# Urban productivity estimation with heterogeneous prices and labour

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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. The opinions, findings, recommendations, and conclusions expressed in this paper are those of the author, not Statistics NZ, Productivity Hub agencies, nor any other organisation. Access to the anonymised data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organisation, and the results in this paper have been confidentialised to protect these groups from identification. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI. Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz.

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## Abstract

This study estimates differences in productivity (mfp) across New Zealand urban areas, with a focus on the size of Auckland's productivity premium. The estimates are based on analysis of firm-level data from Statistics New Zealand's Longitudinal Business Database. The methods used in the paper overcome some of the biases that arise in standard approaches to spatial productivity estimation - biases arising from imperfect competition, spatial price variation, firm heterogeneity, and labour-sorting across cities. Ignoring these factors leads to biased estimates of the Auckland's relative productivity performance. The study also investigates industry differences in spatial productivity patterns.



## JEL codes

D24 Production; Cost; Capital; Capital, Total Factor, and Multifactor Productivity; Capacity
R30 Real Estate Markets, Spatial Production Analysis, and Firm Location: General

## Keywords

Urban productivity; agglomeration; production function estimation; imperfect competition; input price variation


## Summary haiku

Firms in big cities
hire well and price to compete
Are they better firms?

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# 1 Introduction

Cities offer a broad range of productive advantages, which have been analysed extensively both empirically and through a wealth of theoretical models. Urban economic theory provides insights into the mechanisms that give rise to relatively high urban productivity, including a range of effects that operate through enhanced learning within cities; through sharing of infrastructure risk and markets; and through improved matching of firms and workers. (Duranton & Puga, 2004; Henderson, 2003; Rosenthal & Strange, 2004).

Empirical studies consistently find significantly higher productivity in larger, denser cities. Recent reviews of evidence (Combes & Gobillon, 2015; Melo, Graham, & Noland, 2009) report that a doubling of density is associated with productivity that is around 4 to 7 percent higher. This finding is confirmed by studies that measure productivity by wages (Glaeser & Maré, 2001), labour productivity (Ciccone & Hall, 1996), or multi-factor productivity (Henderson, 2003), although there is some systematic variation among estimates. Melo et al (2009) show that multifactor productivity (*mfp*) estimates are typically around 50 percent larger than wage-based estimates, and document further variation by industry, country, and estimation method. Combes and Gobillon (2015) note that controlling for observed and unobserved differences in worker characteristics reduce the estimated advantages of density, although these controls for sorting may absorb some of the dynamic gains of agglomeration (D'Costa & Overman, 2014; de la Roca & Puga, 2016). They also note that controlling for the endogeneity of density or of input choices has relatively minor effects on the strength of estimated agglomeration effects.

The main contribution of the current paper is to obtain estimates of urban *mfp* that adequately control for spatial price differences, and that incorporate adjustments for the quality of labour inputs. Output price differences arise when competition is imperfect, with firms in less competitive local markets charging higher prices. Using revenue-based measures of gross output will lead to an over-estimate of the productive performance of firms in less competitive locations. Adjusting for spatial input price variation is also necessary when inputs are measured by expenditure rather than quantity.

We control for price variation using the approach of Grieco et al (2016), which relies on the use of firms' first order conditions for profit maximisation to distinguish price and quantity variation. This approach also addresses commonly encountered identification problems such as biases arising from endogenous factor choice. We control also for spatial differences in the quality of labour inputs, using estimates of worker quality from two-way worker-firm fixed effects estimation.

We analyse spatial productivity differences using New Zealand data. Eighty-six percent of the New Zealand population is urbanised. Seventeen main urban areas account for 73 percent of the population, and range in size from 1.3 million in the largest city, Auckland, to 30,000. A further 14 secondary urban areas, ranging in size from 10,000 to 30,000 account for a further 6 percent of the population. The remaining urban 8 percent of the population live in minor urban areas of between one and 10 thousand. The largest urban area, Auckland, contained 31 percent of the country's population in 2013. Official statistics on GDP shares are available for the Auckland Region, which is slightly larger than the Auckland urban area. The Auckland region, which contains 33 percent of the population, produces 37 percent of New Zealand's GDP. We focus particularly on the relative productivity performance of the Auckland urban area, compared with other urban and non-urban areas.

Urban productivity is estimated using data from Statistics New Zealand's Longitudinal Business Database, which integrates a broad range of administrative and survey data on most firms in New Zealand (Fabling & Sanderson, 2016). We use a subset of these data for which reliable production measures are available, and focus on urban-focused industries – those in which more than half of industry employment is in urban centres. We use information on around 80,000 firms per year for 12 years (2001-1012), which account for over 60% of national output in the selected industries, and around 75% of employment.

The next section provides a broad overview of urban multi-factor productivity estimation, and the existing evidence on spatial productivity variation in New Zealand. Section 2 documents our approach to estimation. After describing the longitudinal firm-level data that we use for estimation, we present and discuss our estimates in section 4. Section 5 concludes.

## 1.1 Measuring urban productivity

There is a broad consensus on the existence and size of the urban productivity premium. Sveikaukas (1975) established that a doubling of city size is typically associated with a 6% increase in labour productivity. Ciccone and Hall (1996) confirmed this finding, linking the productivity advantage to the density of economic activity. This spurred a wealth of subsequent studies that have refined the identification and estimation of agglomeration elasticities, and tested the robustness of findings, as summarised by Combes and Gobillon (2015) and Melo et al (2009).

Having established the existence of a significant urban premium, the literature has proceeded to distinguish potential sources of that premium, and to identify the nature of agglomeration externalities. Henderson (2003) was the first to undertake a careful analysis of agglomeration externalities using firm-level multi-factor productivity estimation. His study was restricted to firms in machinery and high-tech industries, and focused on distinguishing the strength of different types of agglomeration effects. He found evidence of Marshallian (within-local industry) spillovers for high-tech firms, particularly single-plant firms. Single-plant high-tech firms were also found to benefit from dynamic agglomeration externalities – benefiting from the scale of past own-industry activity. In identifying the correlation between firm productivity and local industry structure, Henderson controlled for between-firm differences in *mfp* within locations, using industry/ time and plant/location fixed effects.

In estimating the magnitude of spatial productivity differences, our objective is more modest than that of studies such as Henderson's that seek to establish a causal relationship between productivity and features of urban industries. Thus, whereas Henderson controls for location fixed effects in order to reduce the influence of confounding locational attributes, we wish to quantify spatial productivity differences.

The current study thus revisits the measurement and identification issues related to the estimation of the urban productivity premium rather than seeking to distinguish the sources of agglomeration advantages. As such, it relates more closely to the agglomeration elasticity literature, as summarised by Melo et al (2009). Our contribution to that literature is to examine the impact on estimated spatial productivity differences of explicitly taking account of spatial variation in prices and labour quality.

A number of recent productivity studies have focused on the nature and magnitude of estimation biases that arise from ignoring heterogeneity in input and output prices. It has long been known that the common practice of estimating productivity using deflated revenues and expenditures leads to problems of identification and interpretation. Marschak and Andrews (1944, p. 150) refer to the resulting estimating equation as a 'mongrel equation' because it yields parameter estimates that represent a mixture of technical coefficients and endogenous responses. Katayama et al. (2009, p. 403) further demonstrate that "the resultant productivity indices have little to do with technical efficiency, product quality, or contributions to social welfare".

There is considerable inter-firm variation in output and input prices, even within industries with relatively homogeneous products. The extent of variation has been confirmed by industry studies and has been documented in firm-level datasets that contain measures of both price and quantity.[1] Significantly for the current study, there is a spatial pattern to this variation. Any bias in productivity estimation that is associated with heterogeneous prices thus has the potential to lead to misleading estimates of spatial productivity differences. Somewhat surprisingly, recent studies that incorporate heterogeneous prices into productivity estimation have not generally focused on spatial variation, despite often linking observed heterogeneity to spatial factors. Atalay (2014) reports that, even for a sample of industries with relatively homogeneous products, plant-level materials prices are 'persistent, spatially correlated, and positively associated with the probability of exit'. Some of the spatial variation reflects local resource availability but Atalay notes that the competitive environment in (local) factor markets also plays a role.

Failing to take account of spatial price differences tends to lead to underestimates of true productivity differences. For instance, stronger competition in dense urban markets leads firms to operate with lower markups and higher volumes. Due to imperfectly elastic demand, revenues rise

[1] Firm-level datasets do not generally measure prices and quantities separately. Valuable insights have been gained from using datasets that do, from Colombia (Eslava, Haltiwanger, Kugler, & Kugler, 2013; Gandhi, Navarro, & Rivers, 2013; Grieco, Li, & Zhang, 2016; Katayama, Lu, & Tybout, 2009; Kugler & Verhoogen, 2012), Spain (Doraszelski & Jaumandreu, 2013; Ornaghi, 2006), Denmark (Fox & Smeets, 2011), France (Abowd, Kramarz, & Moreau, 1996) and the United States (Dunne & Roberts, 1992; Foster, Haltiwanger, & Syverson, 2008; Roberts & Supina, 1996).

less than proportionally with the quantity of output, understating the productive advantages of cities when estimates are based on revenues rather than quantities.[2]

Input price variation also biases estimates of output elasticities due to the dependence of firms' input choices on relative input prices (Ornaghi, 2006). Higher input prices may make urban firms look less productive when expenditures rather than quantities are used for estimation, unless the higher prices reflect higher quality inputs.

Of course, to the extent that price differences reflect the quality of inputs and output rather than imperfect competition per se, using input expenditure may provide a better measure of inputs than a quantity measure unadjusted for quality[3]. Kugler and Verhoogen (2012) observe a positive correlation between input and output prices across firm, which they argue reflects variation in the quality of both inputs and outputs, disproportionately affecting larger firms. They particularly note the potential links between spatially correlated input/ output quality and spatial factors such as transport and forms of local coordination of interfirm production (p. 309).

Our estimation method described in section 2 below is adapted from Grieco (2016), and builds on methods that have been used in other recent studies of productivity. The method incorporates output price variation in the form of Dixit-Stiglitz monopolistic competition. Input price variation is allowed for, identified from firms' first order conditions for input demand within a parametric production function. The assumed parametric forms allow us to substitute out firm-specific productivity effects when estimating production parameters, removing simultaneity bias.

We extend Grieco's approach by also adjusting for spatial difference in labour quality. Combes et al (2008) have argued that the sorting into cities of workers with higher observed and unobserved skills makes a significant contribution to city wage premiums. Subsequent studies have attributed some of this skill difference to the acquisition of skills within cities (D'Costa & Overman, 2014; de la Roca & Puga, 2016). In the context of productivity estimation, failure to control for labour quality differences will lead to an overestimate of the urban productivity premium because the quantity of effective labour input is understated.

## 1.2 Urban productivity differences in New Zealand

The current study contributes not only to the literature on estimation of spatial productivity differences, but also to a relatively small set of studies that use microdata to estimate *mfp* differences between cities within New Zealand. The study closest to the current one is by Maré and Graham (2013). It includes effective employment density in an augmented translog production function, and reports a positive relationship between density and firm productivity. Maré and Graham report an

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2 Revenue may rise less than proportionately with inputs due to decreasing returns to scale as well as to imperfect competition. Separating these two effects requires additional assumptions, as in Klette and Griliches (1996), or Katayama et al. (2009).

3 This would be the case when price variation is solely due to quality differences, so that the price per effective unit of input is constant.

agglomeration elasticity of 0.066, obtained from industry-specific *mfp* estimates regressed on density. Because the study fails to control for spatial price variation, the spatial variation in productivity will be understated. However, the regression of *mfp* on effective density includes regional intercepts, so the bias is not transmitted into the estimated agglomeration elasticity. The authors do provide an estimate of the agglomeration elasticity that does not include regional intercepts and this is, as expected, smaller (0.052), implying that the cross-regional density gradient is smaller than the within-region gradient, consistent with the impact of price variation. Other results from an earlier version of the paper (Maré & Graham, 2009) are also consistent with bias from intermediate price variation. Allowing density to be factor augmenting, as in Graham and Kim (2007), the authors find that intermediate expenditures are less productive in denser areas, which could reflect higher intermediate prices in denser areas.

Other published estimates of spatial productivity variation within New Zealand have tended to focus on the relative performance of Auckland, and have relied on estimates of wage levels or labour productivity. They capture differences in value added or wages per unit of labour – usually per worker, per capita, or per hour. As such, they differ from the *mfp* premium estimated by Maré and Graham, or the measures in the current paper, which capture an unweighted average across firms. It is nevertheless useful to compare estimates.

Maré and Graham's estimated agglomeration elasticity of 0.066 implies that Auckland firms have *mfp* that is around 9.5% higher than *mfp* in non-Auckland firms, and around 7% higher than for firms in other urban areas.[4] Based on National Accounts estimates of regional GDP (Statistics New Zealand, 2007), Infometrics (2015) report estimates of GDP per employed person, which imply that Auckland labour productivity is 10.6% higher than that for people in regions outside Auckland. This is slightly higher than the difference in median weekly earnings from the Income Survey, of 7.3% in 2014.[5]

Maré (2008) estimates labour productivity using firm microdata, and reports a considerably larger productivity premium for the Auckland region, of 44% in 2006. This is reduced to 25% once industry composition is accounted for. The estimated premium for the Auckland urban area is even larger (51%, declining to 36%). A comparison of estimates from the dataset used in the current paper and that used by Maré (2008) is discussed below in Appendix One.

4 These estimates based on firm counts and effective densities in Maré and Graham (2013), and an approximate effective density in other urban areas of 10.

5 Statistics New Zealand (2015) reports median rather than average weekly earnings. I have adjusted the difference between the Auckland median and the national median (4.9%) for Auckland's share of national employment (33.3%).

# 2 Approach to spatial productivity estimation

In measuring spatial differences in productivity, we are interested in whether firms in different locations are able to produce different quantities of output with the same quantities of inputs, compared with a similar firm located elsewhere. Because we are not attempting to identify the causal effect of density or size on productivity, we do not adjust for the potential endogeneity of city characteristics. We do, however wish to obtain unbiased productivity estimates, so our method must deal with issues of endogeneity and identification that characterise production function estimation more generally. We need to control for the impact of unobserved firm-specific productivity on the choice of inputs, which can bias estimates of production function parameters. We do, however, want productivity estimates that include such firm-specific components, to capture the possible spatial sorting of more productive firms, which contributes to inter-urban productivity differences (Combes, Duranton, Gobillon, Puga, & Roux, 2012).

It has long been recognised that ordinary least squares estimates of firm-level production functions and productivity are biased (Griliches & Mairesse, 1998; Marschak & Andrews, 1944). Input choices are correlated with firm-productivity, as is firm survival. Van Beveren (2012) provides a recent review of methods that have been proposed to account for these sources of bias. In addition to the inherent difficulties in identifying production equations, challenges also arise from the fact that required data on quantities of outputs and inputs are rarely available in firm-level datasets. Firm level data more commonly include measures of firm revenues rather than output, and of input expenditures rather than quantities. This is also true of the data used in the current study.

Under the assumption that firms face common input and output prices, generally-available industry-level input and output price indices can be used to deflate revenues and expenditures, separating quantity from price variation. The assumption of common prices is problematic when there is imperfect competition in input and output markets. This is particularly relevant for the estimation of spatial productivity differences, due to clear evidence of spatial price variation. Industry-level price deflation fails to control for spatial differences within industry.

A tractable approach to incorporating output price variation into estimation is to assume that firms operate in monopolistically competitive product markets (Dixit & Stiglitz, 1977; Klette & Griliches, 1996). Each firm is assumed to sell a differentiated variety of output, and has some degree of market power. They can increase the quantity demanded of their variety by charging a lower price. Equivalently, they can increase the markup of price over marginal cost, but only by reducing the quantity of output that they sell.

Under these assumptions, firms face an inverse demand function, whereby firm-specific output prices for firm *j* in period $t$, $P_{jt}$ (relative to industry output price $P_t$) vary inversely with the firm's share of industry output $\left(\frac{\mathrm{Q_{jt}}}{Q_t}\right)$. We allow for a city-specific relative output-price ($\theta_c$), and city-specific demand elasticity ($\eta_c < -1$).[6] The inverse demand function is:

$$\frac{\mathrm{P_{jt}}}{P_t} = \theta_\mathrm{c} \left(\frac{\mathrm{Q_{jt}}}{Q_t}\right)^{\frac{1}{\eta_c}} \tag{1}$$

One implication of this downward sloping demand curve is that observed revenues increase less than proportionally with output. Relying on revenue as a proxy for output quantity will understate the output (and hence the productivity) of high-output firms.

$$\text{Revenue } = \mathrm{P_{jt}Q_{jt}} = \left[\mathrm{P_t}\theta_\mathrm{c} Q_t^{-\frac{1}{\eta_c}}\right] \left(\mathrm{Q_{jt}}\right)^{\frac{1+\eta_c}{\eta_c}} \tag{2}$$

In an urban context, the reliance on revenue measures is likely to lead to an underestimate of the relative productivity of larger cities. Firms in smaller cities tend to be smaller, and may be trading in less competitive local markets. To the extent that they charge higher prices than their large-city counterparts, revenue comparisons will overstate their relative output, leading to an upward bias in their estimated productivity.

