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PRODUCTIVITY AND LOCAL WORKFORCE COMPOSITION

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Abstract

This chapter examines the link between firm productivity and the population composition of the areas in which firms operate. We combine annual firm-level microdata on production, covering a large proportion of the New Zealand economy, with area-level workforce characteristics obtained from population censuses. Overall, the results support the existence of agglomeration effects that operate through labour markets. We find evidence of productive spillovers from operating in areas with high-skilled workers, and with high population density. A high skilled local workforce benefits firms in high-skilled and high-R&D industries, and small firms. The benefits of local population density are strongest for firms in dense areas, and for small and new firms. Firms providing local services are more productive in areas with high shares of migrants and new entrants, consistent with local demand factors.

JEL codes

R1 - General Regional Economics; R3 – Production Analysis and Firm Location; D24 - Production; Cost; Capital, Total Factor, and Multifactor Productivity; Capacity

Keywords

Productivity; agglomeration; workforce composition

CONTENTS

FIGURES AND TABLES

1. INTRODUCTION

The geography of factor inputs has long been identified as a key source of urban agglomeration economies. Smith (1904; I.3.2) highlights the gains from the greater labour specialisation that is made possible in 'great towns'. Marshall (1920; Bk IV.X) famously emphasised the operation of skill accumulation and innovation in urban labour markets, and the improved access to specialised skills in thick labour markets. More recent analyses of the microfoundations of agglomeration continue to place a strong emphasis on urban labour market mechanisms. These include sharing the gains from specialisation and pooling labour market risks, improving the quality of labour market matching, and supporting the generation, diffusion and accumulation of information and knowledge (Duranton and Puga, 2004). There are thus many reasons to expect a positive relationship between firm performance and the density and composition of local labour inputs.

This chapter provides empirical evidence on the relationship between the productivity of firms and the composition of the local population. We combine annual firm-level microdata on production, covering a large proportion of the New Zealand economy, with area-level workforce characteristics obtained from population censuses.

We focus on three characteristics of the local population – the proportion that is highly qualified, the proportion that is newly arrived in the area, and the proportion that is foreign-born. We find a positive bivariate relationship between productivity and each of these three measures. Multivariate analysis highlights workforce qualifications as the single most important of the measures. This finding is maintained once we control for the possible endogeneity of workforce composition. We also test the robustness of our findings to the inclusion of additional controls for firm-level labour quality and labour turnover, and provide separate estimates for various subgroups of firms to test for heterogeneity in the impacts of local workforce characteristics.

Local workforce skills contribute most strongly to productivity for small firms, and for firms in industries with high levels of research and development or high usage of skilled workers. The benefits of operating in densely populated areas are strongest for firms in dense areas, for small firms and for new firms. The presence of newly arrived residents aids productivity most strongly for firms providing local services, consistent with an influence of workforce characteristics in output markets, as well as input markets.

Section 1 provides a brief review of related empirical findings. We outline our empirical approach in section 2 and the data in section 3. Results are summarised in section 4, and we conclude with a discussion of findings in section 5.

2. PRIOR STUDIES

Previous studies have found a clear positive relationship between the productivity of firms and the density of economic activity in the locations where they operate (Ciccone and Hall, 1996). Density is a rather coarse proxy for a broad range of potential advantages associated with agglomeration. Identifying and disentangling the different potential causes of these productivity advantages remains a challenge (Rosenthal and Strange, 2004). There is a well-established body of literature that documents the important role played by labour market interactions and knowledge spillovers.

Moretti (2004a) reviews empirical approaches to estimating local human capital spillovers, distinguishing studies that identify spillovers through their impacts on wages and rents, and those that rely on the estimation of firm productivity. The current paper takes the latter approach. Moretti's own empirical study (Moretti, 2004b) is a leading example of the approach of estimating firm production functions. He finds positive evidence of human capital spillovers between local industries. Moreover, he finds that spillovers are stronger between industries that are close in terms of input-output linkages, technological similarity, and patent citation links, providing support for knowledge transfer explanations.

There is a range of other studies that identify the magnitude and nature of local human capital spillovers. In an influential study using wage and rent variation, Rauch (1993) found that workers in areas with a more highly qualified workforce earn higher wages, controlling for their own human capital, arguably as a result of knowledge spillovers. More broadly, the composition and density of the local workforce can improve a firm's productivity performance through any of the three mechanisms identified by Duranton and Puga (2004) - sharing, matching and learning. Recent studies have found support for each of these mechanisms. Overman and Puga (2010) show the advantages associated with sharing of labour market risks in dense, skilled urban labour markets. Amiti and Pissarides (2005) show the potential agglomeration gains from better matching of heterogeneous workers. Studies of the localisation of patent citations (Jaffe et al, 1993) and the links between patenting and the presence of migrants locally (Hunt and Gauthier-Loiselle, 2010) add further weight to explanations involving knowledge flows. More direct evidence of local knowledge interactions comes from Zucker and Darby's (2009) study of the location patterns of 'star scientists'.

3. EMPIRICAL APPROACH

We estimate the relationship between productivity and local workforce characteristics using a gross output Cobb-Douglas production function augmented with area-level workforce composition measures,

$$GO_{it} = \phi_{it}^{A} + \beta_j^K K_{it} + \beta_j^L L_{it} + \beta_j^M M_{it} + \left(\lambda_i + \alpha_{jt} + \varepsilon_{it}\right), \qquad (1)$$

where i denotes a firm, t refers to time period and j indicates parameters that vary by industry. Output (GO_{it}), capital services (K_{it}), labour input (L_{it}), and intermediate consumption (M_{it}) are all measured in logarithms. The error term potentially has components corresponding to firms, industries, and time periods. The first term (ϕ_{it}^{A}) is the Hicks-neutral contribution to productivity in period t of characteristics of the area (A_i) in which firm i operates. This contribution is entered as a linear combination of local workforce measures,

$$\begin{aligned}\phi_{it}^{A} &= \gamma^{Dens}\left[\text{\% Population Density}\right]_{it}^{A} + \gamma^{HS}\left[\text{\% degree qualified}\right]_{it}^{A} \\ &+ \gamma^{New}\left[\text{\% New to area}\right]_{it}^{A} + \gamma^{Mig}\left[\text{\% Foreign-born}\right]_{it}^{A} + e_{it}\end{aligned} \qquad (2)$$

We use annual production data, combined with area information that is available only every five years. Consequently, we estimate equation (1) in two stages. In the first stage, we estimate productivity using an annual firm-level panel, but omitting area characteristics. We estimate a separate regression for each industry, allowing for clustered errors at the firm-level.

