	Source of new employee hires: PFP productivity decile 1	2	3	4	5	6	7	8	9	10	New Arrivals	Non Market	Firms with L<5	PFP miss. 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.

B.2 Regression result tables for Cobb-Douglas with fixed effects

Tables 10 to 21 replicate the regression results from the main body of the paper for the measure of firm multi-factor productivity derived from the Cobb-Douglas with Fixed Effects by Fabling and Maré (2015).

Table 10: Baseline results – Cobb-Douglas with F.E.

	Coefficent
Productivity gap, hires from (β):	
More prod. firms	0.173***
	(0.052)
Less prod. firms	0.255***
	(0.045)
Hire intensity (λ):	
More prod. firms	0.007
	(0.024)
Less prod. firms	0.002
	(0.022)
$\Delta Q_{i,t}$ due to (γ):	
New hires	0.074
	(0.058)
Exiters	0.072
	(0.058)
Incumbents	0.071
	(0.058)
Parameter tests:	
$\Pr(\beta_M = \beta_L)$	0.227
$\Pr(\lambda_M = \lambda_L)$	0.879
$\Pr(\gamma_{new} = \gamma_{incmb})$	0.103
Obs.	28260

Notes: Dependent variable is the regressions is the change in log value-added ($\Delta \ln A_{i,j,t}$). Standard errors are reported in parentheses. When included in the regression, $\Delta \ln A_{i,j,t-1}$ is instrumented for using $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 11: Between and within industry productivity gaps — Cobb-Douglas with F.E.

	Baseline	**Productivity gaps by ind.**	
		3-digit	**1-digit**
Productivity gap, hires from (β):			
More prod. firms	0.198***		
	(0.042)		
Within same ind.		0.311**	0.287***
		(0.123)	(0.105)
From diff. ind.		0.373***	0.390***
		(0.090)	(0.097)
Less prod. firms	0.282***		
	(0.038)		
Within same ind.		0.278***	0.314***
		(0.103)	(0.079)
From diff. ind.		0.415***	0.418***
		(0.071)	(0.086)
Hire intensity (λ):			
More prod. firms	0.002		
	(0.020)		
Within same ind.		0.008	0.002
		(0.028)	(0.028)
From diff. ind.		-0.059**	-0.066**
		(0.028)	(0.031)
Less prod. firms	0.016		
	(0.019)		
Within same ind.		-0.001	-0.005
		(0.028)	(0.023)
From diff. ind.		0.004	0.010
		(0.025)	(0.029)
Parameter tests:			
$\Pr(\beta_M = \beta_L)$	0.137		
$\Pr(\beta_{M,\text{same}} = \beta_{L,\text{same}})$		0.825	0.832
$\Pr(\beta_{M,\text{diff}} = \beta_{L,\text{diff}})$		0.712	0.824
$\Pr(\beta_{M,\text{same}} = \beta_{M,\text{diff}})$		0.724	0.517
$\Pr(\beta_{L,\text{same}} = \beta_{L,\text{diff}})$		0.302	0.406
$\Pr(\lambda_M = \lambda_L)$	0.626		
$\Pr(\lambda_{M,\text{same}} = \lambda_{L,\text{same}})$		0.846	0.851
$\Pr(\lambda_{M,\text{diff}} = \lambda_{L,\text{diff}})$		0.111	0.095
$\Pr(\lambda_{M,\text{same}} = \lambda_{M,\text{diff}})$		0.124	0.117
$\Pr(\lambda_{L,\text{same}} = \lambda_{L,\text{diff}})$		0.895	0.694
Obs.	38037	38037	38037

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). The 3-digit classification refers to the level of industry classification used by Fabling and Maré (2015) which is very similar to the level 3 ANZSIC06 categories. The 1-digit classification refers to 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 12: Effects of considering worker tenure – Cobb-Douglas with F.E.