Input prices can also vary across firms if differentiated inputs are supplied in imperfectly competitive markets. Using intermediate expenditures instead of input quantities will lead to biased estimates of production parameters. The direction of bias will depend on how substitutable intermediate inputs are with other inputs. [7]

To accommodate spatial variation in input prices, we adopt the approach of Grieco et al (2016), and rely on the assumption that firms choose labour and intermediate inputs optimally, taking capital inputs and input prices as given. Under this assumption, we can infer the firm's quantity of intermediate inputs from its ratio of labour to intermediate expenditures, observed labour quantity, and estimated production parameters. To implement this approach, we assume a specific functional form for the production function.

We assume that gross output is produced with a constant returns CES production function.[8] Firm *j* is assumed to combine labour ($L_{jt}$), capital ($K_{jt}$), and intermediate inputs ($M_{jt}$), with a common elasticity of substitution, $\sigma = \frac{1}{1-\gamma}$. We adopt the normalisation used in Grieco et al (2016), with inputs and outputs normalised relative to overall geometric means $\left(\bar{Z} = \left(\prod_{j=1}^{J} z_j\right)^{1/J}\right)$. We also allow for a Hicks-neutral time-varying firm-specific productivity component $\left(\omega_{\mathrm{jt}}\right)$ which can affect input choices.

6 A city-specific relative price effect may arise in the case of asymmetric consumer preferences if firms in a city disproportionately produce highly value varieties. Under the assumed monopolistic competition structure, a lower quantity demanded in a small city will affect the number of firms, rather than the price.

7 If the elasticity of substitution is greater (less) than one, cost shares are positively (negatively) related to relative quantities. With high substitutability, an increase in relative price induces a more-than-proportional decrease in relative quantity, and a lower cost share. If substitutability is low, a relative price rise induces a less than proportional decrease in relative quantity, and a higher cost share.

8 As noted by Grieco et al (2016), a Cobb Douglas specification is unsuitable due to the implied constancy of optimal expenditure shares.

$$\frac{\mathrm{Q_{jt}}}{\bar{Q}} = \mathrm{e}^{\omega_{\mathrm{jt}}}\left[\alpha_L\left(\frac{L_{jt}}{\bar{L}}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\bar{K}}\right)^{\gamma} + \alpha_M\left(\frac{M_{jt}}{\bar{M}}\right)^{\gamma}\right]^{\frac{1}{\gamma}} \tag{3}$$

Our aim is to estimate the parameters of equation 3 ($\alpha_L, \alpha_K, \alpha_M, \gamma$), based on observed revenues rather than output, and intermediate expenditures rather than quantity. We can then derive an estimate of firm *mfp* $(\omega_{\mathrm{jt}})$. This approach to recovering *mfp* differs from the structural estimation approach introduced by Olley and Pakes (1996) and developed by Levinsohn and Petrin (2003), Ackerberg et al (2015), and Wooldridge (2009), which relies on GMM moment restrictions and Markov-restrictions on the time-series properties of *mfp*. Our approach relies instead on the use of first order conditions for firms' profit maximisation, as in Grieco et al (2016), Doraszelski and Jaumandreu (2013) and Gandhi et al (2013). For profit maximisation, capital inputs are taken as given, and the firm is assumed to choose labour and intermediate inputs to maximise profits:

$$\max_{L_{jt},M_{jt}}\{P_{jt}Q_{jt}\} - P_L L_{jt} - P_M M_{jt}$$

Combining equations 2 and 3 to get an expression for revenue, the firm's maximisation problem can be expressed as:

$$\max_{L_{jt},M_{jt}}\left\{\theta_c P_t (Q_t)^{\frac{-1}{\eta_c}}(\bar{Q})^{\frac{1+\eta_c}{\eta_c}}\mathrm{e}^{\omega_{\mathrm{jt}}\left(\frac{1+\eta_c}{\eta_c}\right)}\left[\alpha_L\left(\frac{L_{jt}}{\bar{L}}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\bar{K}}\right)^{\gamma} + \alpha_M\left(\frac{M_{jt}}{\bar{M}}\right)^{\gamma}\right]^{\frac{1}{\gamma}\left(\frac{1+\eta_c}{\eta_c}\right)}\right\} - P_L L_{jt} - P_M M_{jt} \tag{4}$$

The first order conditions for optimisation are:

$$FOC_L\colon\left\{\theta_c P_t (Q_t)^{\frac{-1}{\eta_c}}(\bar{Q})^{\frac{1+\eta_c}{\eta_c}}\mathrm{e}^{\omega_{\mathrm{jt}}\left(\frac{1+\eta_c}{\eta_c}\right)}\left(\frac{1+\eta_c}{\eta_c}\right)\left[\alpha_L\left(\frac{L_{jt}}{\bar{L}}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\bar{K}}\right)^{\gamma} + \alpha_M\left(\frac{M_{jt}}{\bar{M}}\right)^{\gamma}\right]^{\frac{1}{\gamma}\left(\frac{1+\eta_c}{\eta_c}\right)-1}\right\}\alpha_L\left(\frac{L_{jt}}{\bar{L}}\right)^{\gamma} = E_{L_{jt}} \tag{5}$$

$$FOC_M\colon\left\{\theta_c P_t (Q_t)^{\frac{-1}{\eta_c}}(\bar{Q})^{\frac{1+\eta_c}{\eta_c}}\mathrm{e}^{\omega_{\mathrm{jt}}\left(\frac{1+\eta_c}{\eta_c}\right)}\left(\frac{1+\eta_c}{\eta_c}\right)\left[\alpha_L\left(\frac{L_{jt}}{\bar{L}}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\bar{K}}\right)^{\gamma} + \alpha_M\left(\frac{M_{jt}}{\bar{M}}\right)^{\gamma}\right]^{\frac{1}{\gamma}\left(\frac{1+\eta_c}{\eta_c}\right)-1}\right\}\alpha_M\left(\frac{M_{jt}}{\bar{M}}\right)^{\gamma} = E_{M_{jt}} \tag{6}$$

The first order conditions are used to identify factor demands, allowing us to separate intermediate prices and quantities from expenditure data, and to substitute out firm-specific productivity components when estimating production parameters. The key step in separating the price and quantity of intermediate inputs is to take the ratio of the two first order conditions and express relative material inputs as a function of observed labour inputs and expenditures, intermediate expenditure, and production function parameters.

$$\left(\frac{M_{jt}}{\bar{M}}\right) = \left(\frac{\alpha_L E_{M_{jt}}}{\alpha_M E_{L_{jt}}}\right)^{\frac{1}{\gamma}}\left(\frac{L_{jt}}{\bar{L}}\right) \tag{7}$$

Substituting for $\left(\frac{M_{jt}}{\bar{M}}\right)$ into the first order condition for labour (equation 5) we can express the unobserved productivity component as:

$$\omega_{jt} = \left(\frac{\eta_c}{1+\eta_c}\right) ln\left((\theta_c P_t)^{-1}(Q_t)^{\frac{1}{\eta_c}}(\bar{Q})^{-\left(\frac{1+\eta_c}{\eta_c}\right)}\left(\frac{\eta_c}{1+\eta_c}\right)\left(\frac{L_{jt}}{\bar{L}}\right)^{-\gamma}\frac{1}{\alpha_L}E_{L_{jt}}\left[\alpha_L\left(1+\frac{E_{M_{jt}}}{E_{L_{jt}}}\right)\left(\frac{L_{jt}}{\bar{L}}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\bar{K}}\right)^{\gamma}\right]^{1-\frac{1}{\gamma}\left(\frac{1+\eta_c}{\eta_c}\right)}\right) \tag{8}$$

Substituting this expression into the expression for revenue (in braces in equation 4), yields the following expression for revenue, which provides the structure for the estimating equation.

$$lnR_{jt} = ln\left(\frac{\eta}{1+\eta}\right) + ln\left(E_{M_{jt}} + \left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}/\bar{K}}{L_{jt}/\bar{L}}\right)^{\gamma}\right)E_{L_{jt}}\right) \tag{9}$$

## 2.1 Estimation

The main estimating equation is based on equation 9, with the addition of a random error, to capture measurement error and unanticipated shocks to demand or productivity.

$$lnR_{jt} = ln\left(\frac{\eta_c}{1+\eta_c}\right) + ln\left(E_{M_{jt}} + \left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}/\bar{K}}{L_{jt}/\bar{L}}\right)^{\gamma}\right)E_{L_{jt}}\right) + u_{jt} \tag{10}$$

The log of revenue is estimated as a function of expenditures on optimally-chosen inputs, with a scaling factor that reflects the degree of imperfect competition. The relationship does not depend directly on the firm-specific productivity component $(\omega_{jt})$, nor the local price $(\theta_c)$, and is a function of observable revenue, expenditures, and quantities of capital and labour. The revenue equation is used to simultaneously identify demand $(\eta_c)$ and production $(\alpha_K, \alpha_L, \alpha_M, \gamma)$, parameters, as in Klette and Griliches (1996).

We estimate the competition term as an additive parameter $\mu_c = \ln\left(\frac{\eta_c}{1+\eta_c}\right)$, which provides an index of the firm's ability to charge a higher price, and achieve a higher markup, by restricting the quantity of output. A value of zero corresponds to perfect competition ($\eta_c = -\infty$), and $\mu$ tends to infinity as $\eta_c$ approaches -1. The three distribution parameters are not separately identified from equation 10. We impose two constraints – constant returns to scale, and the restriction on parameters implied by equation 7.[9]

$$\alpha_L + \alpha_K + \alpha_M = 1$$

$$\frac{\alpha_L}{\alpha_M} = \frac{\bar{E}}{\bar{M}} \tag{11}$$

Equation 10 is estimated using constrained non-linear least squares to recover estimates of technology parameters $(\alpha_K, \alpha_L, \alpha_M, \gamma)$, and the scaling term $\mu_c = \ln\left(\frac{\eta_c}{1+\eta_c}\right)$. All of these parameters are constrained to be greater than zero. The constant returns to scale restriction affects the estimate of market power – an interdependence discussed by Klette and Griliches (1996). If there are in fact decreasing returns to scale, output quantity will increase less than proportionately with inputs, affecting revenue in the same way as imperfect competition. The market power should thus be seen as a combination of market power and decreasing returns.[10]

[9] The second constraint is derived by taking the geometric mean of both sides of equation 7, noting that the geometric mean of $L_{jt}/\bar{L}$ = geometric mean of $M_{jt}/\bar{M} = 1$

[10] For some small industries, the market power estimate $(\mu_c)$ approaches its constrained value of zero, consistent with perfect competition, or possibly increasing returns.

### 2.1.1 Identifying mfp

The estimated parameters can be used to obtain an estimate of firm-specific productivity, using the expression in equation 8. The imputed $\omega_{jt}$ is a function of observables, but also includes terms that are not directly observable. In particular, the terms $(\theta_c P_t)^{-1}(Q_t)^{\frac{1}{\eta_c}}(\bar{Q})^{-\left(\frac{1+\eta_c}{\eta_c}\right)}$ require the separation of output prices and output quantities, which are not directly observed. With location-specific output elasticities ($\eta_c$) and price effects ($\theta_c$), it is not possible to identify location-specific productivity differences because of interactions between unobserved quantity variables and spatially indexed parameters. If we impose the constraint that the demand elasticity, and thus the degree of market power is common across locations ($\eta_c = \eta$), firm-level *mfp* can be recovered relative to an industry-year mean level.[11] Equation 8 can then be rewritten as:

$$\omega_{jt} = -\left(\frac{\eta}{1+\eta}\right) ln(\theta_c) + \delta_t + ln\left\{\left(\frac{\eta}{1+\eta}\right)\left(\frac{L_{jt}}{\bar{L}}\right)^{-\gamma}\frac{1}{\alpha_L}E_{L_{jt}}\left[\alpha_L\left(1+\frac{E_{M_{jt}}}{E_{L_{jt}}}\right)\left(\frac{L_{jt}}{\bar{L}}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\bar{K}}\right)^{\gamma}\right]^{1-\frac{1}{\gamma}\left(\frac{1+\eta}{\eta}\right)}\right\} \tag{12}$$

where $\delta_t = \left(\frac{\eta}{1+\eta}\right) ln\left(P_t^{-1} Q_t^{\frac{1}{\eta}} \bar{Q}^{-\left(\frac{1+\eta}{\eta}\right)}\right)$. The final term (the log of the term in braces) can be estimated from observed quantities, expenditures, and estimated parameters. Denoting this term as $\widetilde{\omega}_{jt}$ and normalising it by its mean value in each year yields an estimate of productivity:

$$\left(\widetilde{\omega}_{jt} - E_t[\widetilde{\omega}_{jt}]\right) = \left(\omega_{jt} - E_t[\omega_{jt}]\right) + \left(\frac{\hat{\eta}}{1+\hat{\eta}}\right) \ln\left(\frac{\theta_c}{E_t[\theta_c]}\right) \tag{13}$$

This productivity proxy equals relative annual *mfp*, plus a term that captures city-specific differences in the varieties produced. The normalisation is done by regressing $\widetilde{\omega}_{jt}$ on a set of time dummies, separately for each industry.

### 2.1.2 Spatial variation in competition and input prices

The estimates obtained from equation 10 can be used to estimate a firm-specific price of intermediate inputs in each year. Intermediate expenditure is divided by the optimal quantity of intermediate inputs, as derived from the relationship shown in equation 7. Spatial variation in intermediate prices can be examined by regressing firm-level prices on firms' employment shares by location. Spatial variation in competition is estimated by including location share variables in equation 10. As noted above, it is not possible to derive meaningful *mfp* proxies in the presence of spatially varying competition.

### 2.1.3 Adjusting for labour quality

We examine the sensitivity of our estimates to the sorting of skilled labour across cities. To do this, we use an estimate of average labour quality within each firm, obtained from an auxiliary two-way fixed



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[11] This assumption is more likely to hold for goods and services that are traded across locations. Even if there are location-specific demand elasticities, there will be a common overall demand elasticity, with firms endogenously choosing how much output to supply to different locations.

effects regression. We use linked employer-employee data for all jobs in the New Zealand economy for which PAYE income tax is deducted. For each job, defined by a link between a worker ($n$) and firm ($j$) within a year ($t$), we regress the logged monthly earnings rate $\left(w_{njt}\right)$ on a full set of worker and firm intercepts ($\theta_n$ and $\psi_j$ respectively), and observable worker characteristics ($X'_{\mathrm{nt}}$):

$$w_{njt} = X'_{\mathrm{nt}}\beta + \theta_n + \psi_j + \varepsilon_{njt} \tag{14}$$

The vector $X_{nt}$ consists of sex-specific age-quartics and time-effects. The earnings rate is calculated as the rate for a full-time equivalent worker. The predicted contribution of worker characteristics provides an index of worker skill $\left(\hat{s}_{nt} = X'_{\mathrm{nt}}\hat{\beta} + \hat{\theta}_n\right)$ for each worker, consisting of a time invariant component $\left(\hat{\theta}_n\right)$ and a time-varying component that reflects the average age-earnings profile by sex. The time-invariant component is identified by the movement of workers between firms. Spatial variation in wages will be absorbed primarily by the firm fixed effects, so that the worker effects provide an estimate of labour quality that does not reflect spatial productivity differences between firms. It captures worker ability, motivation and skills, whether or not these are due to formal qualifications. While controlling for worker skills in this way improves the measurement of effective labour input in cities, agglomeration benefits arising from enhanced skill accumulation in cities will be captured as higher levels of worker skills, and will not be reflected in higher estimated firm productivity.

The skill index is estimated from all jobs but normalised to have an FTE-weighted mean of zero across all labour input observed in our data.[12] We use the skill index to create a measure of quality-adjusted labour input ($H_{jt}$) for each firm in each year. Firm-specific average labour quality ($\bar{S}_{jt}$) per FTE worker is estimated annually for all employees. This average quality is then used to scale the standard measure of labour input in the firm (which, in our data, includes working proprietor input):

$$H_{jt} = L_{jt}(1 + \bar{S}_{jt}) \tag{15}$$

This skill-adjusted measure of labour input is used instead of $L_{jt}$ in all the estimating equations, to provide a labour-quality-adjusted estimate of productivity. Note that expenditure on labour $\mathrm{E_L}$ is unaffected by this adjustment, though the price of labour, and thus the implied productivity of labour, is affected. Given the central identification role played by the relationship between input expenditures and quantities as shown in equation 7, adjusting for labour quality could generate quite different parameter estimates, and estimates of spatial productivity and price differences.