In the second stage, we regress the residuals from the first-stage regression (multi-factor productivity) on the right-hand-side terms of equation (2). The second stage regression is estimating using 5-yearly firm-level data, with separate intercepts for industry and for year. We allow for area-clustered errors, since the area level characteristics are common to all firms with the same geographic distribution (Moulton, 1990).[1]

Workforce composition is potentially endogenous, as entrants and high skilled workers may be attracted to areas with high-productivity firms. We use an instrumental variables approach to adjust for this endogeneity. Specifically, we use five-year lags of the composition variables as instruments in the second stage regression.

We also control for selected firm-level workforce characteristics that may be correlated with the area level composition measures. Firms in areas where there is a high proportion of the workforce with a degree qualification will themselves employ more highly qualified personnel. Productivity in equation (1) is estimated using a headcount

[1] In practice, we observe firms operating in more than one location and measure geographic variables as the firm's average (employment-weighted) exposure to area characteristics. Clustering of errors is corrected for based on clusters identified from common combinations of area characteristics. Our standard errors do not allow for the variability associated with the use of generated regressors obtained from the first stage, and will therefore be somewhat understated. We generated one-step estimates for our main specifications and found that coefficients and standard errors were very similar to those obtained using our two-step procedure. On this basis, we judge that our results would be largely unchanged if we were to use one-step estimation or generate bootstrap standard errors for our two-stage estimates.

measure of labour input, which is likely to understate the effective labour input used by firms in high-skilled areas. Similarly, a high proportion of people new to an area may be reflected in higher worker turnover rates for local firms, which may have an independent influence on productivity. Consequently, we augment equation (2) by adding firm-specific labour quality and turnover measures.

4. DATA

We combine firm-level microdata on production with area-level workforce characteristics. The workforce characteristics are drawn from the Census of Population and Dwellings, summarised at Area Unit level (roughly equivalent to a city suburb). Productivity is estimated using rich firm microdata contained in Statistics New Zealand's prototype Longitudinal Business Database (LBD).[2]

4.1. Production data

The LBD dataset is based around the Longitudinal Business Frame (LBF), which provides longitudinal information on all businesses in the Statistics New Zealand Business Frame since 1999, combined with information from the tax administration system. The LBF population includes all employing businesses. We make use of the permanent enterprise identifiers developed by Fabling (2011), which uses plant transfers to improve the tracking of firms over time.

The primary unit of observation in the LBD is an enterprise (firm) year. We make use of business demographic information from the LBF, linked with financial performance measures for the 1999/2000 to 2007/08 years. Plant location and employment information from the Linked Employer-Employee Dataset (LEED) is used to link to local area information from the Population Census.

To calculate multifactor productivity (mfp), we follow Fabling and Maré (2011). Gross output is measured as the value of sales of goods and services, less the value of purchases of goods for resale, with an adjustment for changes in the value of stocks of finished goods and goods for resale. Gross output and factor inputs are measured in current prices.[3] Capital services has four components: depreciation; rental and leasing costs; rates; and the user cost of capital. The inclusion of rental and leasing costs and rates ensures consistent treatment of owned and rented or leased capital. The user cost of capital is calculated as the value of total assets, multiplied by an interest rate equal to the average 90-day bill rate plus a constant risk-adjustment factor of four percentage points. Intermediate consumption is measured as the value of other inputs used in the production process, with an adjustment for changes in stocks of raw materials.

The primary source used to obtain gross output, intermediate consumption and capital services is the Annual Enterprise Survey (AES). This information is available for around ten percent of enterprises, which are disproportionately larger firms, accounting for around 50 percent of total employment in New Zealand. Where AES information is not available, we derive comparable measures from annual tax returns (IR10s). Enterprise total employment comes from LEED and comprises the count of employees in all of the enterprise's plants, annualised from employee counts as at the 15th of each month, plus working proprietor input, as reported in tax returns.

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[2] See Fabling (2009) for further information on the LBD.

[3] Changes over time in current price inputs and outputs will reflect both quantity and price changes. We double deflate to isolate quantity adjustment over time at the (one- or two-digit) industry level using Statistics New Zealand's PPI input and output indices. Measures of productivity premia for firms within the same industry will reflect both quantity and relative price differences. Spatial price indices are not available.

4.2. Local workforce composition

Information on local workforce composition is obtained from the 2001 and 2006 New Zealand Censuses of Population and Dwellings. Within urban areas, we use information for individual Area Units. Outside urban areas, population composition is measured as the average for non-urban Area Units in each territorial authority. This averaging is necessary to ensure that populations are large enough to support the required disaggregation.[4]

From the Census data, we classify each member of the population aged 18 to 65 according to qualification, nativity, and recency of arrival. The workforce is classified into two qualification levels (tertiary qualified and other), two nativity groups (born in New Zealand, born elsewhere), and recency of arrival in the current Area Unit (within previous five years, or earlier).[5] For each qualification group, we have six sub-groups: two groups of people who were in the same location five years earlier (NZ-born and earlier migrants), two of people who were elsewhere in New Zealand five years earlier (NZ-born and earlier migrants), and two of people who were overseas five years earlier (returning NZ-born and recent migrants).

Geographically-smoothed workforce composition measures are calculated as a proportion of the population living within 10 km of each Area Unit centroid.[6] For businesses operating in more than one location, the composition of their 'local' workforce is calculated as a weighted average of the compositions of each of the areas in which they employ, using the distribution of the firms' employment across the different locations.

[4] On average Area Units contain around 2,000 people. Area units with population of less than 100 are dropped from our analysis. There is a small number of Area Units for which disaggregated population information could not be separately released within the protections of the Statistics New Zealand confidentiality policy. Population composition for these areas was measured as the average across all such areas pooled. For the merged non-urban areas, the population within each Area Unit was estimated based on the Area Unit's share of the merged area's population, using data on the distribution of the 20-64 year old population, available from *Table Builder* on the Statistics New Zealand website.