	Baseline	**Tenure at:**	
		Sending	**Sending & hiring**
Prod. gap, hires from (β):			
More prod. firms	0.173***		
	(0.052)		
With long tenure		0.122	0.135
		(0.075)	(0.106)
With short tenure		0.226***	0.183***
		(0.055)	(0.058)
Less prod. firms	0.255***		
	(0.045)		
With long tenure		0.361***	0.557***
		(0.109)	(0.174)
With short tenure		0.189**	0.187***
		(0.080)	(0.054)
Hire intensity (λ):			
More prod. firms	0.007		
	(0.024)		
With long tenure		0.040	0.073*
		(0.035)	(0.043)
With short tenure		-0.029	-0.013
		(0.029)	(0.030)
Less prod. firms	0.002		
	(0.022)		
With long tenure		-0.008	0.084
		(0.037)	(0.058)
With short tenure		0.021	-0.019
		(0.035)	(0.028)
Parameter tests:			
$\Pr(\beta_{M,\text{long}} = \beta_{L,\text{long}})$		0.073	0.042
$\Pr(\beta_{M,\text{short}} = \beta_{L,\text{short}})$		0.708	0.959
$\Pr(\beta_{M,\text{long}} = \beta_{M,\text{short}})$		0.228	0.690
$\Pr(\beta_{L,\text{long}} = \beta_{L,\text{short}})$		0.297	0.065
$\Pr(\lambda_{M,\text{long}} = \lambda_{L,\text{long}})$		0.355	0.884
$\Pr(\lambda_{M,\text{short}} = \lambda_{L,\text{short}})$		0.268	0.882
$\Pr(\lambda_{M,\text{long}} = \lambda_{M,\text{short}})$		0.126	0.110
$\Pr(\lambda_{L,\text{long}} = \lambda_{L,\text{short}})$		0.594	0.140
Obs.	28260	28260	28260

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). The cut off length for distinguishing between long and short tenure is equal to 12 months of previous employment at the respective 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 13: Worker flows by worker skill level — Cobb-Douglas with F.E.

	Baseline	**By skill Group**
Productivity gap, hires from (β):		
More prod. firms	0.173***	
	(0.052)	
Low skilled		0.214
		(0.131)
Medium skilled		0.247***
		(0.091)
High skilled		0.247***
		(0.088)
Less prod. firms	0.255***	
	(0.045)	
Low skilled		0.320
		(0.206)
Medium skilled		0.464**
		(0.210)
High skilled		0.303**
		(0.147)
Hire intensity (λ):		
More prod. firms	0.007	
	(0.024)	
Less prod. firms	0.002	
	(0.022)	
Low skilled		0.004
		(0.051)
Medium skilled		-0.005
		(0.050)
High skilled		0.009
		(0.047)
Unknown skill		0.374
		(0.480)
Parameter tests:		
$\Pr(\beta_{M,low} = \beta_{L,low})$		0.715
$\Pr(\beta_{M,med} = \beta_{L,med})$		0.393
$\Pr(\beta_{M,high} = \beta_{L,high})$		0.775
$\Pr(\beta_{M,low} = \beta_{M,med} = \beta_{M,high})$		0.971
$\Pr(\beta_{L,low} = \beta_{L,med} = \beta_{L,high})$		0.875
Obs.	28260	28260

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). Low, medium, and high skill denotes which third of distribution of worker quality an individual is in relative to the population at the time of hiring. 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 14: Worker flows by worker earnings at hiring firm — Cobb-Douglas with F.E.