# 3 Data

We estimate firm-level productivity using longitudinal business microdata from Statistics New Zealand's Longitudinal Business Database (LBD). The LBD is a comprehensive database of firm

12 A fuller discussion of the estimation and identification of this regression is reported in (Maré, Hyslop, & Fabling, 2015).

information derived by linking a wide range of administrative and survey data (Fabling & Sanderson, 2016). Production measures are constructed from two main sources – Statistics New Zealand's Annual Enterprise Survey, and administrative tax records from the tax agency (Inland Revenue).[13]

We use a subset of these data, on firms for which reliable production information can be derived, and which have positive revenue, labour, capital, and intermediate inputs. We restrict our attention to private, for-profit firms, for which the profit-maximising assumptions that underlie our modelling are more likely to hold. We also confine our analysis to industries in the measured sector, identified by Statistics New Zealand as "industries that mainly contain enterprises that . . . sell their products for economically significant prices that affect the quantity that consumers are willing to purchase" (Statistics New Zealand, 2014). This restriction excludes government, education and health industries. Reflecting our focus on urban productivity, we further exclude industries in which less than half of employment is in urban areas, namely the primary industries of agriculture, forestry, fishing and mining. The resulting dataset used for analysis contains information on 90,000 to 105,000 enterprises per year for 12 years (2001-2012). These enterprises collectively account for around 60% of GDP in the relevant industries, and around 75% of employment[14].

As is commonly the case in productivity studies, the dataset does not contain information on the quantities of output, or capital inputs, and of intermediate inputs. These are instead measured in dollar terms, as revenue, and expenditures on capital services and intermediates. The dataset contains employee and working proprietor counts but lacks information on hours worked. We use an algorithm, documented in Fabling and Maré (2015a), to derive an estimate of annual full-time equivalent employment, including working proprietors, for each enterprise. Firm financial data are available for enterprises, which may operate in multiple locations. Location patterns are available from monthly employment counts by plant, and we use this to derive employment shares by urban area.

Table 1 summarises urban differences in key production variables used in the estimation of urban productivity. The lower panel of the table shows the number of observations on which the summary statistics are based. Our data contain over 300,000 firm-year observations on distinct firms that operate in Auckland. Of those firms, 93% operate only in the Auckland urban area, though the firms that also operate outside Auckland are larger. Single-location firms account for only 46% of the combined revenue of firms that operate within Auckland.

When calculating the share of observations, or the share of key production variables, accounted for by Auckland firms, we weight each firm by the proportion of their employment that is in Auckland. Thus, a firm with half of its employment in Auckland has a weight of 0.5 in the column relating to Auckland. On this basis, the Auckland urban area accounts for 31% of the annual enterprise observations in our sample - a little over 290,000 (weighted) enterprises, or around 24,000

[13] A more detailed description of the data, and the methods to derive measures of revenue, employment, and expenditures, is available in Fabling and Maré (2015a, 2015b).

[14] We repair longitudinal linking of enterprises over time using the approach of Fabling (2011).

enterprises per year. These enterprises are, however, larger than average, and account for 36% of revenue and labour input, 34% of intermediate expenditures, and 39% of overall capital and labour expenditure. The comparative figures in column (2) summarise the characteristics of firms operating in other urban areas.[15] Urban enterprises operating outside Auckland account for 60% of firms, and between 53% and 57% of other production aggregates.

Auckland firms are, on average, larger than firms operating in other urban areas. The first two columns of Table 1 show the mean value of logged revenue, labour, capital, and intermediates for Auckland and other urban firms respectively. The difference in logs is shown in column (3) and is interpreted as an approximate percentage difference. Auckland firms have (geometric) mean revenue that is 25% higher than other urban firms. This size difference is reflected in capital and intermediate inputs (27%) and in the size of the firms' wage bills (18%). In contrast, the level of employment is more similar across the two groups, with Auckland firms only about 2% larger than other urban firms. Although the level of employment is similar between Auckland firms and other urban firms, a larger difference is evident when we use a quality–adjusted measure of labour input. Workers in Auckland firms are, on average, more highly skilled according to the quality-adjusted measure described in section 2.1.3. The difference in quality adjusted labour input between Auckland and other urban firms is 10%, reflecting the relatively higher labour input provided by Auckland workers.[16]

Auckland firms are more labour-intensive than other urban firms, though the differences are smaller when quality-adjusted labour is used. There is a 0.27 log difference in the level of capital and intermediates with a difference in labour inputs of 0.02, or of 0.10 when adjusted for labour quality. Columns (4) and (5) show the corresponding measures for rural firms. They are smaller than urban firms, and less labour-intensive than firms in urban areas outside Auckland.

# 4 Results

The first step in generating estimates of spatial differences in productivity is to estimate industry-specific production function parameters. Before discussing estimates from the preferred specification, we first summarise estimates from constrained versions of equation 10.[17] The first column of Table 2

[15] The 'other urban areas' grouping includes enterprises operating in areas of New Zealand classified as part of urban areas in 2013. There are 16 main urban areas other than Auckland, with 2013 populations of more than 30,000. The grouping also includes 14 secondary urban areas with populations between 10,000 and 30,000, and 103 minor urban areas with populations between 1,000 and 10,000.

[16] The average level of quality adjusted labour is lower than the average level of unadjusted labour due to the sorting of higher-skilled workers into larger firms. Labour quality is normalised to have mean of zero across all employment in our sample. Because equal weight is given to each firm mean quality across firms is negative. The normalisation does not affect the calculation of relative levels.

[17] The reported summary measures combine parameter estimates from 31 separate industry-level regressions using a random-effects meta-regression. For each parameter, we run a regression that has one observation per industry ($I$) and report the estimated intercept (B) from the following regression: $\hat{\beta}_I = B + e_I + \epsilon_I$. For each observation, the dependent variable ($\hat{\beta}_I$) is a parameter estimate from an industry-specific regression with the form of equation 10. Because the dependent variable is an estimated parameter, with an associated standard error, we allow for two components of the error term. The first component ($e_I$) captures the sampling variability of the parameter estimate, and has variance $V(e_I) = \left(se(\hat{\beta})\right)^2$. The second component ($\epsilon_I$) reflects between-industry variance, and is estimated using restricted maximum

summarises estimates from constant-returns-to-scale CES regressions of gross revenue modelled as a function of intermediates expenditures, labour, and capital. Compared with our preferred specification (equation 10), these estimates fail to control for firm-specific productivity components ($\omega_{jt}$) that may be correlated with input choices. They also fail to control for firm-level variation in input prices (including intermediate expenditures), output prices (relying on revenues as a proxy for output), and labour quality. Analysis by Ornaghi (2006) shows that failing to control for input and output price heterogeneity in a Cobb-Douglas model leads to downward bias in returns to scale estimates, and in the estimated returns to labour inputs in particular. Grieco et al (2014) show that, for CES models, the use of input expenditures in place of quantities also leads to a downward bias in estimates of the elasticity of substitution.

The second column of Table 2 presents estimates of equation 10 parameters, with the constraint that the demand elasticity ($\eta$) is constant across all locations. This constraint is required for the estimation of spatial *mfp* differences, as discussed in section 2.1.1. This constraint is relaxed in the third column, which summarises estimates of the parameters in equation 10 as shown in Appendix Table 3 and Appendix Table 4 for each industry.

Comparing the CES estimates in the first column of Table 2 with the preferred estimates in the second and third columns highlights the biases. The CES estimate of the parameter $\gamma$ (0.453) implies an elasticity of substitution ($\sigma$) of 1.8, which is significantly lower than the estimate from the preferred specification ($\gamma$=0.752; $\sigma$=4.0). Similarly, the distributional parameters differ, with the greatest bias in the labour coefficient.

The estimated market power parameter $\mu = ln(\eta/(1+\eta))$ in column 2 is 0.117, implying a demand-share elasticity ($1/\eta$) of -0.11. Relaxing this constraint in column three results in minimal changes in the distributional parameters and elasticity of substitution. The location-specific estimates of firms' abilities to set prices imply slightly less market power in Auckland ($\mu_{Akld} = 0.103$) than in other urban (0.123) or rural (0.114) areas. These estimates imply demand-share elasticities of -0.098 in Auckland, -0.116 in other urban areas, and -0.108 in rural areas. The parameters are not, however, significantly different from each other, and give some confidence that the constraint of common market power is not unduly influencing our measurement of productivity.

Columns 4-6 of Table 2 present production parameters from specifications that are analogous to those in the first 3 columns, but using a quality-adjusted measure of labour input. Using the alternative labour measure affects all estimated parameters, though none of the changes is statistically significant. The estimates in columns 5 and 6 show a slightly lower index of market power.

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likelihood. The estimation is carried out using the *metareg* package in Stata® (Harbord & Higgins, 2008). One consequence of this procedure is that the weighting of industry parameters varies by parameter. The summary estimates of the distributional parameters do not sum exactly to one, even though this (constant returns to scale) constraint holds for each industry.

## 4.1 Estimated productivity premium

There are substantial differences in estimated spatial productivity premiums between those derived from CES estimates, shown in the first and fourth columns of Table 2, and those based on the preferred estimates in the other columns.

Table 3 presents the implied spatial productivity premiums for different urban areas. The premiums are expressed as differences from the productivity of Auckland firms. A negative number thus implies that firms in an area are less productive than comparable firms in Auckland. The first column shows labour productivity differences, obtained by regressing the log of firms' labour productivity (value added divided by labour input) on industry-year dummies and employment shares in each location.[18] The inclusion of industry-year dummies removes the spatial variation in labour productivity that is due to industry composition. Auckland has a higher share of firms in industries that have relatively high labour productivity everywhere. The raw difference in labour productivity between Auckland firms and those in other urban areas is 17.9%. Differences in industry composition explain about a quarter of this premium.

Within industries, labour productivity for firms employing in urban areas outside Auckland is, on average, 13.5% below that of Auckland firms, as shown in the first row and column of Table 3.[19] For rural firms, the difference is slightly smaller, at 11.3%. All other urban areas have lower average labour productivity than Auckland. Wellington firms have the highest labour productivity of firms outside Auckland, with labour productivity only 4.2% lower than that of Auckland. Firms in the remaining urban areas have labour productivity that is 9% to 20% below that of Auckland, with the largest gaps for smaller and less dense urban areas.

The distribution of labour productivity across firms is shown graphically in Figure 1. Panel (a) shows the unadjusted distributions of labour productivity for Auckland, other urban areas, and rural areas. There is substantial overlap in the distributions - although the 17.9% difference between Auckland and other urban firms is sizeable, it is small relative to the variation that exists within Auckland or within other urban areas. Controlling for differences in industry composition (shown in panel b) causes relatively small changes in the shape and position of the distributions, despite reducing the Auckland-other urban by a quarter (to 13.5%), and the gap between Auckland and rural areas by around one third, from 17.0% to 11.3%.

Labour productivity differences do not adjust for differing capital intensity of firms in different urban areas, or for firms' ability to substitute between labour, capital and intermediate inputs. The patterns in Table 1 show that Auckland firms are more capital-intensive and intermediates-intensive than are firms in other urban areas. A crude adjustment for these factors is obtained from CES

[18] The estimates are from two separate regressions. The first includes only two locational share variables ('Other Urban' and 'Rural'). The second includes locational share variables for each of the nine urban areas shown in Table 3, plus a rural share variable. The estimate of the rural share coefficient is taken from the first specification.

[19] This estimate is considerably lower than the estimate of labour productivity differences in Maré (2008). The reasons for this difference are discussed in Appendix One.

production function estimates, summarised in the first column of Table 2.[20] The distribution of residuals from that regression are graphed in the third panel of Figure 1. The variation across firms and across locations is small relative to that of labour productivity. This compression is reflected in a relatively small estimated difference in productivity between Auckland firms and those in other urban areas (2.1%) and between Auckland and rural firms (7.4%). The more detailed spatial disaggregation shown in Table 3 (col 2) shows that Wellington firms are more productive by this measure than Auckland firms in the same industry, by 2.1%. There is relatively little difference among the remaining urban areas. Apart from firms in minor urban areas, which have estimated productivity 5% below that of Auckland firms, firms in other urban areas have productivity levels that are 1.8% to 2.5% below that of Auckland firms.

Estimating spatial productivity differences based on the more refined approach outlined in section 2 confirms that the simple CES approach leads to underestimated spatial variation. Based on estimates from a constrained ($\eta_c = \eta$) version of equation 10, we find that Auckland firms are 7.9% more productive than comparable firms in other urban areas (column 3 of Table 3), and 21.4% more productive than those in rural areas. Within the other urban areas grouping, Wellington continues to show a modest productivity premium over Auckland (3.8%), and firms in non-minor urban areas have productivity that is 7.4% to 10.6% lower than in Auckland. For firms in minor urban areas, productivity is 15.3% lower than in Auckland firms. The increased dispersion of estimated productivity, both within and between locations, is illustrated in panel (d) of Figure 1. Grieco et al. (2016) also found that adjusting for firm-specific price variation increased the estimated variation in productivity, although they did not explicitly consider spatial variation.

Estimated spatial productivity differences are less pronounced when quality-adjusted labour measures are used. A large proportion of Auckland's estimated productivity premium is related to the higher average skills of Auckland workers. Estimates from a CES specification (column 4 of Table 3) show no significant difference between Auckland productivity and that of other urban areas, and a 4.9% premium relative to firms in rural areas. These estimates are biased downward by the failure to control for input and output price differences. Incorporating these adjustments reveals, in column 5, that Auckland's *mfp* productivity is estimated to be 2.2% higher than that of other urban firms, and 13.5% higher than that of rural firms. Wellington firms are estimated to have productivity that is 2.7% higher than that of Auckland firms.

The final column shows median population density[21] within each geographic area. The difference in log density between Auckland and other urban areas is approximately 1, implying that

[20] The patterns of spatial productivity variation estimated from a CES production function regression are very similar to those obtained when using Cobb-Douglas or translog functional forms.

[21] Population density is measured as the density of the median area unit, expressed in logs. The unlogged and logged measures are shown in the final column of Table 3. Median density provides a better indication of density than is obtained by dividing total population by total land area, because of the presence of large low-density areas in some urban areas (notably Hamilton), and the more tightly defined spatial boundaries in some minor urban areas that imply densities similar to those of Auckland (The median population in minor urban areas is around 2,500).

the estimate for Auckland's premium over other urban areas can be interpreted as an agglomeration elasticity. The estimates in columns 3 and 5 thus represents agglomeration elasticity estimates of 0.079 and 0.022 respectively. International evidence suggests a coefficient of between 0.04 and 0.07 (Melo et al., 2009).

The unadjusted estimate of 0.079 in column 3 of Table 3 is slightly above this range, but is similar to the New Zealand estimate of 0.069 in Maré and Graham (2013), which was based on variation within local industries. Maré and Graham found a lower estimate (0.037) when they included between-region as well as within-region variation in density and productivity but ignoring spatial variation in input and output prices.

The impact of labour quality adjustment in the current paper is in line with findings from international studies. The meta-analysis by Melo et al. (2009, Table 4) reports that studies that control for labour quality generally yield agglomeration elasticities that are 5 to 6 percentage points lower than studies that do not. In the current study, labour quality adjustment lowers the estimated agglomeration elasticity by 0.057 (from 0.079 to 0.022).

## 4.2 Input prices and market power

One consequence of the approach to productivity estimation, as described in section 2, is that it yields estimates of input and output price variation. We are therefore able to examine spatial variation in intermediate input prices, and in the ability for firms to affect their output price by restricting quantity. These estimates are summarised in Table 4, together with information on labour price variation.

### *4.2.1 Labour prices*

The firm-specific average price of labour is calculated by dividing the annual payroll amount by annual full-time equivalent employment. Spatial differences are estimated by regressing the log of this price measure on employment shares by location, and a full set of industry*time dummies. Again, separate regressions are run to estimate 3-way spatial variation (Auckland, Other Urban areas, and rural areas) and the more detailed disaggregation of urban areas, and 14.5% more than those in rural areas. The resulting estimates imply that Auckland firms pay 12.1% more per unit of FTE labour input than do firms in other urban areas. Labour prices are only slightly lower in Wellington than in Auckland, by 1.4%. The relatively high measured price of labour in Auckland and Wellington reflects the higher average skills of workers in those cities. Estimates from Lewis and Stillman (2005, Table 1 and Fig 2) suggest that inter-city differences in observed worker characteristics[22] alone contribute around 3% to the gap in hourly earnings between Auckland and other urban areas and about 6% to the Auckland-rural gap. Wellington workers have higher predicted earnings, so the 1.4% premium shown in Table 4 understates the Auckland-Wellington labour price gap that would exist if we could control for skill

[22] They include controls for age, gender, ethnicity, immigration status, educational qualifications, occupation, industry, and employment type (employer, employee, self-employed, family worker)

differences. It appears that adjusting for differences in worker skills would reduce the spatial variation in labour prices but that Auckland firms would still face a 5% to 10% labour price premium relative to other areas.

Estimating quality adjusted labour prices from our data confirms this. The estimates in column 4 of Table 4 show that the price of quality-adjusted labour in Auckland is 6.0% higher than in other urban areas, and 7% higher than in rural areas. The Auckland premium relative to Wellington is increased, reflecting the higher average skill of workers in Wellington firms.