[5] The Census collects information on each person's location (Area Unit) five years prior to the Census. Where responses identified prior location less precisely than Area Unit, it was assumed that respondents had not moved, unless their response indicated a Territorial Authority, Regional Council, island, or country different from their Census-night location.

[6] Measures are smoothed using an Epanechnikov kernel with bandwidth of ten kilometres. Weights are calculated as $\frac{3}{4}*(1-(\text{distance}/10)^2)$ where distance<10, and zero otherwise.

5. RESULTS

Table 1 summarises the productivity and workforce composition variables that are the main focus of the analysis. The first two rows show summary statistics for each of the two census years, with comparable figures for the pooled data in the third row. Productivity (mfp) is zero mean within each year, by construction. Workforce characteristics reflect the average composition faced by New Zealand firms. Because firms cluster in high employment-density areas, these 'exposure' means differ from population averages. On average, firms are located in areas where 21.3 percent of the population aged 18 and over is foreign-born, with a slightly higher migrant penetration in 2006 than in 2001. Around half of the population (48.2%) is new to the area, and 13.7 percent are degree qualified. Population density increased between 2001 and 2006, due mainly to the greater clustering of firms in densely populated areas.

The final column of Table 1 presents comparable statistics for the subsample of firms that have no employees. In some of the analysis that follows, we control for the composition and turnover of each firm's workforce. These measures are available only for employees, so we are unable to include working-proprietor-only (*WPO*) firms in that analysis. *WPO* firms account for around one half of all firms but these are smaller, have lower mean productivity than the total population of firms, and have a standard deviation of mfp that is 0.15 higher.

Table 1: Data Summary

	N	*Productivity (MFP)*	*Percent Migrants within 10km*	*Percent new to area within 10km*	*Percent degree-qualified within 10km*	*ln(Population density within 10km)*
2001	173,022	0.00	19.1%	44.9%	11.1%	4.21
		(0.68)	(10.9%)	(8.7%)	(6.6%)	(2.37)
2006	186,747	0.00	23.4%	51.3%	16.1%	4.47
		(0.67)	(12.8%)	(6.6%)	(7.9%)	(2.37)
Total	359,769	0.00	21.3%	48.2%	13.7%	4.35
		(0.67)	(12.1%)	(8.3%)	(7.7%)	(2.37)
Working proprietor	190,071	-0.05	21.4%	48.0%	13.6%	4.27
only		(0.82)	(12.0%)	(8.3%)	(7.8%)	(2.36)

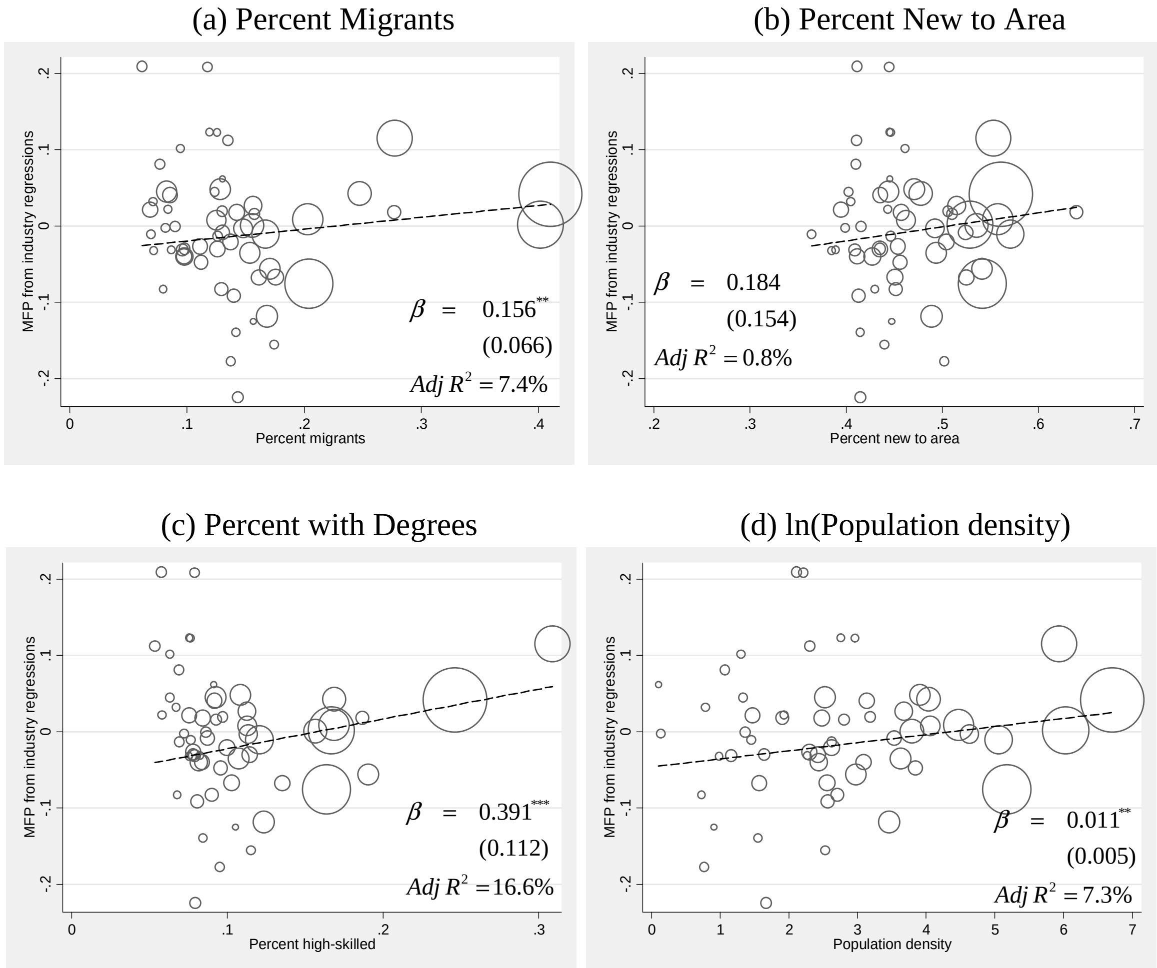
Note: standard errors in brackets. Counts are random-rounded (base 3) in compliance with Statistics New Zealand confidentiality rules.