	Baseline	**High earning cutoff value**	
		10%	**20%**
Prod. gap, hires from (β):			
More prod. firms	0.173***		
	(0.052)		
High paid workers		-0.018	-0.136
		(0.128)	(0.108)
Low paid workers		0.186***	0.217***
		(0.054)	(0.060)
Less prod. firms	0.255***		
	(0.045)		
High paid workers		0.148	0.162
		(0.396)	(0.283)
Low paid workers		0.265***	0.273***
		(0.055)	(0.069)
Hire intensity (λ):			
More prod. firms	0.007		
	(0.024)		
With long tenure		0.075	0.116**
		(0.074)	(0.054)
With short tenure		0.002	-0.009
		(0.026)	(0.028)
Less prod. firms	0.002		
	(0.022)		
With long tenure		0.139	0.035
		(0.132)	(0.094)
With short tenure		-0.006	-0.001
		(0.023)	(0.026)
Parameter tests:			
$\Pr(\beta_{M,high} = \beta_{L,high})$		0.697	0.344
$\Pr(\beta_{M,low} = \beta_{L,low})$		0.304	0.540
$\Pr(\beta_{M,high} = \beta_{M,low})$		0.151	0.010
$\Pr(\beta_{L,high} = \beta_{L,low})$		0.784	0.739
Obs.	28260	28260	28260

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$), where the measure of productivity differs by column. Low and high skill is determined by the cutoff value using the new worker's earnings ranking in the first full month of employment relative to all other workers at the 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 15: Benchmark regression by firm size — Cobb-Douglas with F.E.

	$\mathbf{FTE} \leq 20$	$20 < \mathbf{FTE} \leq 50$	$\mathbf{FTE} > 50$
Prod. gap, hires from (β):			
More prod. firms	0.215**	0.134*	0.155
	(0.095)	(0.071)	(0.097)
Less prod. firms	0.159***	0.314***	0.277***
	(0.061)	(0.077)	(0.083)
Hire intensity (λ):			
More prod. firms	-0.008	0.009	0.019
	(0.041)	(0.036)	(0.056)
Less prod. firms	-0.066**	0.033	0.022
	(0.028)	(0.035)	(0.055)
$\Delta Q_{i,t}$ due to (γ):			
New hires	0.158**	0.145	-0.198
	(0.065)	(0.094)	(0.202)
Exiters	0.153**	0.149	-0.208
	(0.065)	(0.094)	(0.201)
Incumbents	0.152**	0.142	-0.195
	(0.065)	(0.093)	(0.201)
Parameter tests:			
$\Pr(\beta_M = \beta_L)$	0.626	0.088	0.342
$\Pr(\lambda_M = \lambda_L)$	0.249	0.636	0.967
$\Pr(\gamma_{new} = \gamma_{incmb})$	0.047	0.365	0.606
Obs.	9912	9660	8673

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). 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 $\leq$ 20), medium sized firms (20 $<$ FTE $\leq$ 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 16: Effect of additional instruments for lagged productivity — Cobb-Douglas with F.E.

	Baseline	**Blundell-Bond**
Productivity gap, hires from (β):		
More prod. firms	0.173***	0.157*
	(0.052)	(0.082)
Less prod. firms	0.255***	0.252***
	(0.045)	(0.067)
Hire intensity (λ):		
More prod. firms	0.007	-0.003
	(0.024)	(0.026)
Less prod. firms	0.002	0.005
	(0.022)	(0.021)
Obs.	28260	38049

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 17: Alternative measures of worker quality — Cobb-Douglas with F.E.

Measure of worker quality:	**Baseline**	**WFE**	**Wages-FFE**
Productivity gap, hires from (β):			
More prod. firms	0.173***	0.173***	0.174***
	(0.052)	(0.052)	(0.051)
Less prod. firms	0.255***	0.254***	0.255***
	(0.045)	(0.045)	(0.045)
Hire intensity (λ):			
More prod. firms	0.007	0.011	0.007
	(0.024)	(0.024)	(0.024)
Less prod. firms	0.002	0.006	0.004
	(0.022)	(0.022)	(0.022)
Parameter tests:			
$\Pr(\beta_M = \beta_L)$	0.227	0.240	0.226
$\Pr(\lambda_M = \lambda_L)$	0.879	0.879	0.927
Obs.	28260	28260	28260

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). Each column denotes a different measure of worker quality ($Q_{i,t}$). WFE denotes worker quality measured by the Worker Fixed Effect. Wages-FFE denotes worker quality measured as the log of wages less the Firm Fixed Effect. 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 18: Scale effect from hiring margin — Cobb-Douglas with F.E.