### *4.2.2 Intermediate input prices*

Firm-specific intermediate prices are estimated from equation 7, and are influenced by whether labour input is quality adjusted. Spatial differences are subsequently estimated using the same approach as is used for labour prices, with estimates shown in the second and fifth columns of Table 4.[23] Estimates based on FTE labour input imply that Auckland firms face intermediate input prices that are 5.7% higher than those faced by other urban firms, and 14.7% higher than those faced by rural firms. Wellington firms are again an exception, with intermediate prices 8.3% above those faced by Auckland firms. While Auckland firms face higher prices for both labour and intermediate inputs, the premium paid for labour is the higher of the two. Given the relatively high elasticity of substitution implied by the estimates in Table 2, this would lead Auckland firms to spend relatively more on intermediate inputs and less on labour, consistent with the descriptive patterns shown in Table 1.

Adjusting for labour quality greatly reduces the estimated spatial differences in intermediate prices. Implied prices in Auckland are only 0.3% higher than in other urban areas, and 7.4% higher than in rural areas. Wellington prices for intermediate inputs are estimated to be 6.1% higher than in Auckland.

### *4.2.3 Output prices*

Columns 3 and 6 of Table 4 summarise the spatial differences in firms' ability to affect output prices, due to imperfectly elastic demand for output. The summary estimates combine coefficients from 31 industry-specific regressions, each with spatially varying competition parameters ($\mu_c = ln(\eta_c/(1+\eta_c))$). The estimates are combined using a meta-regression of parameter estimates as described in footnote 17. These differences in market power were shown at a coarse spatial scale in the third column of Table 2, with more detailed breakdown shown as well in Table 4. On average, Auckland firms are estimated to face more elastic demand for their output, consistent with a higher degree of competition in output markets. The average index of market power faced by Auckland firms ($\mu_{Akld} = \ln(\eta_{Akld}/(1+\eta_{Akld})$) is 0.103, which is lower than the average estimate for firms in other urban areas (0.123). The variation in estimated market power between urban areas is consistent with somewhat weaker competition in smaller areas, though the differences are not statistically significant.

[23] The standard errors have not been adjusted for the dependence of the intermediate price measure on estimated coefficients. Standard errors in the second column of Table 4 are thus be biased downward.

Adjusting for labour quality reduces the estimated strength of market power, by 0.01 to 0.02 in all areas but the relative size of coefficients across locations is relatively stable. This lower level of estimated market power reflects the pattern reported in Table 2, whereby observed revenues are more closely proportional to predicted output when labour inputs are quality-adjusted. Although the parameter $\mu$ is interpreted as a measure of market power within our model, it could also reflect deviations from the assumed constant returns to scale. The lower estimated market power based on quality-adjusted labour could thus indicate more weakly declining (or increasing) returns to scale. The separate identification of returns to scale and market power is not crucial for our estimates of productivity differences, though must be acknowledged when interpreting the level of $\mu$.

## 4.3 Industry variation

### *4.3.1 Productivity premiums*

The results so far have summarised spatial productivity variation across all industries, based on combining (within-industry) estimates from industry-specific regressions. There is, of course, considerable variation across industries in the relative performance of firms in different locations. Industry-specific production function estimates using FTE labour or quality-adjusted labour are shown in Appendix Table 3 and Appendix Table 4 respectively. In this section, we investigate whether the spatial differences across industries are systematic, by regressing estimates of spatial productivity and price premiums on selected industry characteristics.

A separate estimate of the Auckland *mfp* premium is obtained from each industry. Estimated *mfp* for each firm ($j$) and year ($t$) is calculated using equation 12, with industry specific coefficients. For each industry, *mfp* is regressed on firm employment shares by location, and time dummies.[24]

$$\widehat{\omega}_{jt} = \beta_t + \beta_{\mathrm{OthUrb}} OthUrbShare_{jt} + \beta_{\mathrm{Rural}} RuralShare_{jt} + \epsilon_{jt} \qquad (16)$$

The resulting coefficients ($\beta_{\mathrm{OthUrb}}, \beta_{\mathrm{Rural}}$) are shown in Appendix Table 5 and Appendix Table 6 for each industry. The productivity advantage of Auckland firms over same-industry firms in other urban areas is highest for the auxiliary finance and insurance sector (41%) and is over 30% in information media services and non-metallic mineral product manufacturing. Mean productivity is estimated to be lower in Auckland firms for 3 industries (telecommunications internet and library services, 11.2%; rail water and air transport, 1.6%; and accommodation and food services, 0.7%), though in none of these cases is the difference statistically significantly different from zero.

In order to shed light on the nature of these inter-industry differences in the size of Auckland's productivity advantage, we examine the relationship between the differences and various industry-level characteristics. The characteristics we consider are chosen to detect links between spatial productivity variation and self-selection of firms, trade links, workforce skill, and type of output.

24 The standard errors are not adjusted for the fact that the *mfp* measure depends on the estimated parameters of equation 10.

Self-selection of firms is reflected in the proportion of an industry's employment that is in Auckland. We would expect that industries that benefit most from being in Auckland are over-represented in Auckland. Figure 2 summarises the bivariate relationship. Each point on the graph represents the coefficient $\hat{\beta}_{OthUrb}$ from one of 31 industry-specific regressions, as shown in the first column of Appendix Table 5. The vertical bars represent 95% confidence intervals for the estimated productivity premium relative to Auckland. In industries that have a relatively strong presence in Auckland, there is a larger gap between productivity in Auckland and productivity in other urban areas.[25] The industry that is most concentrated in Auckland; telecommunications, internet and library services (JJ12) has 45% of its employment in Auckland. In this industry, firms are actually *less* productive in Auckland than in other urban areas, though the premium is not statistically significant. For other industries with a high proportion of their employment in Auckland, such as Finance and Insurance industries (KK1_ and KK13), Printing (CC41), and Information media services (JJ11), firms in other urban areas are 15% to 40% less productive than similar Auckland firms. In contrast, firms in the industry that is least concentrated in Auckland; food, beverage and tobacco manufacturing (CC1), with 14% of its employment in Auckland is equally productive in Auckland as in other urban areas.

Clearly, an industry's concentration in Auckland is not the only characteristic that may be related to the size of the Auckland productivity premium for firms in the industry. Greater inter-city trade is expected to reduce the size of spatial productivity differences, as more productive firms are able to out-compete competitors in other cities. We test for this effect by including measures of industry tradeability over distance, and international import and export trade. Firm-level variation in these measures is summarised in Table 5, with industry-level values shown in Appendix Table 7.

We use an index of domestic tradeability introduced by Jensen et al. (2005) and calculated for New Zealand industries by Conway and Zheng (2014).[26] The index value is lowest for locally focused industries such as accommodation and food services (4%), and building construction (5%), and highest (above 35%) for spatially concentrated industries such as heavy manufacturing industries, telecommunications, and auxiliary finance and insurance services. Trade exposure of industries is measured as the proportion of industry output that is exported, and the proportion of inputs that are imported, based on input-output tables (Statistics New Zealand, 2012).

The advantages of operating in a dense urban environment are expected to be larger for skill-intensive industries, due to the greater scope for knowledge spillovers, specialisation and differentiated goods and services. Two measures of industry skill composition are included – the share

[25] The mean premium as estimated by the meta-regression of industry-specific coefficients is 11.3%. This differs from the estimated average premium of 7.9% as shown in Table 3 due to the different weightings implied by the different estimation approaches.

[26] The index draws on input-output relationships and captures the extent to which an industry's location pattern differs from that of its customer industries. Conway and Zheng (2014) present tradeability measures by NZSIOC industry. We group some NZSIOC industries, and use a revenue-weighted average of NZSIOC values.

of workers with a bachelor's degree or higher, and the share of workers in skilled occupations (managers, professionals, and technicians and trade workers).[27]

We also allow for the Auckland productivity premium to vary across broad output sector, classifying industries according to whether they are goods producing (45% of firms in our sample), distributive (16%), information (23%), or person-centred (16%).[28]

We analyse the combined influence of industry characteristics using a random-effects meta-regression, as shown in equation 17, of the urban premium coefficients on industry characteristics.[29]

$$\hat{\beta}^{I}_{OthUrb} = a + Z_I \Gamma + e_I + \varepsilon_I \tag{17}$$

This regression has one observation for each of 31 industries. With this limited number of observations, we consider a limited range of industry characteristics, summarised in Table 5 with industry-specific values included as Appendix Table 7.

Estimates of equation 17 are shown in the first column of Table 6. None of the coefficients is statistically significant, implying that the industry characteristics that we have included are not strongly related to the differing size of the Auckland productivity premium across industries. It is possible that high correlation among the characteristics we have included has resulted in imprecise parameter estimates. However, even if the characteristics are entered separately in the regression, only one (domestic tradeability) is (weakly, and negatively) significantly related to the productivity premium. The negative coefficient on domestic tradeability suggests that in industries that supply primarily to local customers (low tradeability) there is a smaller (less negative) productivity difference between Auckland and other urban firms. The other (insignificant) parameter estimates suggest that Auckland productivity premium is relatively small for more skill-intensive industries, and industries that serve export markets.

The lower panel of Table 6 presents analogous estimates based on *mfp* variation that adjusts for labour quality differences. The coefficients are smaller than those in the upper panel, consistent with the lower spatial variation in quality-adjusted *mfp*. The general pattern is, however, similar. Only one coefficient changes in significance – the size of the Auckland premium is positively related to industries' export-intensity, though this is significant only at the 10% level.

### *4.3.2 Intermediate prices and market power*

The meta-regression approach used to examine industry variation in the Auckland productivity premium can also be applied to examine spatial differences in intermediate prices and market power. The results of this analysis are shown in the remaining columns of Table 6.

[27] These measures have been used in New Zealand to identify knowledge intensive industries. Department of Labour (2009) classifies 3-digit ANZSIC06 industries as knowledge intensive if at least 25% of workers have a Bachelor's degree of higher, and at least 30% of workers are in high-skilled occupations.
[28] This grouping of industries is used by the Productivity Commission (2014). Their classification also includes primary and health/education sectors, which are excluded from our analysis. Appendix Table 2 documents how the grouping is applied.
[29] The meta-regressions are based on an extended version of the regressions described in footnote 17. The extension is that the regressions in equation 17 include industry-level covariates, whereas the earlier regressions estimated only an intercept.

The estimated pattern of intermediate-price differences between Auckland and other urban firms is similar to the pattern of productivity differences. None of the estimated coefficients is statistically significant. The parameter estimates imply a relatively small spatial difference in input prices for firms in high-skill and exporting industries, and a larger difference in industries that trade over distance.

The third column of Table 6 presents the correlates of market power differences between industries. It shows what sort of industries have more or less market power. It does not show spatial differences in market power, which are discussed below. The dependent variable here is the industry-specific estimate of market power, constrained to be the same across all urban areas: $\mu = ln\big(\eta/(1+\eta)\big)$. A higher value implies that firms face less elastic demand for their output, and are able to secure higher markups by restricting the amount they supply. A lower elasticity reflects lower competitive pressure, possibly due to a low number of competitors or because firms produce highly differentiated products. The clearest pattern is that industries that export a high proportion of their output have a significantly lower ability to set output prices. Market power is also lower in information service and person-centred service industries than in goods-producing and distribution service industries. Firms in industries with a high proportion of degree-qualified workers have greater market power, possibly due to greater differentiation of outputs in knowledge-intensive industries.

The final column of Table 6 tests for spatial differences in market power within industries, derived from the estimates of location-specific market power ($\mu_{Akld}$ and $\mu_{OthUrb}$) as shown in Appendix Table 3. The dependent variable for the meta-regression is the difference between two market power coefficients ($\mu_{OthUrb} - \mu_{Akld}$). A higher value arises if urban firms outside Auckland have greater market power (less elastic output demand) than Auckland firms. The summary of estimates in Table 2 showed that the degree of market power did not vary significantly across locations. It is perhaps not surprising, therefore, that industry-level characteristics are not significantly related to spatial market power differences. None of the coefficients shown in the final column of Table 6 is statistically significant. The evidence is thus very weak, but the pattern of estimates suggests that relatively high market power for urban firms outside Auckland is more likely for industries that are concentrated in Auckland, in industries that trade less over distance, and for skilled industries.

As is the case for industry variation in productivity premiums, adjusting for labour quality changes the magnitude of coefficients in columns 2 to 4 of Table 6 but does not provide substantially different insights. Lower market power in export-intensive industries, and in personal services industries (the omitted category) are the only findings that are significant at the 0.05% level of significance.

# 5 Summary and conclusions

The main objective of this paper has been to estimate the extent of spatial variation in multi-factor productivity, controlling for spatial variation in input and output prices and labour sorting, and to examine the biases that arise from ignoring these sources of variation. The method we use relies on the assumption that firms are profit-maximising, and that they sell their output in imperfectly competitive markets.

We adapt the approach of Grieco et al. (2016), which can be applied using available data that records revenue and intermediate expenditures rather than input and output quantities. The method provides estimates of firm-specific multi-factor productivity, as well as firm-specific input prices, and an industry-specific index of market power. We examine firm level *mfp* and price variation according to the location(s) where firms have employees.

We document an urban labour productivity premium, with Auckland firms having labour productivity that is 17.9% higher than that of firms in other urban areas, and 17.0% higher than firms in rural areas. Some of this premium is due to the mix of industries in different cities. Auckland has a disproportionately high share of employment in industries that have above average labour productivity. Adjusting for this composition reveals a smaller, but still sizeable, premium of 13.5% relative to other urban areas, and 11.3% relative to firms in rural areas. This estimate is lower than previous estimates using microdata, for reasons that are documented in Appendix One.

For urban areas other than Auckland, Wellington firms have relatively high average labour productivity, with (composition-adjusted) levels that are 4.2% lower than Auckland. For other urban areas, the gap ranges from 9.4% to 20.1%, with lower estimated *mfp* in less dense urban areas.

Some of Auckland's labour productivity advantage is due to more intensive use of non-labour inputs by Auckland firms. Controlling for labour, capital, and intermediate inputs our preferred estimates show a premium of 7.9% relative to other urban areas when labour inputs are measures as FTE employment (Table 3, Col 3). The quality of labour inputs makes a significant contribution to this premium. Estimates that measure labour input in quality-adjusted terms (as described in section 2.1.3) show an Auckland premium of 2.2% relative to other urban areas (Table 3, Col 5). Labour quality differences thus contribute around 5.5% to Auckland's relative productivity performance. Auckland firms disproportionately employ workers who would be more productive anywhere. It should be noted that the higher labour quality may reflect the agglomeration-related benefits of living in a dense urban area (D'Costa & Overman, 2014; de la Roca & Puga, 2016).

We estimate *mfp* differences separately for a more disaggregated set of urban areas, and find spatial productivity differences of between 7% and 15% (2% to 6% if adjusted for labour quality). Wellington is an exception, with Wellington firms having productivity that is estimated to be slightly higher (by 3.8%) than that of comparable Auckland firms (2.7% if adjusted for labour quality).

One of the main contributions of the current paper is to produce estimates that control for spatial variation in output and input prices. We find that a simple estimate of spatial productivity differences that is based on a revenue production function using intermediate expenditures in place of the quantity of intermediate inputs understates the productivity advantages associated with operating in a large dense city. Auckland firms face higher labour and input prices, and are, on average, larger than other urban firms. Because of the assumed structure of imperfect competition, the larger size implies that Auckland firms charge lower output prices. Taking into account the higher input prices and lower output prices faced by Auckland firms reveals that Auckland firms are producing a greater quantity of output, and using a smaller quantity of inputs than is apparent from estimates that do not take account of spatial price variation.

Using *mfp* estimates from a CES production function that ignores price variation (relying on revenue and expenditure as measures of output and input quantities) yields smaller estimates of the Auckland premium. With labour measured as FTE employment, the estimated premium is 2.1%, compared with the 7.9% preferred estimate. Estimates that adjust for labour quality but ignore price variation fail to show a significant Auckland premium (Table 3, Cols 2 and 4).

We examine whether the size of Auckland's productivity premium is related to industry characteristics but fail to find strong systematic patterns. Similarly, although we find lower market power in exporting industries and greater market power in industries employing highly qualified workers, spatial differences in market power are small.

The paper provides improved estimates of urban productivity differences in New Zealand than have been available to date. It confirms the higher labour productivity of firms in Auckland (13.5%) relative to firms in other urban areas. It attributes 5.6 percentage points of this to the greater quantity of other inputs used by Auckland, and a further 5.7 percentage points to the higher quality of Auckland workers. Finally, we have demonstrated that failing to account for spatial variation in input and output prices biases downward the estimates of the Auckland premium, by 3 to 6 percentage points.