We provide an initial graphical indication of the relationship between productivity and local workforce composition in Figure 1. High productivity firms are disproportionately located in areas with a high proportion of skilled workers, new entrants, and immigrants. The bivariate relationships are summarised in Figure 1, for 58 Labour Market Areas (LMAs).[7] Figure 1 shows the LMA means of firm-level productivity (MFP) and local

[7] Labour market areas are defined using travel to work information following Papps & Newell (2002).

workforce composition within a 10km radius of firms operating in the LMA.[8] The strongest relationship is between productivity and the fraction of the workforce with a degree qualification. A one percentage point higher degree-share is associated with productivity that is 48% higher ($e^{0.391}$-1). The comparable figure for a higher migrant share is 17%, and for the share of the population new to the area is 20% but not statistically significant. Population density has a clear positive relationship with productivity, with a 10% higher density associated with productivity that is 0.1% higher.

Figure 1: Relationship between productivity (mfp) and workforce characteristics (2006)



Notes: Each symbol represents a Labour Market Area (LMA). The size of the symbol reflects employment in the LMA. Dashed lines are weighted regression lines. Workforce composition is measured as an average within a 10km radius of each Area Unit, See text for fuller explanation. Significance indicators: 1%. (***); 5% (**).

[8] The LMA means are calculated by regressing (a) firm mfp and (b) local workforce exposure, on a full set of LMA share dummies, where the shares represent the proportion of firm employment in each LMA. The coefficients on these share dummies are the measures that are graphed in Figure 1.

5.1. Regression analysis

It is clear from Figure 1 that LMA size is positively correlated not only with productivity but also with each of the workforce composition measures. In Table 2, we use multivariate regression methods to evaluate the independent contribution of each of these to productivity variation. In the first four columns, we enter each of the workforce composition measures separately into a productivity regression that includes industry and year intercepts. As in figure 1, each of the relationships is positive.[9] When the measures are entered together in the same regression (shown in column 5), the influence of density and the proportion of the workforce with a degree qualification remain positive and significant, with coefficients of similar magnitude to those in columns 3 and 4. In contrast, the relationship between productivity and the presence of migrants is small and no longer significant, and the influence of people new to the area is negative.

Table 2: Basic specifications

	OLS	*OLS*	*OLS*	*OLS*	*OLS*	*IV*	*IV*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Dependent variable	*mfp*	*mfp*	*mfp*	*mfp*	*mfp*	*mfp*	*Δmfp*
Percent migrants	0.292***				0.0263	0.0237	-0.852
	[0.0177]				[0.0318]	[0.0327]	[0.699]
Percent new to area		0.312***			-0.282***	-0.492***	2.422***
		[0.0400]			[0.0586]	[0.0747]	[0.726]
Percent degree qualified			0.616***		0.586***	0.695***	1.377*
			[0.0368]		[0.0651]	[0.0685]	[0.813]
ln(population density)				0.0172***	0.0112***	0.0139***	0.750**
				[0.00122]	[0.00195]	[0.00214]	[0.323]
Industry intercepts	Y	Y	Y	Y	Y	Y	N
Year intercept	Y	Y	Y	Y	Y	Y	N
	-	-	-	-			-
Constant	0.0665***	0.158***	0.0965***	0.0743***	-0.0029	0.112***	0.248***
	[0.00534]	[0.0199]	[0.00666]	[0.00629]	[0.0230]	[0.0292]	[0.0880]
Observations	359,769	359,769	359,769	359,769	359,769	359,769	63,069
AdjR2	0.20%	0.09%	0.34%	0.23%	0.42%	0.40%	-0.78%
UnderId F-stat (p)						266.3 (0)	21.66 (0)
WeakInst F-stat						1653	5.935

Note: standard errors, clustered on Area Unit, in brackets (***;**;* significant at 1%;5%;10% level respectively). Counts are random-rounded (base 3). For specifications (6) and (7), the instrument set is (five-year) lagged workforce characteristics (including population density). Kleibergen-Paap F statistics for tests of weak identification and underidentification reported. Specification (7) is estimated in first differences (both dependent and independent variables) for firms located and staying in a single Area Unit.

Columns 6 and 7 present estimates that control for the possible endogeneity of local workforce characteristics. In both columns, actual workforce composition measures are instrumented using their own lags.[10] Column 6 is a level regression, as in previous

[9] The coefficients differ from those in Figure 1 because the regressions in Table 2 use firm-level variation, including within-LMA variation, which is ignored in Figure 1.

[10] The specification passes an underidentification F-test on the first-stage equation, as shown at the bottom of the table. The Kleibergen-Paap F statistic for weak identification is also shown, and has a high value of 1653

columns, while column 7 estimates the relationship between mfp and workforce composition in first differences. Consequently, the latter regression is estimated only on the subsample of firms present in both time periods. We further restrict this regression to firms that operate in a single Area Unit and that remain in that Area Unit over time. Thus, the first difference regression, as well as controlling for time-invariant firm characteristics, also removes potentially confounding fixed Area Unit characteristics.

Both sets of IV estimates confirm the general findings of a positive relationship between productivity and both density and degree share. While column 7 represents the more stringent test of the relationships we are interested in, our preferred specification in subsequent tables is the levels IV (column 6). We make this choice since both approaches suggest that workforce characteristics matter, but the first differences approach seriously reduces the sample size, raising questions of the broader applicability of the findings and restricting our ability to estimate effects for smaller subpopulations of firms. Additionally, the increase in the size of coefficients and standard errors associated with instrumenting in the first difference IV is suggestive of a weak instrument problem (despite the estimates passing the Kleibergen-Paap test with an F-statistic of 5.9).

The positive relationship between local skills and productivity may in part reflect the higher average quality of labour that firms employ, rather than an external effect of local skills. Similarly, the negative relationship between productivity and the proportion of the population new to the area may reflect the negative effect of higher average labour turnover at the firm level. In order to control for these firm-level factors, we present, in Table 3 estimates that include measures of firm-level skill and turnover.

Unfortunately, the LBD does not contain comprehensive firm-level information about worker skills. We use a proxy for worker quality derived from a two-way fixed effect model estimated using LEED data. The estimated worker effect is an index of each worker's portable wage premium. For each firm in a given year, we calculate the weighted average of worker fixed effects, using as weights a measure of the workers' employment intensity during the year.[11] Worker effects are estimated only for employees, so firms that employ only working proprietors are excluded from the analysis.