	Baseline	**Firms that hire from**	
		More productive	**Less productive**
Prod. gap, hires from (β):			
More prod. firms	0.173***	0.171***	0.078*
	(0.052)	(0.051)	(0.041)
Less prod. firms	0.255***	0.273***	0.255***
	(0.045)	(0.058)	(0.044)
Hire intensity (λ):			
More prod. firms	0.007	-0.010	0.053***
	(0.024)	(0.025)	(0.020)
Less prod. firms	0.002	0.008	0.025
	(0.022)	(0.025)	(0.023)
Parameter tests:			
$\Pr(\beta_M = \beta_L)$	0.227	0.183	0.002
$\Pr(\lambda_M = \lambda_L)$	0.879	0.632	0.362
Obs.	28260	22392	22203

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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 19: Additional productivity gap dynamics — Cobb-Douglas with F.E.

	Baseline	**+ non-norm gap**	**+ sqrd prod gap**
Productivity gap, hires from (β):			
More prod. firms	0.173***	0.084	0.221***
	(0.052)	(0.057)	(0.047)
Less prod. firms	0.255***	0.223***	0.387***
	(0.045)	(0.065)	(0.067)
Non-normalized prod. gap			
More prod. firms		-0.002	
		(0.007)	
Less prod. firms		0.030**	
		(0.013)	
Squared productivity gap			
More prod. firms			-0.064
			(0.060)
Less prod. firms			0.088***
			(0.030)
Hire intensity (λ):			
More prod. firms	0.007	0.028	-0.008
	(0.024)	(0.027)	(0.022)
Less prod. firms	0.002	0.011	0.038
	(0.022)	(0.027)	(0.025)
Parameter tests:			
$\Pr(\beta_M = \beta_L)$	0.227	0.092	0.035
$\Pr(\lambda_M = \lambda_L)$	0.879	0.643	0.187
Obs.	28260	18441	28260

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). The second and third column adds to the baseline model the average productivity difference, and the squared productivity gap respectively. 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 20: Additional controls for the types on new workers hired — Cobb-Douglas with F.E.

	Baseline	**Additional controls:**	
		real earn. ranking	**quality ranking**
Productivity gap, hires from (β):			
More prod. firms	0.173***	0.171***	0.077*
	(0.052)	(0.051)	(0.040)
Less prod. firms	0.255***	0.255***	0.278***
	(0.045)	(0.045)	(0.058)
Earnings pctile rank within:			
More prod. firms		0.014**	
		(0.006)	
Less prod. firms		-0.013**	
		(0.006)	
Worker qual. pctile rank within:			
More prod. firms			-0.001
			(0.012)
Less prod. firms			-0.010
			(0.012)
Parameter tests:			
$\Pr(\beta_M = \beta_L)$	0.227	0.213	0.003
$\Pr(\lambda_M = \lambda_L)$	0.879	0.881	0.818
Obs.	28260	28260	18441

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$).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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 21: Regressions using a functional form similar to Stoyanov and Zubanov — Cobb-Douglas with F.E.

	Baseline	**S-Z like**
Productivity gap, hires from (β):		
More prod. firms	0.173***	0.267***
	(0.052)	(0.041)
Less prod. firms	0.255***	0.604***
	(0.045)	(0.072)
Hire intensity (λ):		
More prod. firms	0.007	0.029
	(0.024)	(0.019)
Less prod. firms	0.002	0.048*
	(0.022)	(0.023)
Parameter tests:		
$\Pr(\beta_M = \beta_L)$	0.227	0.000
$\Pr(\lambda_M = \lambda_L)$	0.879	0.528
Obs.	28260	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 4 and 3, 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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 22: Benchmark regression by industry (1-digit level) — Cobb-Douglas with F.E.