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# Figures, charts, and tables

Table 1: Descriptive statistics – production variables: 2001-2012 pooled

| | Auckland | Other Urban Areas | (Rel to Akld) | Rural | (Rel to Akld) |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(Revenue) | 12.85 | 12.60 | -0.25 | 12.40 | -0.45 |
| share | 36% | 54% | | 10% | |
| ln(Labour) | 0.94 | 0.92 | -0.02 | 0.58 | -0.36 |
| share | 36% | 57% | | 7% | |
| Ln(Qual adjusted L) | 0.91 | 0.81 | -0.10 | 0.46 | -0.45 |
| share | 38% | 56% | | 6% | |
| ln(Wagebill) | 11.50 | 11.33 | -0.18 | 10.97 | -0.53 |
| share | 39% | 54% | | 6% | |
| ln(Capital) | 10.62 | 10.34 | -0.27 | 10.26 | -0.36 |
| share | 39% | 53% | | 8% | |
| ln(Intermediates) | 11.98 | 11.70 | -0.27 | 11.66 | -0.32 |
| share | 34% | 55% | | 12% | |
| | | | | | |
| Number of Firm-year observations | | | | | |
| • for firms operating in area | 300,465 | 585,255 | | 94,923 | |
| • Share-weighted count | 290,175 | 570,318 | | 87,333 | |
| share | 31% | 60% | | 9% | |
| • Single location firms | | | | | |
| % of firms operating in area | 93% | 95% | | 87% | |
| % of revenue | 46% | 44% | | 41% | |

Source: Author's calculations based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Firm counts have been randomly rounded to base 3. The share-weighted count weights each firm-year observation by the proportion of its FTE employment that is in the specified location.

Table 2: Production function parameters (metaregression summary of industry-specific regressions)

| | FTE Labour | | | Quality-adjusted Labour | | |
|---|---|---|---|---|---|---|
| | Gross revenue (CES with constant returns to scale) (1) | Preferred (Equation 10 with $\eta_c = \eta$) (2) | Preferred (Equation 10) (3) | Gross revenue (CES with constant returns to scale) (4) | Preferred (Equation 10 with $\eta_c = \eta$) (5) | Preferred (Equation 10) (6) |
| Capital: $\alpha_K$ | 0.105 | 0.095 | 0.094 | 0.109 | 0.112 | 0.110 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.012) | (0.011) |
| Labour: $\alpha_L$ | 0.301 | 0.332 | 0.332 | 0.306 | 0.319 | 0.320 |
| | (0.012) | (0.012) | (0.012) | (0.011) | (0.011) | (0.011) |
| Intermediates: $\alpha_M$ | 0.593 | 0.579 | 0.579 | 0.585 | 0.569 | 0.570 |
| | (0.016) | (0.017) | (0.017) | (0.016) | (0.018) | (0.018) |
| γ=(σ-1)/σ | 0.453 | 0.752 | 0.756 | 0.453 | 0.761 | 0.766 |
| | (0.017) | (0.024) | (0.024) | (0.018) | (0.023) | (0.023) |
| Implied elasticity of substitution $\left(\sigma = \frac{1}{1-\gamma}\right)$ | 1.8 | 4.0 | 4.1 | 1.8 | 4.2 | 4.3 |
| market power: $\mu = ln(\eta/(1+\eta))$ | | 0.117 | | | 0.097 | |
| | | (0.007) | | | (0.007) | |
| mkt power (Akld): $\mu_{Akld}$ | | | 0.103 | | | 0.089 |
| | | | (0.008) | | | (0.007) |
| mkt power (OthUrb): $\mu_{OthUrb}$ | | | 0.123 | | | 0.107 |
| | | | (0.008) | | | (0.006) |
| mkt power (Rural): $\mu_{rural}$ | | | 0.114 | | | 0.097 |
| | | | (0.011) | | | (0.008) |

Source: Regression estimates based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Each cell contains the estimate of the mean value from a random effects metaregression of parameter estimates from 31 industry-specific regressions. Although constant returns to scale are imposed for each industry, the sum of output elasticities shown in this table may differ from 1 due to the different weightings of the industry-specific estimates when estimating the metaregressions. The elasticity of substitution estimate is obtained as a transformation of the value of γ. All coefficients are significantly different from zero at a 1% significance level.

Table 3: Spatial productivity premium

| Location | VAPW (adjusted for industry mix) | FTE Labour input *Mfp* (CES - CRS) | *Mfp* (Eq 10) | Quality-adjusted labour *Mfp* (CES - CRS) | *Mfp* (Eq 10) | Median Pop. density(a) (pop/ hectare) [ln(density)] |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Auckland** | **0** | **0** | **0** | **0** | **0** | **2,520 [7.83]** |
| **Other Urban** | **-13.5% (0.2%)** | **-2.1% (0.1%)** | **-7.9% (0.2%)** | **0.04% (0.1%)** | **-2.2% (0.1%)** | **910 [6.81]** |
| Wellington | -4.2% (0.3%) | 2.1% (0.2%) | 3.8% (0.3%) | 1.4% (0.2%) | 2.7% (0.2%) | 1,550 [7.35]] |
| Christchurch | -12.1% (0.3%) | -2.1% (0.2%) | -7.4% (0.3%) | -0.1% (0.2%) | -1.8% (0.2%) | 1,860 [7.53] |
| Hamilton | -13.1% (0.4%) | -2.3% (0.2%) | -8.8% (0.3%) | 0.1% (0.2%) | -2.9% (0.3%) | 1,160 [7.06] |
| Tauranga | -9.4% (0.5%) | -1.8% (0.2%) | -10.6% (0.4%) | 0.5% (0.3%) | -4.8% (0.3%) | 980 [6.89] |
| Napier | -12.4% (0.5%) | -2.2% (0.2%) | -9.8% (0.4%) | 0.2% (0.3%) | -2.2% (0.4%) | 1,180 [7.07] |
| Dunedin | -18.3% (0.6%) | -2.3% (0.3%) | -7.8% (0.5%) | -0.5% (0.3%) | -3.2% (0.4%) | 1,190 [7.08] |
| Other main | -16.0% (0.3%) | -2.5% (0.1%) | -8.8% (0.2%) | 0.2% (0.1%) | -2.0% (0.2%) | 900 [6.80] |
| Other Secondary | -14.6% (0.4%) | -2.5% (0.2%) | -9.1% (0.3%) | 0.5% (0.2%) | -1.2% (0.3%) | 620 [6.43] |
| Other Minor | -20.1% (0.3%) | -5.0% (0.2%) | -15.3% (0.3%) | -1.7% (0.2%) | -6.4% (0.2%) | 380 [5.94] |
| **Rural** | **-11.3% (0.3%)** | **-7.4% (0.2%)** | **-21.4% (0.3%)** | **-4.9% (0.2%)** | **-13.5% (0.2%)** | **6 [1.79]** |

Source: Regression estimates based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Each of the first 5 columns contains estimates from two distinct regressions: One regresses the dependent variable on a set of 3 location share variables (shown in bold); the second replaces the 'Other Urban' covariate with the 9 unbolded location shares. Each regression has 980,643 observations (the sum of firm-year observations shown in Table 1). The dependent variable for columns 2 to 6 is derived from industry-specific production regressions. Standard errors in brackets. Standard errors are not adjusted for the fact that the dependent variable is estimated.
(a) Density of the median area unit

Table 4: Spatial premium in input prices and market power

| Location | FTE Labour input | | | Quality adjusted labour | | |
|---|---|---|---|---|---|---|
| | Labour price (1) | Intermediates price (2) | Market Power (3) | Labour price (4) | Intermediates price (5) | Market Power (6) |
| **Auckland** | **0** | **0** | **0.103** | **0** | **0** | **0.089** |
| | | | **(0.008)** | | | **(0.007)** |
| **Other Urban** | **-12.1%** | **-5.7%** | **0.123** | **-6.0%** | **-0.3%** | **0.107** |
| | **(0.1%)** | **(0.2%)** | **(0.008)** | **(0.1%)** | **(0.1%)** | **(0.006)** |
| Wellington | -1.4% | 8.3% | 0.118 | -2.4% | 6.1% | 0.108 |
| | (0.1%) | (0.3%) | (0.011) | (0.1%) | (0.2%) | (0.009) |
| Christchurch | -11.0% | -5.7% | 0.126 | -5.4% | -0.5% | 0.107 |
| | (0.1%) | (0.3%) | (0.009) | (0.1%) | (0.2%) | (0.007) |
| Hamilton | -12.5% | -6.8% | 0.127 | -5.5% | -0.4% | 0.109 |
| | (0.2%) | (0.4%) | (0.008) | (0.1%) | (0.3%) | (0.007) |
| Tauranga | -13.0% | -8.4% | 0.134 | -6.7% | -2.7% | 0.119 |
| | (0.2%) | (0.4%) | (0.008) | (0.2%) | (0.4%) | (0.006) |
| Napier | -13.7% | -8.8% | 0.132 | -6.9% | -2.3% | 0.114 |
| | (0.2%) | (0.4%) | (0.009) | (0.2%) | (0.4%) | (0.008) |
| Dunedin | -13.5% | -5.9% | 0.124 | -8.5% | -1.5% | 0.111 |
| | (0.3%) | (0.5%) | (0.012) | (0.2%) | (0.4%) | (0.011) |
| Other main | -14.1% | -6.1% | 0.136 | -6.8% | 0.4% | 0.117 |
| | (0.1%) | (0.3%) | (0.009) | (0.1%) | (0.2%) | (0.007) |
| Other Secondary | -14.0% | -9.2% | 0.140 | -5.8% | -1.4% | 0.120 |
| | (0.2%) | (0.3%) | (0.010) | (0.1%) | (0.3%) | (0.008) |
| Other Minor | -17.4% | -14.9% | 0.120 | -8.2% | -4.4% | 0.101 |
| | (0.1%) | (0.3%) | (0.008) | (0.1%) | (0.2%) | (0.007) |
| **Rural** | **-14.5%** | **-14.7%** | **0.114** | **-7.0%** | **-7.4%** | **0.097** |
| | **(0.1%)** | **(0.3%)** | **(0.011)** | **(0.1%)** | **(0.2%)** | **(0.008)** |

Source: Regression estimates based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Each column contains estimates from two distinct regressions: One regresses the dependent variable on a set of 3 location share variables (shown in bold); the second replaces the 'Other Urban' covariate with the 9 unbolded location shares. Each regression has 980,643 observations (the sum of firm-year observations shown in Table 1). Market power coefficients are from production function regressions (equation 10) with spatially varying $\mu_c$. The dependent variables for columns 2 and 5 are estimates of intermediates prices as described in section 2.1.2. Standard errors in brackets. Standard errors in columns 2 and 5 are not adjusted for the fact that the dependent variable is estimated.

Table 5: Industry characteristics

| | Un-weighted mean | Firm-weighted mean | Auckland (emp-share weighted) | Other urban (emp-share weighted) | Rural (emp-share weighted) |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Share of empl. in Auckland | 29.0% | 27.3% | 28.2% | 27.2% | 25.9% |
| | (1.3%) | (0.0%) | (0.0%) | (0.0%) | (0.0%) |
| Import share of inputs | 10.1% | 7.9% | 7.9% | 7.8% | 8.4% |
| | (1.4%) | (0.0%) | (0.0%) | (0.0%) | (0.0%) |
| Export share of output | 15.3% | 11.8% | 11.8% | 11.7% | 12.3% |
| | (2.9%) | (0.0%) | (0.0%) | (0.0%) | (0.0%) |
| Domestics tradability | 21.1% | 17.0% | 19.1% | 16.3% | 15.1% |
| | (2.2%) | (0.0%) | (0.0%) | (0.0%) | (0.0%) |
| Share of highly qualified workers | 15.2% | 16.3% | 18.3% | 15.7% | 12.9% |
| | (1.9%) | (0.0%) | (0.0%) | (0.0%) | (0.0%) |
| Share of skilled occupations | 48.7% | 51.0% | 51.4% | 50.9% | 50.3% |
| | (2.8%) | (0.0%) | (0.0%) | (0.0%) | (0.1%) |
| I(Goods producing industry) | 45.2% | 30.1% | 26.5% | 30.3% | 40.8% |
| | (9.1%) | (0.0%) | (0.1%) | (0.1%) | (0.2%) |
| I(Information services industry) | 16.1% | 15.8% | 20.5% | 14.6% | 8.1% |
| | (6.7%) | (0.0%) | (0.1%) | (0.0%) | (0.1%) |
| I(Distribution services industry) | 22.6% | 27.4% | 28.7% | 27.3% | 23.5% |
| | (7.6%) | (0.0%) | (0.1%) | (0.1%) | (0.1%) |
| I(Personal Services industry) | 16.1% | 26.7% | 24.3% | 27.8% | 27.5% |
| | (6.7%) | (0.0%) | (0.1%) | (0.1%) | (0.1%) |
| | | | | | |
| Distinct observations | 31 | 947,823 | 300,465 | 585,255 | 94,923 |
| Sum of employment shares | | | 290,175 | 570,318 | 87,333 |

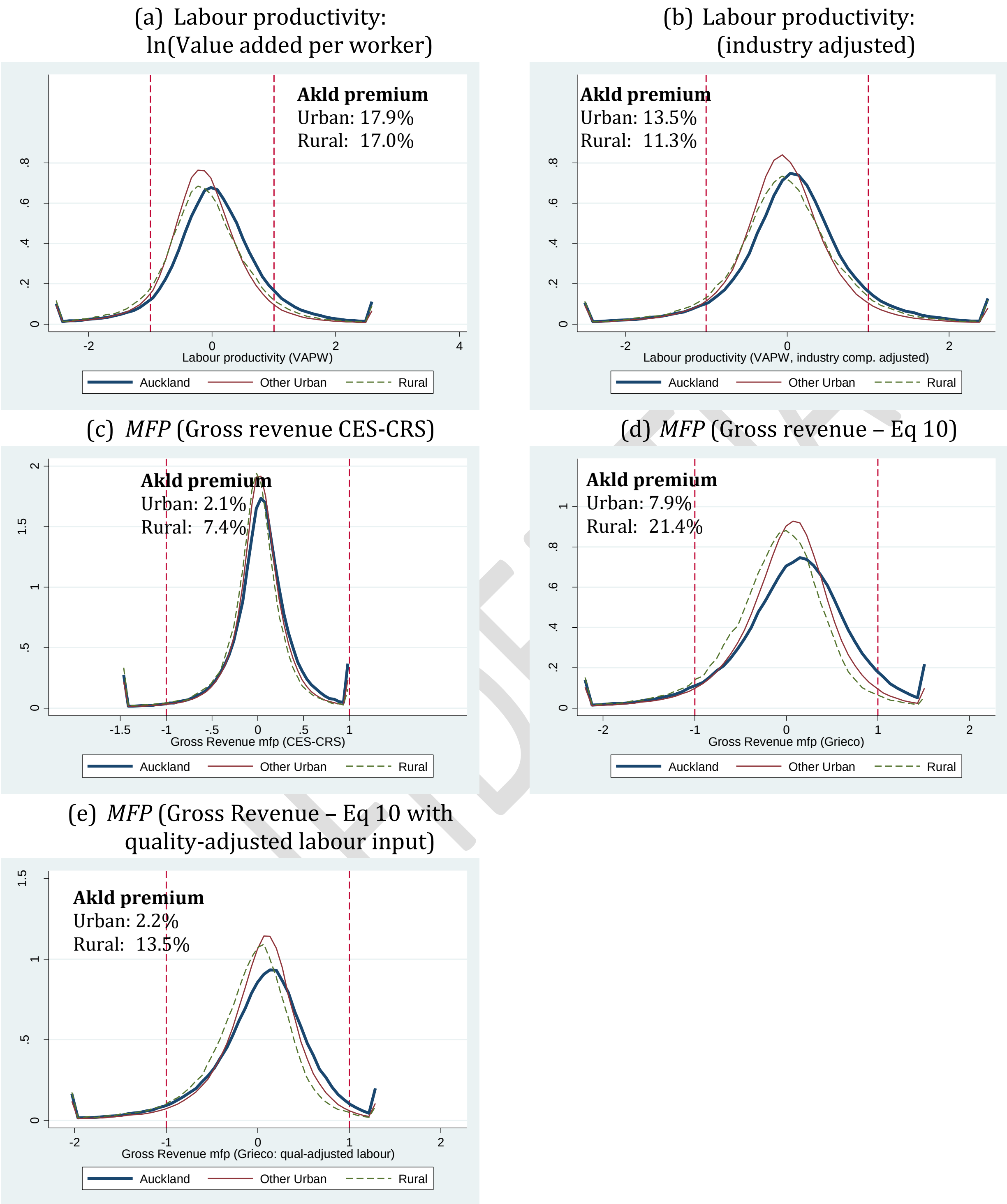
Note: See section 4.3.1 for a description of variables. Observation counts in columns 2-5 have been randomly rounded to base 3. The observation count in the first column is the number of distinct industries, as listed in Appendix Table 2.