Worker turnover at the firm is also calculated using LEED data, and is based on average quarterly turnover of employees.[12] We include two variables to capture variation in turnover rates. The first is gross turnover, calculated as the sum of accessions and separations during the year. The second is net turnover, which is the difference between accessions and separations. By including both measures, we can interpret the gross turnover as a measure of turnover in excess of what was required to achieve the observed employment growth or decline. Each is expressed as a proportion of average quarterly employment, so that the underlying accessions and separations measures range from -2 to 2.

The first column of Table 3 (panel b) shows the same IV specification as in column 6 of Table 2, for the subsample of working-proprietor-only firms, which account for most of

for column 6, confirming the joint relevance of the instruments. In both cases, the equation is exactly identified, so it is not possible to test for instrument validity.

[11] For further details of the two-way fixed effects estimation method and the employment intensity measure, see Maré and Hyslop (2006).

[12] Excluding quarters related to the first transition into employment and the last transition out of employment.

the firms excluded from the analysis of firm level labour quality and turnover. The second column (panel b) shows the same specification but for firms for which we have labour quality and turnover measures. The coefficients on local workforce measures are significantly smaller for the subset of firms with employees. They are also estimated with greater precision, reflecting the greater volatility in the productivity measure for self-employed firms. The findings of a positive effect of local skills and population density are maintained.

In the third column of the table, we include the proxy for worker skills within the firm. Focusing on the IV estimates, we see that, as expected, the coefficient on local skills is reduced (by 55%). A one percentage point higher share of degree-qualified residents is nevertheless still associated with 12% higher productivity ($e^{0.112}$-1). The relationship between local population density and productivity remains significant and the insignificant coefficients on the percent new to the area and the migrant share do not change materially.

Including controls for labour turnover within the firm has a negligible impact on the other coefficients. Column 4 of Table 3 presents the estimates. Gross turnover is associated with lower productivity, though the effect is modest in size. On average, gross turnover is 53% of average employment during the year. The coefficient of -0.031 implies that a 10 percentage point increase in this figure is associated with productivity that is 0.3% lower. Net turnover has a very small positive and statistically insignificant relationship with productivity. The fifth column includes both labour quality and turnover measures, and is our preferred specification. The only local workforce characteristics that are significantly related to productivity are population density (elasticity of 0.01) and the proportion of people with a degree qualification (β = 0.114).

Table 3: Adding selected firm-level controls

Dependent variable: mfp	*(1)* *Working Proprietors only*	*(2)* *Employing firms*	*(3)* *Employing firms*	*(4)* *Employing firms*	*(5)* *Employing firms*
			(a) OLS Estimates		
Percent migrants	0.0636	0.0279	-0.00433	0.0315	-0.000789
	[0.0424]	[0.0249]	[0.0226]	[0.0247]	[0.0226]
Percent new to area	-0.513***	0.0599*	0.0610*	0.0590*	0.0602*
	[0.0823]	[0.0348]	[0.0343]	[0.0350]	[0.0345]
Percent degree qualified	0.909***	0.142**	0.0651	0.145**	0.0692
	[0.0823]	[0.0600]	[0.0492]	[0.0595]	[0.0490]
ln(population density)	0.0138***	0.00976***	0.0103***	0.00920***	0.00982***
	[0.00277]	[0.00138]	[0.00138]	[0.00138]	[0.00138]
Average Worker Fixed Effects			0.242***		0.236***
			[0.00774]		[0.00769]
Gross turnover				-0.0306***	-0.0237***
				[0.00261]	[0.00246]
Net turnover				0.000389	-0.0012
				[0.00336]	[0.00338]
Industry intercepts	Y	Y	Y	Y	Y
Year intercept	Y	Y	Y	Y	Y
Constant	-0.00818	-0.0498***	-0.0498***	-0.0324**	0.00322
	[0.0330]	[0.0134]	[0.0134]	[0.0135]	[0.0136]
Observations	190,071	160,719	160,719	160,719	160,719
AdjR2	0.79%	2.11%	3.48%	2.28%	3.58%
			(b) Instrumental Variables Estimates		
Percent migrants	0.0575	0.0357	0.00272	0.0384	0.00563
	[0.0435]	[0.0245]	[0.0224]	[0.0244]	[0.0225]
Percent new to area	-0.754***	-0.056	-0.0222	-0.0513	-0.0192
	[0.102]	[0.0455]	[0.0431]	[0.0458]	[0.0434]
Percent degree qualified	1.028***	0.204***	0.112**	0.204***	0.114**
	[0.0870]	[0.0630]	[0.0512]	[0.0626]	[0.0512]
ln(population density)	0.0173***	0.0108***	0.0110***	0.0102***	0.0105***
	[0.00295]	[0.00149]	[0.00147]	[0.00149]	[0.00148]
Average Worker Fixed Effects			0.241***		0.236***
			[0.00771]		[0.00766]
Gross turnover				-0.0307***	-0.0237***
				[0.00261]	[0.00246]
Net turnover				0.000405	-0.00119
				[0.00336]	[0.00338]
Industry intercepts	Y	Y	Y	Y	Y
Year intercept	Y	Y	Y	Y	Y
Constant	0.0811**	0.135***	0.170***	0.162***	0.190***
	[0.0399]	[0.0178]	[0.0174]	[0.0180]	[0.0176]
Observations	190,071	160,719	160,719	160,719	160,719
AdjR2	0.00769	0.021	0.0347	0.0227	0.0357
UnderId F-stat (p)	291.4 (0)	200.7 (0)	200.6 (0)	200.7 (0)	200.7 (0)
WeakInst F-stat	1262	1862	1873	1860	1872

Note: standard errors, clustered on Area Unit (AU), in brackets (***;**;* denote significance at the 1%;5%;10% level respectively). Counts are random-rounded (base 3). Only workforce characteristic variables (including population density) are instrumented, using their (five-year) lags. Kleibergen-Paap F statistics for tests of weak identification and underidentification reported.