	Baseline	**Industry**					
		Manufac.	**Prof. services**	**Constr.**	**Transport**	**Agri & Forest**	**Mining**
Prod. gap, hires from (β):							
More prod. firms	0.173***	0.017	-0.002	0.167*	0.698***	0.118**	0.160
	(0.052)	(0.140)	(0.059)	(0.093)	(0.228)	(0.059)	(0.132)
Less prod. firms	0.255***	0.146**	0.268*	0.762**	0.697***	0.474***	0.257***
	(0.045)	(0.065)	(0.151)	(0.372)	(0.254)	(0.139)	(0.069)
Hire intensity (λ):							
More prod. firms	0.007	0.121	0.054	0.037	-0.152	0.028	0.009
	(0.024)	(0.074)	(0.033)	(0.048)	(0.126)	(0.031)	(0.068)
Less prod. firms	0.002	0.006	-0.119***	0.044	0.103	0.032	0.110*
	(0.022)	(0.044)	(0.043)	(0.100)	(0.111)	(0.043)	(0.061)
Parameter tests:							
$\Pr(\beta_M = \beta_L)$	0.227	0.401	0.100	0.098	0.998	0.012	0.512
$\Pr(\lambda_M = \lambda_L)$	0.879	0.188	0.002	0.951	0.148	0.944	0.294
Obs.	28260	1257	7146	2700	2826	5565	3990

Notes: Dependent variable is the regressions is the change in log productivity ($\Delta \ln A_{i,j,t}$). 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 $\ln A_{i,j,t-2}$ in response to the presence of Nickell bias. Productivity lag length is chosen to eliminate autocorrelation in the residual term. 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.

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

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 labor 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 (labor 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 labor productivity than more labor 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.

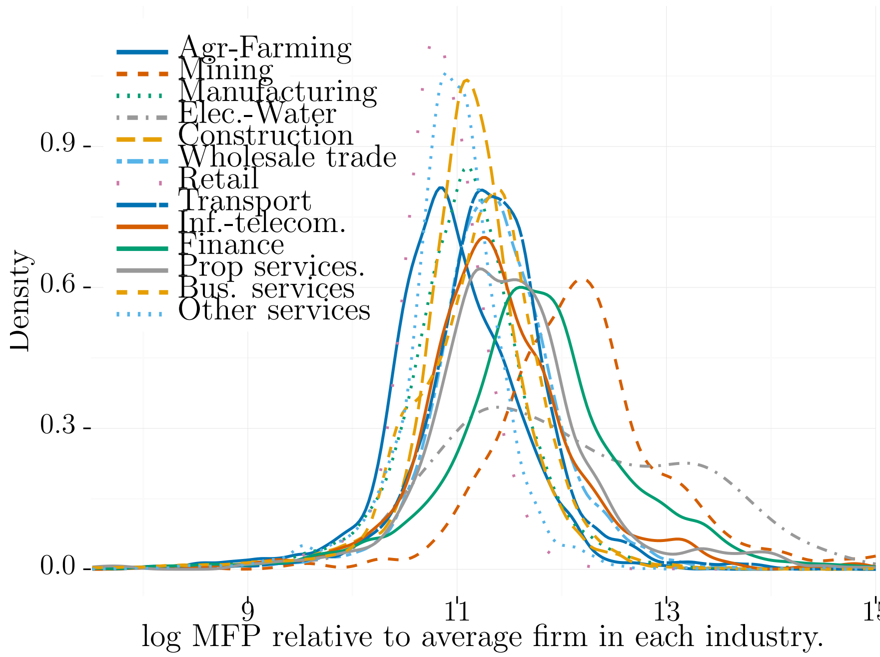
C.2 Productivity dynamics

Table 23 presents a summary of the productivity transition dynamics within the sample. For each productivity decile in a given year (row), table 23 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).