Table 6: Correlates of industry variation

| | Urban *mfp* (rel to Akld) | Urban $P_M$ (rel to Akld) | Industry mkt power ($\mu$) | Difference in market power $\mu_{Urban}$-$\mu_{Akld}$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | | (a) FTE labour input specification | | |
| % of empl. in Auckland | -0.477 | -0.427§ | -0.121 | 0.099 |
| | (0.376) | (0.273) | (0.114) | (0.115) |
| Imports | -0.109 | -0.044 | 0.032 | -0.014 |
| | (0.322) | (0.234) | (0.097) | (0.099) |
| Exports | 0.194 | 0.086 | -0.132**§ | 0.002 |
| | (0.150) | (0.110) | (0.044) | (0.046) |
| Domestic trad | -0.225§ | -0.135 | 0.053 | -0.053 |
| | (0.230) | (0.170) | (0.070) | (0.070) |
| % High qual | 0.123 | 0.379 | 0.227* | 0.032 |
| | (0.431) | (0.313) | (0.129) | (0.132) |
| % skilled occ | 0.245 | 0.087 | -0.021 | 0.024 |
| | (0.192) | (0.138) | (0.058) | (0.059) |
| Goods | -0.065 | 0.001 | 0.056** | -0.006 |
| | (0.076) | (0.055) | (0.023) | (0.023) |
| Info Serv | -0.061 | -0.072 | 0.023 | -0.001 |
| | (0.114) | (0.082) | (0.034) | (0.035) |
| Distr Serv | 0.039 | 0.039 | 0.056** | 0.013 |
| | (0.070) | (0.051) | (0.021) | (0.021) |
| | | (b) Quality-adjusted labour specification | | |
| % of empl. in Auckland | -0.159 | -0.120 | -0.183 | 0.078 |
| | (0.263) | (0.200) | (0.114) | (0.115) |
| Imports | -0.218 | -0.165 | 0.052 | -0.001 |
| | (0.225) | (0.171) | (0.097) | (0.098) |
| Exports | 0.188*§ | 0.097 | -0.110** | 0.005 |
| | (0.105) | (0.081) | (0.044) | (0.045) |
| Domestic trad | -0.158 | -0.049 | 0.038 | -0.050 |
| | (0.161) | (0.125) | (0.070) | (0.071) |
| % High qual | 0.016 | 0.248 | 0.217 | 0.038 |
| | (0.301) | (0.228) | (0.129) | (0.130) |
| % skilled occ | 0.140 | 0.038 | 0.013 | 0.031 |
| | (0.134) | (0.101) | (0.058) | (0.058) |
| Goods | -0.070§ | -0.019 | 0.052** | -0.003 |
| | (0.053) | (0.040) | (0.023) | (0.023) |
| Info Serv | -0.002 | -0.044 | -0.028 | 0.003 |
| | (0.080) | (0.060) | (0.034) | (0.035) |
| Distr Serv | 0.026 | 0.031 | 0.059** | 0.015 |
| | (0.049) | (0.038) | (0.021) | (0.021) |

Source: Regression estimates based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Each column contains estimates from a random effects meta-regression, as described in section 4.2 and footnote 17. Each regression has 31 industry-level observations. The dependent variable in columns 1 and 2 is the coefficient on 'Other Urban' as shown in Appendix Table 5. The dependent variable in column 3 is the industry-specific estimate of $\mu$ from equation 10. The dependent variable in column 4 is the difference in coefficients from the regressions shown in Appendix Table 3 and Appendix Table 4. *: significant at 10%. **: significant at 5%. §: The bivariate relationship is significant at 10%. The omitted industry group is the Personal Services group.

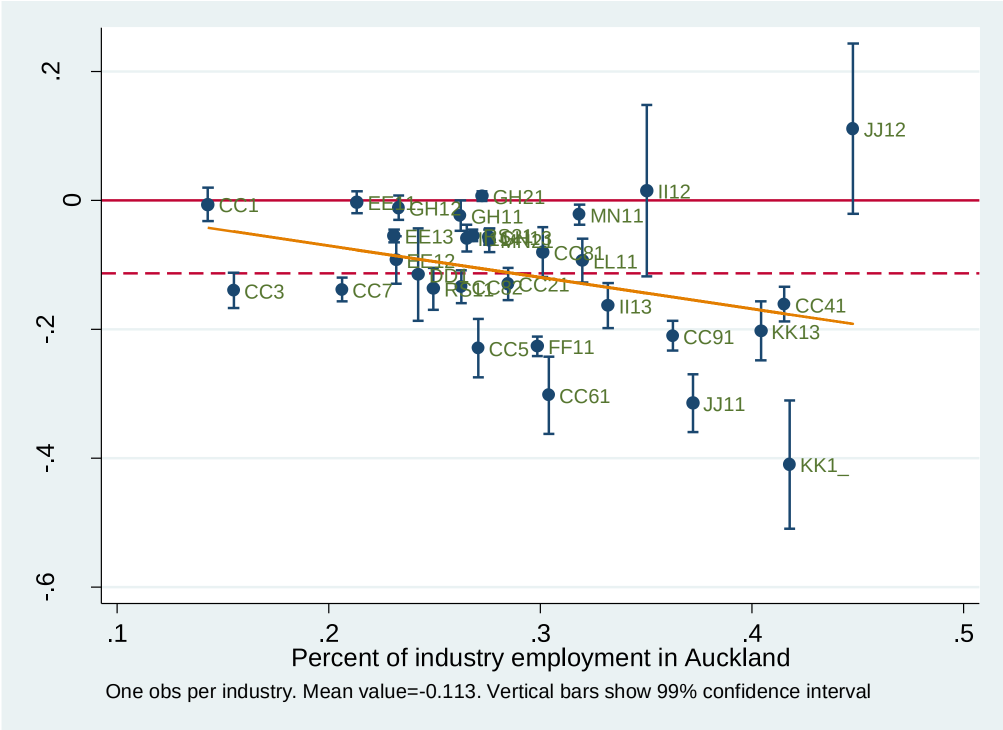
Figure 1: Productivity distribution



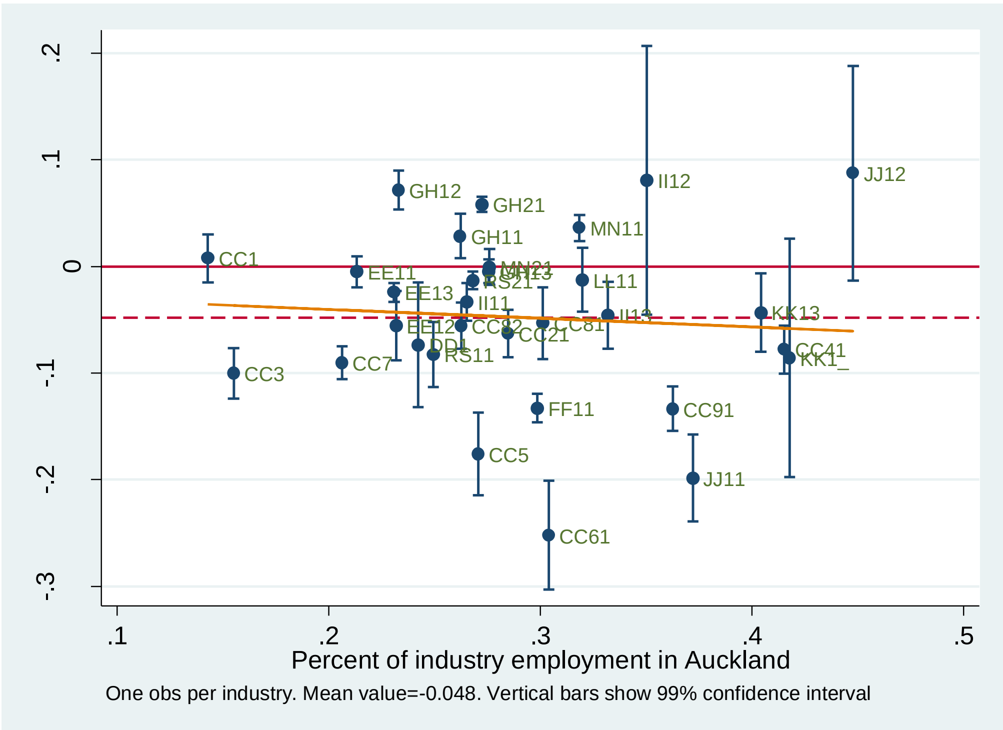

Source: Density estimates based on regressions using data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Values for the top and bottom 1% of observations have been censored for presentational convenience but are uncensored for other analyses.

Figure 2: Industry variation: Spatial productivity premium and concentration in Auckland

(a) FTE labour input




(b) Quality-adjusted labour




Source: Regression coefficients obtained from data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Vertical bars show 95% confidence intervals. The mean value differs from that shown in Table 3 because of the precision-based weighting used in meta-regression analysis.

# Appendices

### Appendix One: Comparison of labour productivity estimates with Maré (2008)

The purpose of this appendix is to investigate and explain the difference between the estimated Auckland labour productivity premium of 51% reported in Maré (2008), and the much lower value-added per worker premium of 13.5% reported in Table 3. Although these estimates are both valid estimates of labour productivity, they are not comparable for a number of reasons:

Difference in measure

- Value added measures
  - Value added data in Maré (2008) were derived from the Annual Enterprise Survey (AES), or from net GST sales where AES data were not available (with a stock adjustment using IR10 tax returns).
  - The current paper uses more carefully derived measures for production variables, included value added. The methods are documented in Fabling and Maré (2015a, 2015b).
- Labour measure
  - Maré (2008) measures value added per employee, using the average number of employees on the payroll each month (rolling mean employment), plus a share of working proprietor input, derived from IR10 tax data.
  - The current paper measures value added per unit of labour input, where labour input includes working proprietor input and is adjusted to full-time equivalent units.
- Weighting
  - Maré (2008) reports mean value added per worker, averaged over all workers, whereas the current paper reports the mean of log(value added per FTE), giving each firm equal weight.
    - Maré (2008):$\sum_j \frac{E_j}{E}\left(\frac{VA_j}{E_j}\right)$
    - Current: : $\sum_j \frac{1}{J} ln\left(\frac{VA_j}{L_j}\right)$

Difference in coverage

- Maré (2008) excludes firms with abs(VAPW) greater than $1m
- The current paper focuses on a subset of industries, for which input and output measurement is more reliable. Maré (2008) does not impose any industry restrictions.
- The current paper excludes firms with zero values for any of the following: output labour, capital, or intermediate inputs, whereas Maré (2008) excludes only firms with zero employment (since VAPW is undefined in such cases)
- Due to the use of natural logs, the current paper excludes firms with zero or negative VA.

Difference in data source

- Maré (2008) uses a prototype Longitudinal Business Database (LBD), as it existed in 2008. The current paper uses the December 2014 archive of the LBD.

Appendix Table 1 compares a range of labour productivity estimates based on the data used in Maré (2008) with analogous estimates based on the data used in the current paper. The comparison is for the 2006 year, which is the latest year included in the Maré (2008) study.

The first row of the table reproduces the urban area estimates from Table 1 of Maré (2008). Auckland VAPW is 51 percent higher than VAPW outside Auckland. The first step in aligning estimates from the two datasets is to impose a common set of industry restrictions. This is done in the rows labelled with the number 1. The number of firms in the Maré (2008) data declines by 17%. Although the employment measures in the two studies are not directly comparable, the (FTE) labour input count in the current dataset (798,600 = 288,200 + 510,400) is considerably lower than the employment counts from the less restrictive Maré (2008) sample (1,782,920 = 556,286 + 1,226,634). The impact of imposing common industry restrictions is that the estimated productivity premium using data from Maré (2008) declines to 40%. We also present an estimate of the labour productivity difference between Auckland and other urban areas (32%). The comparable number from the current dataset (excluding firms with abs(VAPW)>$1m) is 31%.

The Maré (2008) data include firms with negative estimated VAPW. Taking logged values excludes these firms, decreasing the employment count by 6%, to 1,392,200 (488,900 + 903,300). The more careful data construction for the current dataset already excludes firms with unrealistically low, or zero, output, so the loss of employment coverage when taking log of value added is small (0.4% decline, to 795,300). The labour input coverage in the current dataset is 57% of the employment coverage in the restricted version of the Maré (2008) data.

The estimated labour productivity premium based on spatial differences in employment-weighted ln(VAPW) $\left(\sum_j \frac{E_j}{E} ln\left(\frac{VA_j}{E_j}\right)\right)$ is shown in rows labelled as 2. Taking log values not only excludes zero or negative values, it also places less weight on observations with unusually large VAPW. Such firms are over-represented in Auckland, so the ln(VAPW) estimates of the Auckland premium are somewhat smaller that the unlogged estimates (rows labelled as 1) in both datasets. The estimates are again similar between the two studies. The Auckland premium over other urban areas is 26% in the current data and 24% in the earlier data.

One adjustment that is imposed in both studies is to control for between-industry labour productivity variation – measuring each firm's labour productivity relative to the average for their industry. The estimates for this adjusted measure are shown in rows labelled as 3. The estimated premium is 17% in the current data, and 16% in the earlier data. Row numbers 4 and 5 show estimates that give equal weight to each firm, rather than weighting them by their share of labour, either adjusting for industry differences (rows 5) or not (rows 4). The estimated Auckland premium over other urban areas is 14% in the earlier data, and 21% in the current data. Adjusting for industry differences reduces both estimates, to 11% and 16% respectively. The estimates in row 5 of panel b are comparable to the estimates in the first column of Table 3. They differ only because Table 3 summarises the premium over all years whereas Appendix Table 1 uses data from 2006 only.

Overall, the differences in the measures, coverage, and dataset can account for a large proportion of the difference in estimates between the two studies.

Appendix Table 1: Comparison with VAPW estimates from Maré (2008)

| Measure | Ind. -adj | Wtd | Auckland urban area | Other Urban areas | Rural | All non-Auckland | Auckland premium: Relative to Other Urban | Auckland premium: Relative to all non-Akld |
|---|---|---|---|---|---|---|---|---|
| | | | | (a) Estimates using 2006 data from Maré (2008) | | | | |
| As published (all industries) | | | | | | | | |
| VAPW | N | Emp | $68,435 | | | $45,440 | | 51% |
| | | | 556,286[a] | | | 1,226,634[a] | | |
| 1.VAPW | N | Emp | $68,400 | $51,700 | $43,100 | $48,700 | 32% | 40% |
| | | | 519,000 | 650,500 | 311,700 | 962,200 | | |
| 2.Ln(VAPW) | N | Emp | 10.77 | 10.53 | 10.77 | 10.48 | 24% | 29% |
| 3.Ln(VAPW) | Y | Emp | 10.72 | 10.56 | 10.39 | 10.51 | 16% | 21% |
| 4.Ln(VAPW) | N | No | 10.33 | 10.18 | 10.02 | 10.12 | 14% | 20% |
| 5.Ln(VAPW) | Y | No | 10.30 | 10.19 | 10.05 | 10.14 | 11% | 16% |
| | | | 488,900 | 613,700 | 289,600 | 903,300 | | |
| | | | | (b) Estimates using 2006 data from current paper | | | | |
| 1.VAPW | | | $108,800 | $82,900 | $85,200 | $83,100 | 31% | 31% |
| | | | 288,200 | 457,800 | 52,600 | 510,400 | | |
| 2.Ln(VAPW) | N | Emp | 11.39 | 11.13 | 11.18 | 11.14 | 26% | 25% |
| 3.Ln(VAPW) | Y | Emp | 11.33 | 11.17 | 11.22 | 11.17 | 17% | 16% |
| 4.Ln(VAPW) | N | No | 11.19 | 10.98 | 10.99 | 10.98 | 21% | 21% |
| 5.Ln(VAPW) | Y | No | 11.16 | 11.00 | 11.01 | 11.00 | 16% | 16% |
| | | | 286,400 | 456,600 | 52,300 | 508,900 | | |

Source: Author calculations using data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). All employment counts and dollar amounts have been rounded using graduated random rounding, in accordance with Statistics New Zealand guidelines. (a.): Unrounded counts are reproduced from Maré (2008).