Table 4: Sample Statistics for Subgroups of Firms

	N	*mfp*	*Percent Migrants within 10km*	*Percent new to area within 10km*	*Percent degree-qualified within 10km*	*ln(Population density within 10km)*	*Average Worker Fixed Effects*	*Gross turnover*	*Net turnover*
High-skilled industries	46,275	0.03	25.5%	51.4%	16.6%	5.44	-0.03	39.2%	4.8%
		(0.48)	(12.4%)	(6.9%)	(8.2%)	(1.80)	(0.26)	(48.6%)	(36.2%)
High R&D industries	28,812	0.04	25.0%	51.0%	16.3%	5.25	-0.02	45.5%	4.8%
		(0.48)	(12.6%)	(7.2%)	(8.3%)	(2.02)	(0.26)	(55.9%)	(39.7%)
Dense areas	40,131	0.06	36.9%	55.0%	21.4%	6.99	-0.04	42.2%	4.7%
		(0.45)	(9.1%)	(2.3%)	(5.7%)	(0.30)	(0.25)	(49.2%)	(37.2%)
Small firms ($L \leq 5$)	101,754	0.07	20.4%	47.7%	13.2%	4.19	-0.12	63.6%	5.9%
		(0.47)	(12.1%)	(8.5%)	(7.6%)	(2.45)	(0.24)	(72.9%)	(51.5%)
Large firms ($L > 5$)	58,965	0.04	23.2%	49.9%	14.9%	4.97	-0.05	35.2%	2.0%
		(0.37)	(12.4%)	(7.6%)	(7.7%)	(2.08)	(0.17)	(29.1%)	(13.1%)
New firms	10,374	0.04	22.8%	49.7%	14.6%	4.76	-0.10	93.5%	41.5%
		(0.59)	(12.3%)	(7.8%)	(7.7%)	(2.23)	(0.23)	(73.6%)	(79.5%)
Local service industries	46,521	0.02	22.3%	49.7%	14.6%	4.97	-0.13	46.0%	5.0%
		(0.40)	(12.0%)	(7.8%)	(7.8%)	(1.98)	(0.19)	(48.0%)	(36.7%)
Total	160,719	0.06	21.4%	48.5%	13.8%	4.47	-0.10	53.2%	4.5%
		(0.43)	(12.3%)	(8.3%)	(7.7%)	(2.35)	(0.22)	(62.2%)	(41.8%)

Note: standard errors in brackets. Counts are random-rounded (base 3) in compliance with Statistics New Zealand confidentiality rules.

These results reflect the influence of workforce composition on productivity, averaged across all firms. It is unlikely, however, that all firms are affected equally by the composition of their local workforce. We consider seven subsets of firms, chosen to highlight different accounts of what sort of firms benefit most from local labour and density spillovers. Descriptive statistics for these subsets of firms are presented in Table 4, with regression estimates of the relationship between productivity and local workforce composition for each subset presented in Table 5. The upper panel of Table 5 presents OLS estimates and the lower panel shows the corresponding IV estimates, as in Table 3.

Users of high-skilled labour are more likely to benefit from a highly qualified local workforce, through mechanisms such as labour market pooling and matching. The first two subsets of firms shown in Table 4 are firms in industries that employ a high proportion of high-skilled workers, and for industries where research and development expenditure is relatively high.[13] These groups are located in relatively high density areas

[13] High-skilled industries are identified from the Business Operations Survey (BOS) as those in which more than 10% of the workforce are in skilled occupations (*managers and professionals* or *technicians and associate*

with higher-than-average proportions of migrants, degree-holders, and newcomers. They also have slightly higher-than-average labour quality, as captured by average worker fixed effects, and lower worker turnover rates.

The first two columns of Table 5 show regression estimates for these two groups. The IV estimates in the lower panel of the table show a strong positive association of productivity with the percent of the local population with degree qualifications (coefficients of 0.205 and 0.432 respectively, compared with 0.114 overall). As expected, the coefficients on average worker quality are also strongly positive for these two groups of firms, 0.382 and 0.440 respectively, compared with 0.236 overall, confirming the direct effect on measured productivity of having higher quality labour input within such firms.

Many theories of local labour market spillovers emphasise the operation of these effects in dense urban markets where interactions are greatest. In the third column, we show estimates for the quarter of firms operating in the areas with the highest population density. Within this group, the density of population is positively linked to productivity (β=0.040) – more strongly than it is for firms generally. This suggests that there may be positive sorting on the basis of returns to density. The firms that have the most to gain from density are the ones that are disproportionately located in higher density areas. However, there are no significant spillovers from the composition of the local workforce for these firms. Firms in dense areas face even higher proportions of migrants, newcomers, and degree-holder than do firms in high skill or high-research and development industries, yet there is no significant relationship between productivity and these composition measures in dense areas.

professionals. The 2-digit industries are: B12, C28, D36, D37, F46, G52, I63, I66, J71, K73, K74, K75, L77, L78, N84, O86, P91. High R&D industries are also identified from the BOS as those where more than 0.5% of industry expenditure is on R&D. The 2-digit industries are: A02, B11, B13, C25, C28, C29, L78, N84.