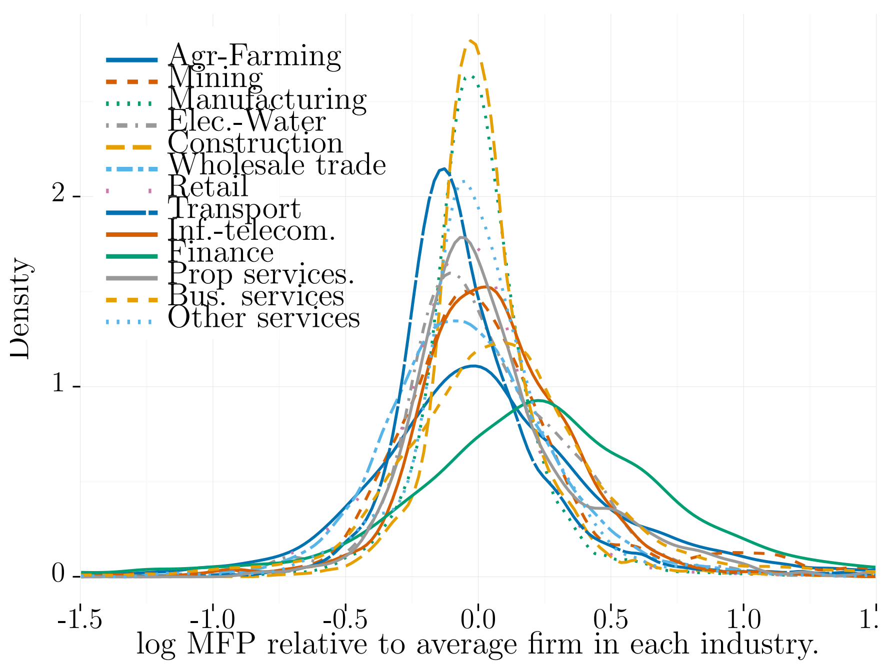
The transition matrices in table 23 show that there is some persistence in the firm's productivity ranking. Depending upon the productivity measure and productivity decile, a firm has around a 20 to 50 percent chance of been in the same productivity decile in the previous year. If firms do transition 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