Appendix Table 2: Industry-Codes

| Code | NZSIOC level 3 | Description | Classification |
|---|---|---|---|
| CC1 | CC11 | Food, Beverage and Tobacco Product Manufacturing | Goods Producing |
| CC21 | CC21 | Textile, leather, cloth, and footwear manufacturing | Goods Producing |
| CC3 | CC31 | Wood and Paper Products Manufacturing | Goods Producing |
| CC41 | CC41 | Printing | Goods Producing |
| CC5 | CC51 | Petroleum, Chemical, Polymer and Rubber Product Mfrg | Goods Producing |
| CC61 | CC61 | Non-metallic mineral product manufacturing | Goods Producing |
| CC7 | CC71 | Metal Product Manufacturing | Goods Producing |
| CC81 | CC81 | Transport equipment manufacturing | Goods Producing |
| CC82 | CC82 | Machinery and other equipment manufacturing | Goods Producing |
| CC91 | CC91 | Furniture and other manufacturing | Goods Producing |
| DD1 | DD11 | Electricity, Gas, Water and Waste Services | Goods Producing |
| EE11 | EE11 | Building construction | Goods Producing |
| EE12 | EE12 | Heavy and civil engineering construction | Goods Producing |
| EE13 | EE13 | Construction services | Goods Producing |
| FF11 | FF | Wholesale trade | Distribution services |
| GH11 | GH11 | Motor vehicle & parts, and fuel retailing | Distribution services |
| GH12 | GH12 | Supermarket, grocery, and specialised food retailing | Distribution services |
| GH13 | GH13 | Other store-based and non-store retailing | Distribution services |
| GH21 | GH21 | Accommodation and food services | Personal Services |
| II11 | II11 | Road transport | Distribution services |
| II12 | II12 | Rail, water, air, and other transport | Distribution services |
| II13 | II13 | Post, courier support, and warehouse services | Distribution services |
| JJ11 | JJ11 | Information media services | Information Services |
| JJ12 | JJ12 | Telecommunication, Internet, and library services | Information Services |
| KK1_ | KK11/12 | Finance, Insurance and superannuation funds | Information Services |
| KK13 | KK13 | Auxiliary finance and insurance services | Information Services |
| LL11 | LL11 | Rental and hiring services | Personal Services |
| MN11 | MN11 | Professional, scientific, and tech services | Information Services |
| MN21 | MN21 | Administrative and support services | Information Services |
| RS11 | RS11 | Arts and recreation services | Personal Services |
| RS21 | RS21 | Other services | Personal Services |

Appendix Table 3: Industry-specific production function estimates

| Industry | $\alpha_K$ | $\alpha_L$ | $\alpha_M$ | $\gamma$ | $\mu_{Akld}$ | $\mu_{OthUrb}$ | $\mu_{Rural}$ | $N$ |
|---|---|---|---|---|---|---|---|---|
| CC1 | 0.023 | 0.243 | 0.734 | 0.820 | 0.116 | 0.106 | 0.038 | 18141 |
| | (0.003) | (0.001) | (0.002) | (0.032) | (0.004) | (0.003) | (0.005) | |
| CC21 | 0.084 | 0.353 | 0.563 | 0.756 | 0.076 | 0.065 | 0.000 | 10425 |
| | (0.004) | (0.001) | (0.002) | (0.019) | (0.004) | (0.004) | | |
| CC3 | 0.021 | 0.279 | 0.699 | 0.897 | 0.106 | 0.110 | 0.079 | 13332 |
| | (0.003) | (0.001) | (0.002) | (0.034) | (0.004) | (0.003) | (0.004) | |
| CC41 | 0.115 | 0.329 | 0.555 | 0.882 | 0.073 | 0.101 | 0.112 | 8070 |
| | (0.004) | (0.002) | (0.003) | (0.016) | (0.005) | (0.005) | (0.014) | |
| CC5 | 0.027 | 0.277 | 0.696 | 0.749 | 0.147 | 0.154 | 0.208 | 7614 |
| | (0.005) | (0.002) | (0.004) | (0.063) | (0.007) | (0.006) | (0.012) | |
| CC61 | 0.015 | 0.310 | 0.675 | 0.775 | 0.181 | 0.153 | 0.133 | 3885 |
| | (0.006) | (0.002) | (0.004) | (0.131) | (0.008) | (0.007) | (0.010) | |
| CC7 | 0.071 | 0.297 | 0.632 | 0.771 | 0.088 | 0.101 | 0.135 | 18369 |
| | (0.002) | (0.001) | (0.002) | (0.013) | (0.003) | (0.003) | (0.005) | |
| CC81 | 0.056 | 0.384 | 0.559 | 0.663 | 0.086 | 0.109 | 0.112 | 7233 |
| | (0.006) | (0.003) | (0.004) | (0.042) | (0.007) | (0.007) | (0.010) | |
| CC82 | 0.063 | 0.319 | 0.618 | 0.693 | 0.106 | 0.136 | 0.102 | 17340 |
| | (0.003) | (0.001) | (0.002) | (0.022) | (0.004) | (0.004) | (0.006) | |
| CC91 | 0.027 | 0.320 | 0.653 | 1.016 | 0.126 | 0.137 | 0.103 | 12000 |
| | (0.003) | (0.001) | (0.002) | (0.030) | (0.003) | (0.003) | (0.006) | |
| DD1 | 0.119 | 0.261 | 0.620 | 0.734 | 0.117 | 0.177 | 0.183 | 3957 |
| | (0.006) | (0.002) | (0.004) | (0.013) | (0.009) | (0.007) | (0.010) | |
| EE11 | 0.033 | 0.220 | 0.747 | 0.680 | 0.101 | 0.099 | 0.091 | 50970 |
| | (0.001) | (0.000) | (0.001) | (0.011) | (0.002) | (0.001) | (0.002) | |
| EE12 | 0.085 | 0.266 | 0.650 | 0.746 | 0.103 | 0.117 | 0.119 | 7341 |
| | (0.004) | (0.001) | (0.003) | (0.019) | (0.005) | (0.005) | (0.006) | |
| EE13 | 0.046 | 0.316 | 0.637 | 0.750 | 0.122 | 0.144 | 0.149 | 106803 |
| | (0.001) | (0.000) | (0.001) | (0.008) | (0.001) | (0.001) | (0.002) | |
| FF11 | 0.104 | 0.371 | 0.525 | 0.770 | 0.153 | 0.173 | 0.152 | 74175 |
| | (0.002) | (0.001) | (0.001) | (0.009) | (0.003) | (0.003) | (0.005) | |
| GH11 | 0.121 | 0.404 | 0.475 | 0.817 | 0.079 | 0.130 | 0.114 | 20601 |
| | (0.004) | (0.002) | (0.002) | (0.012) | (0.005) | (0.004) | (0.006) | |
| GH12 | 0.165 | 0.431 | 0.403 | 0.928 | 0.123 | 0.154 | 0.110 | 28068 |
| | (0.004) | (0.002) | (0.002) | (0.009) | (0.005) | (0.004) | (0.006) | |
| GH13 | 0.164 | 0.412 | 0.425 | 0.822 | 0.115 | 0.160 | 0.055 | 91011 |
| | (0.002) | (0.001) | (0.001) | (0.006) | (0.003) | (0.003) | (0.005) | |
| GH21 | 0.123 | 0.285 | 0.593 | 0.898 | 0.019 | 0.061 | 0.000 | 101970 |
| | (0.001) | (0.000) | (0.001) | (0.004) | (0.002) | (0.001) | | |
| II11 | 0.134 | 0.319 | 0.547 | 0.771 | 0.123 | 0.143 | 0.153 | 28587 |
| | (0.003) | (0.001) | (0.002) | (0.008) | (0.004) | (0.003) | (0.004) | |
| II12 | 0.097 | 0.235 | 0.668 | 0.405 | 0.016 | 0.079 | 0.142 | 4344 |
| | (0.009) | (0.002) | (0.007) | (0.030) | (0.012) | (0.011) | (0.012) | |
| II13 | 0.148 | 0.316 | 0.535 | 0.689 | 0.063 | 0.079 | 0.002 | 12990 |
| | (0.005) | (0.002) | (0.003) | (0.010) | (0.006) | (0.006) | (0.009) | |

| Industry | $\alpha_K$ | $\alpha_L$ | $\alpha_M$ | $\gamma$ | $\mu_{Akld}$ | $\mu_{OthUrb}$ | $\mu_{Rural}$ | $N$ |
|---|---|---|---|---|---|---|---|---|
| JJ11 | 0.041 | 0.237 | 0.722 | 0.972 | 0.097 | 0.079 | 0.093 | 7800 |
| | (0.004) | (0.001) | (0.003) | (0.030) | (0.007) | (0.007) | (0.019) | |
| JJ12 | 0.135 | 0.313 | 0.552 | 0.470 | 0.000 | 0.017 | 0.000 | 2499 |
| | (0.012) | (0.004) | (0.007) | (0.035) | | (0.014) | | |
| KK1_ | 0.137 | 0.374 | 0.488 | 0.604 | 0.134 | 0.244 | 0.271 | 15912 |
| | (0.007) | (0.003) | (0.004) | (0.020) | (0.008) | (0.008) | (0.023) | |
| KK13 | 0.093 | 0.382 | 0.525 | 0.668 | 0.143 | 0.171 | 0.000 | 5610 |
| | (0.015) | (0.006) | (0.009) | (0.042) | (0.018) | (0.017) | | |
| LL11 | 0.253 | 0.257 | 0.489 | 0.736 | 0.024 | 0.096 | 0.000 | 12360 |
| | (0.005) | (0.002) | (0.003) | (0.008) | (0.007) | (0.007) | | |
| MN11 | 0.169 | 0.427 | 0.404 | 0.530 | 0.127 | 0.171 | 0.140 | 117786 |
| | (0.002) | (0.001) | (0.001) | (0.005) | (0.003) | (0.002) | (0.004) | |
| MN21 | 0.090 | 0.422 | 0.488 | 0.692 | 0.071 | 0.096 | 0.079 | 44415 |
| | (0.003) | (0.001) | (0.001) | (0.010) | (0.003) | (0.003) | (0.005) | |
| RS11 | 0.061 | 0.352 | 0.588 | 0.890 | 0.195 | 0.152 | 0.032 | 14586 |
| | (0.004) | (0.002) | (0.003) | (0.024) | (0.006) | (0.005) | (0.007) | |
| RS21 | 0.111 | 0.403 | 0.486 | 0.827 | 0.074 | 0.110 | 0.087 | 79635 |
| | (0.002) | (0.001) | (0.001) | (0.006) | (0.002) | (0.002) | (0.003) | |

Source: Regression estimates based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Each row contains industry-specific estimates of equation 10. See Appendix Table 2 for a list of industry codes. Observation counts have been randomly rounded to base 3.

Appendix Table 4: Industry-specific production function estimates (Quality adjusted labour)

| | $\alpha_K$ | $\alpha_L$ | $\alpha_M$ | $\gamma$ | $\mu_{Akld}$ | $\mu_{OthUrb}$ | $\mu_{Rural}$ | N |
|---|---|---|---|---|---|---|---|---|
| CC1 | 0.025 | 0.243 | 0.733 | 0.862 | 0.113 | 0.105 | 0.038 | 18141 |
| | (0.003) | (0.001) | (0.002) | (0.030) | (0.004) | (0.003) | (0.005) | |
| CC21 | 0.084 | 0.353 | 0.563 | 0.791 | 0.077 | 0.061 | 0.000 | 10425 |
| | (0.004) | (0.001) | (0.002) | (0.018) | (0.004) | (0.004) | | |
| CC3 | 0.025 | 0.278 | 0.696 | 0.890 | 0.102 | 0.105 | 0.072 | 13332 |
| | (0.003) | (0.001) | (0.002) | (0.030) | (0.004) | (0.003) | (0.005) | |
| CC41 | 0.121 | 0.327 | 0.552 | 0.880 | 0.069 | 0.090 | 0.092 | 8070 |
| | (0.004) | (0.002) | (0.003) | (0.015) | (0.005) | (0.005) | (0.014) | |
| CC5 | 0.043 | 0.273 | 0.684 | 0.765 | 0.130 | 0.136 | 0.185 | 7614 |
| | (0.005) | (0.002) | (0.004) | (0.042) | (0.007) | (0.006) | (0.012) | |
| CC61 | 0.021 | 0.308 | 0.671 | 0.812 | 0.174 | 0.147 | 0.126 | 3885 |
| | (0.006) | (0.002) | (0.004) | (0.099) | (0.008) | (0.007) | (0.010) | |
| CC7 | 0.078 | 0.295 | 0.627 | 0.795 | 0.081 | 0.092 | 0.121 | 18369 |
| | (0.002) | (0.001) | (0.002) | (0.012) | (0.003) | (0.003) | (0.005) | |
| CC81 | 0.073 | 0.378 | 0.549 | 0.691 | 0.068 | 0.090 | 0.089 | 7233 |
| | (0.006) | (0.003) | (0.004) | (0.032) | (0.007) | (0.007) | (0.010) | |
| CC82 | 0.087 | 0.311 | 0.602 | 0.709 | 0.078 | 0.108 | 0.070 | 17340 |
| | (0.003) | (0.001) | (0.002) | (0.016) | (0.004) | (0.004) | (0.006) | |
| CC91 | 0.036 | 0.317 | 0.647 | 0.933 | 0.118 | 0.125 | 0.090 | 12000 |
| | (0.003) | (0.001) | (0.002) | (0.026) | (0.004) | (0.003) | (0.006) | |
| DD1 | 0.126 | 0.259 | 0.615 | 0.825 | 0.111 | 0.166 | 0.166 | 3957 |
| | (0.006) | (0.002) | (0.004) | (0.013) | (0.009) | (0.007) | (0.010) | |
| EE11 | 0.038 | 0.219 | 0.743 | 0.711 | 0.093 | 0.091 | 0.081 | 50970 |
| | (0.001) | (0.000) | (0.001) | (0.009) | (0.002) | (0.001) | (0.002) | |
| EE12 | 0.098 | 0.262 | 0.640 | 0.727 | 0.092 | 0.101 | 0.100 | 7341 |
| | (0.004) | (0.001) | (0.003) | (0.017) | (0.005) | (0.005) | (0.006) | |
| EE13 | 0.056 | 0.313 | 0.631 | 0.745 | 0.112 | 0.133 | 0.133 | 106803 |
| | (0.001) | (0.000) | (0.001) | (0.007) | (0.001) | (0.001) | (0.002) | |
| FF11 | 0.115 | 0.367 | 0.519 | 0.755 | 0.143 | 0.157 | 0.131 | 74175 |
| | (0.002) | (0.001) | (0.001) | (0.008) | (0.003) | (0.003) | (0.005) | |
| GH11 | 0.143 | 0.394 | 0.463 | 0.789 | 0.058 | 0.106 | 0.082 | 20601 |
| | (0.004) | (0.002) | (0.002) | (0.011) | (0.005) | (0.004) | (0.006) | |
| GH12 | 0.181 | 0.423 | 0.396 | 0.909 | 0.113 | 0.133 | 0.084 | 28068 |
| | (0.004) | (0.002) | (0.002) | (0.008) | (0.005) | (0.004) | (0.006) | |
| GH13 | 0.162 | 0.412 | 0.426 | 0.824 | 0.119 | 0.158 | 0.052 | 91011 |
| | (0.002) | (0.001) | (0.001) | (0.006) | (0.003) | (0.003) | (0.005) | |
| GH21 | 0.127 | 0.283 | 0.590 | 0.920 | 0.017 | 0.051 | 0.000 | 101970 |
| | (0.001) | (0.000) | (0.001) | (0.004) | (0.002) | (0.001) | | |
| II11 | 0.146 | 0.315 | 0.539 | 0.781 | 0.111 | 0.129 | 0.138 | 28587 |
| | (0.003) | (0.001) | (0.002) | (0.007) | (0.004) | (0.003) | (0.004) | |
| II12 | 0.102 | 0.234 | 0.665 | 0.411 | 0.014 | 0.073 | 0.137 | 4344 |
| | (0.009) | (0.002) | (0.007) | (0.031) | (0.012) | (0.011) | (0.013) | |
| II13 | 0.153 | 0.315 | 0.532 | 0.713 | 0.066 | 0.070 | 0.000 | 12990 |
| | (0.004) | (0.001) | (0.002) | (0.009) | (0.005) | (0.005) | | |
| JJ11 | 0.049 | 0.235 | 0.716 | 0.958 | 0.091 | 0.065 | 0.071 | 7800 |

| | $\alpha_K$ | $\alpha_L$ | $\alpha_M$ | $\gamma$ | $\mu_{Akld}$ | $\mu_{OthUrb}$ | $\mu_{Rural}$ | N |
|---|---|---|---|---|---|---|---|---|
| | (0.005) | (0.001) | (0.004) | (0.028) | (0.007) | (0.007) | (0.019) | |
| JJ12 | 0.145 | 0.310 | 0.545 | 0.571 | 0.000 | 0.000 | 0.000 | 2499 |
| | (0.010) | (0.004) | (0.006) | (0.032) | | | | |
| KK1_ | 0.202 | 0.346 | 0.452 | 0.640 | 0.061 | 0.162 | 0.173 | 15912 |
| | (0.007) | (0.003) | (0.004) | (0.014) | (0.009) | (0.008) | (0.023) | |
| KK13 | 0.200 | 0.337 | 0.463 | 0.520 | 0.043 | 0.059 | 0.000 | 5610 |
| | (0.017) | (0.007) | (0.010) | (0.025) | (0.020) | (0.019) | | |
| LL11 | 0.258 | 0.256 | 0.486 | 0.798 | 0.022 | 0.076 | 0.000 | 12360 |
| | (0.005) | (0.002) | (0.003) | (0.008) | (0.007) | (0.007) | | |
| MN11 | 0.222 | 0.399 | 0.378 | 0.580 | 0.064 | 0.105 | 0.065 | 117786 |
| | (0.002) | (0.001) | (0.001) | (0.004) | (0.003) | (0.003) | (0.004) | |
| MN21 | 0.113 | 0.412 | 0.476 | 0.706 | 0.049 | 0.069 | 0.046 | 44415 |
| | (0.003) | (0.001) | (0.001) | (0.008) | (0.003) | (0.003) | (0.005) | |
| RS11 | 0.067 | 0.349 | 0.583 | 0.906 | 0.187 | 0.142 | 0.020 | 14586 |
| | (0.004) | (0.002) | (0.003) | (0.022) | (0.006) | (0.005) | (0.007) | |
| RS21 | 0.107 | 0.405 | 0.488 | 0.839 | 0.077 | 0.111 | 0.088 | 79635 |
| | (0.002) | (0.001) | (0.001) | (0.006) | (0.002) | (0.002) | (0.003) | |

Source: Regression estimates based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Each row contains industry-specific estimates of equation 10, using a quality adjusted labour measure. See Appendix Table 2 for a list of industry codes. Observation counts have been randomly rounded to base 3.