Table 5: Subgroups of Firms

Dependent variable: mfp	(1) High-skilled industries	(2) High R&D industries	(3) Dense areas	(4) Small firms: L≤5	(5) Large firms: L>5	(6) New firms	(7) Local service industries
				(a) OLS Estimates			
Percent migrants	-0.00333	-0.105**	-0.00929	-0.00977	0.0166	-0.0771	0.0978***
	[0.0396]	[0.0505]	[0.0386]	[0.0266]	[0.0298]	[0.0744]	[0.0306]
Percent new to area	-0.0237	-0.201***	-0.0572	0.0344	0.116***	-0.239**	0.217***
	[0.0577]	[0.0770]	[0.253]	[0.0412]	[0.0446]	[0.119]	[0.0496]
Percent degree qualified	0.192**	0.395***	0.122	0.165***	-0.0766	0.0664	-0.0161
	[0.0746]	[0.110]	[0.105]	[0.0503]	[0.0673]	[0.124]	[0.0506]
ln(population density)	0.00656***	0.00518*	0.0397***	0.0123***	0.00574***	0.00928**	0.00465***
	[0.00229]	[0.00268]	[0.0137]	[0.00169]	[0.00151]	[0.00435]	[0.00163]
Average Worker Fixed Effects	0.382***	0.440***	0.286***	0.231***	0.285***	0.223***	0.200***
	[0.0115]	[0.0149]	[0.0106]	[0.00818]	[0.0157]	[0.0314]	[0.0113]
Gross turnover	-0.0754***	-0.0517***	-0.0477***	-0.0228***	-0.0964***	-0.0193**	-0.0557***
	[0.00643]	[0.00751]	[0.00741]	[0.00249]	[0.00959]	[0.00913]	[0.00527]
Net turnover	0.0153*	0.0116	-0.0166**	-0.00327	0.0351**	-0.0133	-0.0126*
	[0.00820]	[0.00867]	[0.00843]	[0.00344]	[0.0157]	[0.00827]	[0.00673]
Industry intercepts	Y	Y	Y	Y	Y	Y	Y
Year intercept	Y	Y	Y	Y	Y	Y	Y
Constant	-0.0000939	0.102***	-0.188	0.016	0.00203	0.140***	-0.0873***
	[0.0228]	[0.0295]	[0.145]	[0.0166]	[0.0181]	[0.0494]	[0.0200]
Observations	46,275	28,812	40,131	101,754	58,965	10,374	46,521
AdjR2	5.62%	7.33%	3.33%	3.79%	4.18%	2.63%	4.55%
				(b) Instrumental Variables Estimates			
Percent migrants	0.00149	-0.102**	-0.0217	-0.00306	0.0217	-0.0742	0.0985***
	[0.0394]	[0.0503]	[0.0457]	[0.0265]	[0.0298]	[0.0759]	[0.0309]
Percent new to area	-0.0592	-0.286***	-0.364	-0.0849	0.114**	-0.414***	0.201***
	[0.0670]	[0.0939]	[0.665]	[0.0518]	[0.0524]	[0.140]	[0.0580]
Percent degree qualified	0.205***	0.432***	0.214	0.232***	-0.0722	0.174	0.00167
	[0.0770]	[0.115]	[0.201]	[0.0531]	[0.0697]	[0.129]	[0.0521]
ln(population density)	0.00682***	0.00607**	0.0402***	0.0135***	0.00549***	0.0107**	0.00464***
	[0.00232]	[0.00274]	[0.0146]	[0.00178]	[0.00156]	[0.00437]	[0.00168]
Average Worker Fixed Effects	0.382***	0.440***	0.286***	0.230***	0.285***	0.222***	0.200***
	[0.0115]	[0.0150]	[0.0106]	[0.00816]	[0.0157]	[0.0313]	[0.0113]
Gross turnover	-0.0754***	-0.0517***	-0.0476***	-0.0228***	-0.0965***	-0.0193**	-0.0557***
	[0.00643]	[0.00750]	[0.00746]	[0.00249]	[0.00961]	[0.00910]	[0.00527]
Net turnover	0.0153*	0.0115	-0.0166**	-0.00323	0.0351**	-0.0132	-0.0127*
	[0.00819]	[0.00867]	[0.00844]	[0.00343]	[0.0157]	[0.00825]	[0.00673]
Industry intercepts	Y	Y	Y	Y	Y	Y	Y
Year intercept	Y	Y	Y	Y	Y	Y	Y
Constant	0.111***	0.101***	0.109	0.214***	0.144***	0.402***	-0.0649***
	[0.0368]	[0.0362]	[0.339]	[0.0210]	[0.0216]	[0.0597]	[0.0231]
Observations	46,275	28,812	40,131	101,754	58,965	10,374	46,521
AdjR2	5.62%	7.32%	3.33%	3.77%	4.18%	4.53%	2.63%
UnderId F-stat (p)	117.6 (0)	191.5 (0)	12.76 (0)	222.2 (0)	155.5 (0)	158.7 (0)	109.3 (0)
WeakInst F-stat	1169	1420	3.199	1722	1869	1455	1555

Note: standard errors, clustered on Area Unit (AU), in brackets (***;**;* denote significance at the 1%;5%;10% level respectively). Counts are random-rounded (base 3). Only workforce characteristic variables (including population density) are instrumented, using their (five-year) lags. Kleibergen-Paap F statistics for tests of weak identification and underidentification reported.

Existing studies point to the importance of dense urban environments especially for small and newly established firms (Duranton and Puga, 2001). Columns 4 and 5 of Table 5 show estimates for two size-classes of firms – those with employment of five or fewer, and those with employment greater than five. The smaller group accounts for around two-thirds of firms with employees, so perhaps not surprisingly, the estimates are similar to the overall estimates in the previous table. The advantages of operating in a dense area do appear to be more modest for larger firms, with the coefficient on population density being only half as big as for smaller firms. Smaller firms benefit more from being in a highly skilled local labour market, with an IV coefficient of 0.232 on the percent with degree qualifications. New firms (column 6) also benefit relatively strongly from being in densely populated areas, and appear to have lower productivity in areas with many newcomers (β= -0.414).

The composition of the local workforce may affect the pattern of demand for local goods and services as well as the operation of the labour market. The final column of Table 5 contains estimates for firms in industries that provide a high proportion of their output locally.[14] These firms are more productive in areas where new entrants (β=0.201) and migrants (β=0.099) are a relatively high proportion of the local workforce. The effect of being in a high-skilled area is small and statistically insignificant. For local services firms, the composition of the local workforce appears to raise productivity primarily through output markets rather than through factor markets.

Our final analysis of the interaction of productivity and workforce composition examines more disaggregated measures of the local workforce. Specifically, we classify the local population into eight share components, defined by combinations of being new to the area, being a migrant, and having a degree qualification. The regression estimates are shown in Table 6. The omitted share component is that for low-qualified New Zealand-born residents who lived in the area five years earlier, who on average account for 39.5 percent of population. The coefficients for included components show the productivity contribution relative to the contribution of this omitted group. As for the main specification, instrumental variables estimates are presented using lagged values of the composition variables as instruments.[15]

[14] Industries are identified from Statistics New Zealand's most recent published Input-Output tables (the 126 industry, 1996 classification) as those with approximately half or more of their output used directly by the household sector (defined as households plus the ownership of owner-occupied dwellings industry). We then drop Financial and Insurance Services (ANZSIC K) from the resulting industry group on the basis that they provide services largely to households outside the local area.