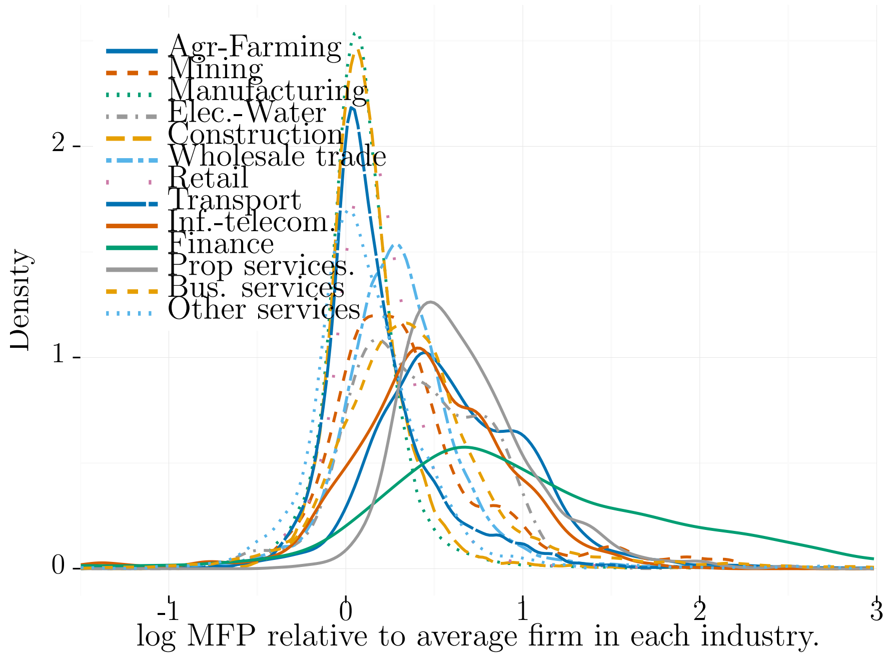
(a) Value-added per worker



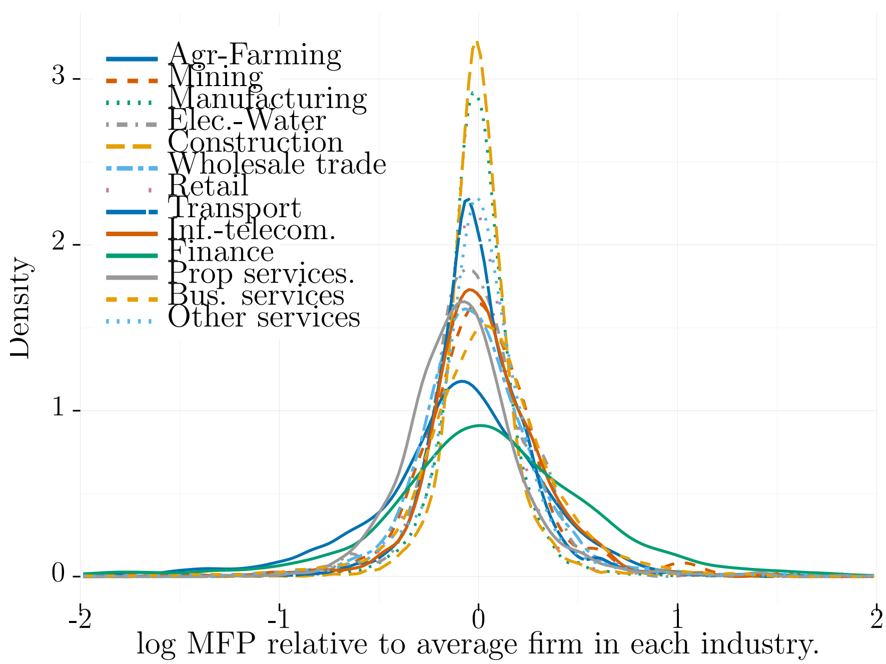
(b) Cobb-Douglas



(c) Cobb-Douglas with fixed effects



(d) 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 23: Firm productivity transition matrices

(a) Value-added per worker

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	0.05	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 1	2	3	4	5	6	7	8	9	10	Missing prod data	L<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) Cobb-Douglas with Fixed Effects

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	0.3	0.12	0.06	0.04	0.03	0.02	0.02	0.01	0.01	0.01	0.26	0.1
2	0.12	0.24	0.14	0.07	0.04	0.03	0.02	0.01	0.01	0.01	0.21	0.1
3	0.06	0.13	0.2	0.14	0.08	0.04	0.03	0.02	0.01	0.01	0.2	0.09
4	0.04	0.07	0.14	0.18	0.13	0.08	0.04	0.03	0.01	0.01	0.19	0.08
5	0.03	0.04	0.07	0.13	0.17	0.14	0.08	0.04	0.02	0.01	0.19	0.09
6	0.02	0.03	0.04	0.07	0.13	0.17	0.14	0.07	0.04	0.02	0.2	0.08
7	0.02	0.02	0.02	0.04	0.07	0.14	0.2	0.15	0.07	0.02	0.18	0.07
8	0.01	0.01	0.01	0.02	0.04	0.07	0.15	0.23	0.16	0.04	0.18	0.07
9	0.01	0.01	0.01	0.01	0.02	0.03	0.06	0.15	0.3	0.14	0.18	0.07
10	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.13	0.46	0.19	0.08

(d) 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 labor 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

$$\Pr[S \geq s] = \left(\frac{\lambda}{s}\right)^{\alpha} \tag{4}$$

where s is the size of the firm (measured in labor 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 24. 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 24: 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.

References

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