Appendix Table 5: Industry-specific productivity and price premiums (relative to Auckland)

| | *MFP* | | Intermediates price | | Labour price | |
|---|---|---|---|---|---|---|
| | Other Urban | Rural | Other Urban | Rural | Other Urban | Rural |
| CC1 | -0.006 | 0.055* | 0.019* | 0.092* | -0.011 | 0.112* |
| | (0.010) | (0.015) | (0.007) | (0.009) | (0.006) | (0.008) |
| CC21 | -0.129* | -0.367* | -0.110* | -0.256* | -0.120* | -0.178* |
| | (0.010) | (0.021) | (0.010) | (0.021) | (0.006) | (0.013) |
| CC3 | -0.139* | -0.225* | -0.106* | -0.158* | -0.118* | -0.163* |
| | (0.011) | (0.014) | (0.007) | (0.009) | (0.006) | (0.008) |
| CC41 | -0.161* | -0.396* | -0.148* | -0.324* | -0.162* | -0.301* |
| | (0.010) | (0.038) | (0.008) | (0.030) | (0.007) | (0.027) |
| CC5 | -0.229* | -0.266* | -0.103* | -0.175* | -0.127* | -0.129* |
| | (0.018) | (0.034) | (0.011) | (0.021) | (0.008) | (0.016) |
| CC61 | -0.302* | -0.331* | -0.165* | -0.125* | -0.157* | -0.111* |
| | (0.023) | (0.034) | (0.016) | (0.023) | (0.012) | (0.018) |
| CC7 | -0.138* | -0.230* | -0.124* | -0.166* | -0.111* | -0.151* |
| | (0.007) | (0.014) | (0.007) | (0.014) | (0.005) | (0.010) |
| CC81 | -0.080* | -0.275* | -0.073* | -0.211* | -0.095* | -0.163* |
| | (0.015) | (0.025) | (0.016) | (0.026) | (0.008) | (0.013) |
| CC82 | -0.134* | -0.368* | -0.121* | -0.241* | -0.141* | -0.243* |
| | (0.010) | (0.017) | (0.010) | (0.017) | (0.006) | (0.010) |
| CC91 | -0.210* | -0.408* | -0.153* | -0.231* | -0.152* | -0.230* |
| | (0.009) | (0.018) | (0.005) | (0.011) | (0.006) | (0.011) |
| DD1 | -0.115* | -0.343* | -0.094* | -0.257* | -0.123* | -0.199* |
| | (0.028) | (0.038) | (0.023) | (0.032) | (0.016) | (0.023) |
| EE11 | -0.002 | -0.047* | 0.041* | 0.014 | -0.121* | -0.147* |
| | (0.007) | (0.009) | (0.008) | (0.010) | (0.004) | (0.005) |
| EE12 | -0.092* | -0.232* | -0.084* | -0.173* | -0.120* | -0.154* |
| | (0.014) | (0.018) | (0.013) | (0.016) | (0.009) | (0.011) |
| EE13 | -0.054* | -0.133* | -0.037* | -0.094* | -0.104* | -0.119* |
| | (0.004) | (0.005) | (0.004) | (0.005) | (0.002) | (0.003) |
| FF11 | -0.226* | -0.442* | -0.154* | -0.309* | -0.191* | -0.238* |
| | (0.006) | (0.013) | (0.004) | (0.009) | (0.003) | (0.007) |
| GH11 | -0.023* | -0.293* | -0.087* | -0.280* | -0.107* | -0.268* |
| | (0.009) | (0.015) | (0.007) | (0.011) | (0.005) | (0.008) |
| GH12 | -0.011 | -0.162* | -0.043* | -0.092* | -0.063* | -0.101* |
| | (0.007) | (0.012) | (0.004) | (0.006) | (0.003) | (0.005) |
| GH13 | -0.057* | -0.324* | -0.072* | -0.193* | -0.104* | -0.164* |
| | (0.005) | (0.010) | (0.003) | (0.006) | (0.002) | (0.005) |
| GH21 | 0.007 | -0.084* | -0.030* | -0.026* | -0.047* | -0.010* |
| | (0.003) | (0.004) | (0.002) | (0.003) | (0.002) | (0.003) |
| II11 | -0.058* | -0.045* | -0.080* | -0.122* | -0.053* | -0.013 |
| | (0.008) | (0.010) | (0.006) | (0.008) | (0.005) | (0.007) |
| II12 | 0.016 | -0.206* | 0.019 | -0.347* | -0.211* | -0.226* |
| | (0.052) | (0.060) | (0.069) | (0.081) | (0.015) | (0.018) |
| II13 | -0.163* | -0.405* | -0.038* | -0.168* | -0.235* | -0.377* |
| | (0.014) | (0.021) | (0.014) | (0.022) | (0.008) | (0.012) |

| | *MFP* | | Intermediates price | | Labour price | |
|---|---|---|---|---|---|---|
| | Other Urban | Rural | Other Urban | Rural | Other Urban | Rural |
| JJ11 | -0.314* | -0.441* | -0.243* | -0.334* | -0.254* | -0.332* |
| | (0.017) | (0.045) | (0.011) | (0.029) | (0.011) | (0.029) |
| JJ12 | 0.112 | -0.170 | 0.088 | -0.158 | -0.140* | -0.198* |
| | (0.051) | (0.172) | (0.073) | (0.246) | (0.022) | (0.074) |
| KK13 | -0.202* | -0.431* | -0.200* | -0.329* | -0.224* | -0.322* |
| | (0.018) | (0.062) | (0.020) | (0.070) | (0.009) | (0.031) |
| KK1_ | -0.410* | -1.009* | -0.238* | -0.520* | -0.305* | -0.500* |
| | (0.039) | (0.094) | (0.035) | (0.085) | (0.020) | (0.047) |
| LL11 | -0.093* | -0.304* | -0.139* | -0.217* | -0.177* | -0.165* |
| | (0.013) | (0.025) | (0.012) | (0.024) | (0.008) | (0.015) |
| MN11 | -0.022* | -0.399* | 0.049* | -0.296* | -0.136* | -0.230* |
| | (0.006) | (0.014) | (0.009) | (0.020) | (0.003) | (0.007) |
| MN21 | -0.061* | -0.220* | -0.003 | -0.202* | -0.136* | -0.219* |
| | (0.007) | (0.013) | (0.009) | (0.016) | (0.004) | (0.008) |
| RS11 | -0.137* | -0.275* | -0.083* | -0.131* | -0.097* | -0.108* |
| | (0.013) | (0.016) | (0.008) | (0.010) | (0.007) | (0.009) |
| RS21 | -0.054* | -0.161* | -0.083* | -0.194* | -0.093* | -0.110* |
| | (0.004) | (0.007) | (0.003) | (0.006) | (0.002) | (0.005) |
| Total | -0.079* | -0.214* | -0.057* | -0.147* | -0.121* | -0.145* |
| | (0.002) | (0.003) | (0.002) | (0.003) | (0.001) | (0.001) |

Source: Regression estimates based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Each row contains estimates from three industry-specific regressions (dependent variables: *mfp*, intermediates price, labour price). Each regression also contains time dummies (not reported). Standard errors in *MFP* and intermediates price regressions have not been adjusted for the fact that the dependent variables are a function of estimated parameters. *: significant with p<.01.

Appendix Table 6: Industry-specific productivity and price premiums (relative to Auckland) (Quality-adjusted labour)

| | *MFP* | | Intermediates price | | Labour price | |
|---|---|---|---|---|---|---|
| | Other Urban | Rural | Other Urban | Rural | Other Urban | Rural |
| CC1 | 0.007 | 0.001 | 0.029* | 0.035* | 0.006 | 0.050* |
| | (0.009) | (0.013) | (0.005) | (0.007) | (0.004) | (0.006) |
| CC21 | -0.063* | -0.267* | -0.038* | -0.144* | -0.046* | -0.078* |
| | (0.009) | (0.019) | (0.008) | (0.018) | (0.005) | (0.010) |
| CC3 | -0.100* | -0.139* | -0.068* | -0.071* | -0.081* | -0.076* |
| | (0.009) | (0.012) | (0.005) | (0.007) | (0.005) | (0.006) |
| CC41 | -0.078* | -0.229* | -0.062* | -0.155* | -0.077* | -0.131* |
| | (0.009) | (0.032) | (0.006) | (0.024) | (0.006) | (0.021) |
| CC5 | -0.176* | -0.164* | -0.064* | -0.088* | -0.088* | -0.043* |
| | (0.015) | (0.029) | (0.009) | (0.017) | (0.006) | (0.012) |
| CC61 | -0.252* | -0.276* | -0.120* | -0.079* | -0.113* | -0.069* |
| | (0.020) | (0.029) | (0.012) | (0.018) | (0.009) | (0.013) |
| CC7 | -0.090* | -0.159* | -0.076* | -0.099* | -0.065* | -0.086* |
| | (0.006) | (0.012) | (0.005) | (0.011) | (0.004) | (0.007) |
| CC81 | -0.053* | -0.204* | -0.051* | -0.153* | -0.070* | -0.111* |
| | (0.013) | (0.021) | (0.013) | (0.021) | (0.006) | (0.010) |
| CC82 | -0.056* | -0.233* | -0.052* | -0.131* | -0.070* | -0.133* |
| | (0.008) | (0.014) | (0.008) | (0.014) | (0.004) | (0.007) |
| CC91 | -0.133* | -0.305* | -0.077* | -0.132* | -0.085* | -0.133* |
| | (0.008) | (0.016) | (0.005) | (0.009) | (0.004) | (0.008) |
| DD1 | -0.074* | -0.245* | -0.055* | -0.154* | -0.073* | -0.122* |
| | (0.023) | (0.031) | (0.015) | (0.021) | (0.011) | (0.015) |
| EE11 | -0.005 | -0.032* | 0.034* | 0.025* | -0.106* | -0.113* |
| | (0.006) | (0.008) | (0.007) | (0.009) | (0.003) | (0.004) |
| EE12 | -0.056* | -0.178* | -0.042* | -0.119* | -0.082* | -0.098* |
| | (0.013) | (0.016) | (0.012) | (0.015) | (0.007) | (0.009) |
| EE13 | -0.024* | -0.095* | -0.008 | -0.055* | -0.076* | -0.081* |
| | (0.003) | (0.005) | (0.003) | (0.005) | (0.002) | (0.003) |
| FF11 | -0.133* | -0.327* | -0.059* | -0.197* | -0.099* | -0.120* |
| | (0.005) | (0.012) | (0.004) | (0.008) | (0.002) | (0.005) |
| GH11 | 0.028* | -0.143* | -0.032* | -0.139* | -0.057* | -0.125* |
| | (0.008) | (0.013) | (0.006) | (0.010) | (0.004) | (0.006) |
| GH12 | 0.072* | -0.031* | 0.052* | 0.044* | 0.026* | 0.032* |
| | (0.007) | (0.011) | (0.003) | (0.006) | (0.003) | (0.005) |
| GH13 | -0.005 | -0.249* | -0.014* | -0.111* | -0.045* | -0.083* |
| | (0.004) | (0.009) | (0.002) | (0.005) | (0.002) | (0.004) |
| GH21 | 0.058* | -0.037* | 0.029* | 0.025* | 0.014* | 0.038* |
| | (0.003) | (0.004) | (0.002) | (0.003) | (0.001) | (0.002) |
| II11 | -0.033* | -0.039* | -0.053* | -0.110* | -0.028* | -0.006 |
| | (0.007) | (0.009) | (0.005) | (0.007) | (0.004) | (0.005) |
| II12 | 0.081 | -0.125 | 0.086 | -0.262* | -0.134* | -0.148* |
| | (0.049) | (0.057) | (0.066) | (0.077) | (0.011) | (0.013) |
| II13 | -0.046* | -0.227* | 0.077* | 0.018 | -0.109* | -0.179* |





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| | *MFP* | | Intermediates price | | Labour price | |
|---|---|---|---|---|---|---|
| | Other Urban | Rural | Other Urban | Rural | Other Urban | Rural |
| | (0.012) | (0.019) | (0.013) | (0.020) | (0.006) | (0.009) |
| JJ11 | -0.199* | -0.246* | -0.125* | -0.139* | -0.142* | -0.135* |
| | (0.016) | (0.041) | (0.009) | (0.024) | (0.009) | (0.023) |
| JJ12 | 0.087 | -0.122 | 0.060 | -0.131 | -0.089* | -0.156* |
| | (0.039) | (0.131) | (0.048) | (0.161) | (0.015) | (0.051) |
| KK13 | -0.043* | -0.189* | -0.080* | -0.156* | -0.099* | -0.150* |
| | (0.014) | (0.050) | (0.015) | (0.053) | (0.006) | (0.021) |
| KK1_ | -0.086 | -0.518* | -0.006 | -0.175 | -0.132* | -0.132* |
| | (0.043) | (0.105) | (0.055) | (0.133) | (0.014) | (0.034) |
| LL11 | -0.013 | -0.214* | -0.046* | -0.126* | -0.074* | -0.089* |
| | (0.012) | (0.022) | (0.009) | (0.017) | (0.006) | (0.011) |
| MN11 | 0.036* | -0.220* | 0.079* | -0.157* | -0.070* | -0.103* |
| | (0.005) | (0.011) | (0.007) | (0.015) | (0.002) | (0.005) |
| MN21 | -0.001 | -0.130* | 0.050* | -0.110* | -0.073* | -0.127* |
| | (0.006) | (0.011) | (0.008) | (0.014) | (0.003) | (0.006) |
| RS11 | -0.083* | -0.201* | -0.027* | -0.049* | -0.038* | -0.030* |
| | (0.012) | (0.015) | (0.006) | (0.008) | (0.006) | (0.007) |
| RS21 | -0.013* | -0.131* | -0.039* | -0.158* | -0.048* | -0.081* |
| | (0.003) | (0.006) | (0.002) | (0.005) | (0.002) | (0.004) |
| Total | -0.021* | -0.135* | -0.003* | -0.074* | -0.060* | -0.070* |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) |

Source: Regression estimates based on data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). Each row contains estimates from three industry-specific regressions (dependent variables: *mfp*, intermediates price, labour price). Each regression also contains time dummies (not reported). Standard errors in *MFP* and intermediates price regressions have not been adjusted for the fact that the dependent variables are a function of estimated parameters. *: significant with p<.01.

Appendix Table 7: Selected industry characteristics

| | % of empl. in Auckland | Import share of inputs | Export share of output | Domestic tradability | High-qualified employees | High-skilled occupations |
|---|---|---|---|---|---|---|
| CC1 | 14% | 7% | 60% | 35% | 10% | 29% |
| CC21 | 28% | 14% | 52% | 24% | 8% | 35% |
| CC3 | 16% | 7% | 34% | 26% | 6% | 42% |
| CC41 | 42% | 11% | 10% | 32% | 10% | 66% |
| CC5 | 27% | 39% | 18% | 53% | 16% | 43% |
| CC61 | 30% | 10% | 4% | 12% | 9% | 41% |
| CC7 | 21% | 16% | 27% | 39% | 7% | 57% |
| CC81 | 30% | 23% | 29% | 12% | 7% | 70% |
| CC82 | 26% | 24% | 40% | 25% | 16% | 60% |
| CC91 | 36% | 17% | 27% | 37% | 9% | 60% |
| DD1 | 24% | 2% | 0% | 17% | 21% | 50% |
| EE11 | 21% | 5% | 0% | 5% | 6% | 77% |
| EE12 | 23% | 6% | 0% | 9% | 8% | 49% |
| EE13 | 23% | 12% | 1% | 16% | 4% | 66% |
| FF11 | 30% | 6% | 12% | 30% | 16% | 44% |
| GH11 | 26% | 7% | 6% | 5% | 6% | 39% |
| GH12 | 23% | 2% | 8% | 10% | 8% | 28% |
| GH13 | 28% | 4% | 5% | 13% | 14% | 36% |
| GH21 | 27% | 7% | 28% | 4% | 11% | 40% |
| II11 | 27% | 11% | 4% | 12% | 5% | 15% |
| II12 | 35% | 22% | 40% | 7% | 14% | 43% |
| II13 | 33% | 3% | 13% | 21% | 11% | 23% |
| JJ11 | 37% | 14% | 9% | 27% | 31% | 68% |
| JJ12 | 45% | 8% | 7% | 43% | 36% | 64% |
| KK13 | 40% | 3% | 1% | 25% | 32% | 59% |
| KK1_ | 42% | 2% | 2% | 35% | 32% | 47% |
| LL11 | 32% | 7% | 7% | 15% | 14% | 45% |
| MN11 | 32% | 6% | 6% | 25% | 47% | 70% |
| MN21 | 28% | 6% | 7% | 21% | 18% | 35% |
| RS11 | 25% | 7% | 8% | 17% | 25% | 48% |
| RS21 | 27% | 8% | 9% | 7% | 14% | 62% |
| Total | 29% | 10% | 15% | 21% | 15% | 49% |

Note: See section 4.3.1 for a description of variables.

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