[15] The specification passes a weak instruments test, but the higher standard errors and inflated coefficients on the composition variables indicate that the IV estimates may be less reliable for the disaggregated composition measures.

Table 6: Disaggregated workforce composition measures

	(1)	(2)	(3)	(4)
Dependent variable: mfp	*OLS*	*IV*	*Mean shares*	*Implied share elasticities*
High skilled migrants new to the area	1.527***	3.447***	3.4%	0.12
	[0.398]	[0.718]		
High skilled migrant stayers	-3.622***	-6.730***	1.4%	-0.10
	[0.816]	[1.428]		
Low skilled migrants new to the area	-0.510***	-1.338***	9.9%	-0.13
	[0.141]	[0.235]		
Low skilled migrants stayers	0.910***	1.921***	6.7%	0.13
	[0.183]	[0.298]		
High skilled NZ-born new to the area	0.507**	0.680**	5.1%	0.03
	[0.247]	[0.327]		
High skilled NZ-born stayers	-0.134	-0.491	3.9%	-0.02
	[0.367]	[0.543]		
Low skilled NZ-born new to the area	0.125**	0.245***	30.2%	0.07
	[0.0543]	[0.0751]		
Low skilled NZ-born stayers	0	0	39.5%	0.00
	[]	[]		
ln(population density)	0.00928***	0.00899***		
	[0.00136]	[0.00144]		
Average Worker Fixed Effects	0.235***	0.234***		
	[0.00759]	[0.00758]		
Gross turnover	-0.0235***	-0.0233***		
	[0.00247]	[0.00248]		
Net turnover	-0.00116	-0.00109		
	[0.00337]	[0.00337]		
Industry intercepts	Y	Y		
Year intercept	Y	Y		
Constant	-0.0212	0.103***		
	[0.0210]	[0.0283]		
Observations	160719	160719		
AdjR2	3.63%	3.58%		
UnderId F-stat (p)		204.1 (0)		
WeakInst F-stat		76.36		

Note: standard errors, clustered on Area Unit (AU), in brackets (***;**;* denote significance at the 1%;5%;10% level respectively). Counts are random-rounded (base 3). Only workforce characteristic variables (including population density) are instrumented, using their (five-year) lags. Kleibergen-Paap F statistics for tests of weak identification and underidentification reported.

The largest positive IV coefficient (3.45) is for degree-qualified migrants new to the area. On average, firms are located in areas where 3.4 percent of the workforce falls into this category, so the coefficient implies a share-elasticity at means (ξ) of 0.12 (3.45*3.4%). A 10 percent increase in the number of entering degree-qualified migrants is associated with 1.2 percent higher productivity. A similar share elasticity is estimated for the presence of non-new low-skilled migrants, who account for around 6.7% of the local workforce (ξ = 0.13 = (1.92*6.7%)). In contrast, the impact of highly qualified staying migrants and newly arrived (in the area, though not necessarily in the country) low skilled migrants are *negative*, with share elasticities of -0.10 (-6.730*1.4%) and -0.13 (-1.338*9.9%) respectively. For the New Zealand born, elasticities are positive for high-skilled ($\xi = 0.03$) and low skilled ($\xi = 0.07$) entrants, and insignificantly negative for the high-qualified stayers.

The results for the New Zealand-born are consistent with there being productivity spillovers from newly arrived workers. The patterns for the foreign-born are less easily interpreted, and we are cautious in interpreting the results. Taken at face value, the results imply that high-skilled migrants are associated with higher productivity when they first arrive in an area, but that this contribution is reversed for longer-staying migrants. Low-skilled migrants on the other hand have a stronger positive effect only when they have been in the area for at least five years. More detailed analysis would be needed to examine the possible role of changing migrant composition – as a result of selection policies, self-selection, or selective remigration – in explaining these patterns.

6. DISCUSSION

Overall, our findings support the existence of agglomeration effects that operate through labour markets. Firms operating in areas where a high proportion of the workforce is degree qualified have higher multi-factor productivity, even controlling for the quality of the firms' own labour input. The benefits of a skilled local workforce are relatively strong for firms in industries that use skilled labour intensively, and for firms in high R&D industries. This is consistent with the advantages of thick labour markets. It may also indicate positive sorting based on the returns to local skill spillovers.

We confirm a positive relationship between productivity and population density, which is consistent with a range of agglomeration mechanisms. We find that the relationship is strongest for firms operating in the densest areas. In fact, in dense areas, the composition of the local workforce is not significantly related to productivity once we have controlled for density. The benefits of density are stronger for small firms and for new firms, consistent with firm life cycle models of agglomeration (Duranton and Puga, 2001).

In contrast, the proportion of the population that is new to the area, and the proportion that are foreign born are not positively related to firm productivity. An exception is that firms in industries that provide local goods and services are more productive in areas where more migrants and new entrants to the area are found. This suggests that some of the productivity advantages associated with new entrants may stem from product market effects rather than from knowledge spillovers.

When we disaggregate the local workforce more finely, by skill, nativity and recency of arrival, we find some evidence of a positive productivity effect of highly skilled migrants who have recently arrived in the area[16]. The pattern of results across groups does not, however, tell a consistent story, and may reflect the changing composition of migrants over time. The productivity advantages of locating in areas where there is a high proportion of New Zealand-born entrants are positive but more modest than for foreign born. They are also stronger with highly qualified New Zealand-born entrants than for those who are lower skilled.

The findings of the current study contrast with those of a related study, which used similar data to examine whether local workforce composition is positively related to innovation outcomes reported by firms (Maré et al, 2010). In that study, we found that the positive raw correlation between innovation outcomes and local workforce composition was completely accounted for by controlling for local industry mix, and key firm-level measures such as firm size, labour quality, or having any research and development expenditure.

The existence of human capital spillovers raises the possibility that productivity may be increased by spatial policies that promote the accumulation and spatial distribution of skills. As noted by Glaeser and Gottlieb (2008), however, a national policy to exploit such spillovers requires knowledge of which areas are likely to benefit most. Our study highlights heterogeneity in the benefits firms receive from different dimensions of workforce composition. This is an important step in the design and targeting of potential spatially-oriented policies.

[16] Note that migrants who have recently arrived in the area are not necessarily recent arrivals in New Zealand – they may have been in New Zealand for many years.

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