New Zealand Economic Papers

ISSN: 0077-9954 (Print) 1943-4863 (Online) Journal homepage: https://www.tandfonline.com/loi/rnzp20

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To cite this article: Lisa Meehan (2020) Productivity in New Zealand: the role of resource allocation among firms, New Zealand Economic Papers, 54:1, 39-66, DOI: 10.1080/00779954.2019.1573846

To link to this article: https://doi.org/10.1080/00779954.2019.1573846

NEW ZEALAND ECONOMIC PAPERS
2020, VOL. 54, NO. 1, 39–66
https://doi.org/10.1080/00779954.2019.1573846

Productivity in New Zealand: the role of resource allocation among firms

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ABSTRACT
This paper analyses the role of resource allocation in New Zealand's productivity performance by applying a three-factor revenue productivity measure of within-industry misallocation to firm-level data. It finds that if all market distortions were eliminated, total factor productivity could increase by more than a third. However, resource allocation has improved somewhat over the 2000s due to improvements in the manufacturing and service sectors, while allocation has worsened in the primary and utilities sectors. This paper is the first to use a three-factor decomposition method to examine which distortions have contributed to changes in allocative efficiency over time. These decompositions show that the worsening resource allocation in the primary and utilities sectors mainly reflects increased distortions in the allocation of capital. The results also suggest that many small firms are larger than their optimal size given their low productivity levels, which is consistent with previous research showing a comparatively poor 'up-or-out' dynamic among New Zealand firms.

ARTICLE HISTORY
Received 6 April 2017
Accepted 21 January 2019

KEYWORDS
Total factor productivity; resource allocation

JEL
D22; D24

1. Introduction

In comparison with other developed countries, New Zealand's productivity performance has been poor. New Zealand not only had economy-wide labour productivity that was below the OECD average in 1980, it also experienced below-average labour productivity growth between 1980 and 2010 (Conway & Meehan, 2013).

Moreover, like many other countries, New Zealand's total factor productivity (TFP) growth has slowed over the 2000s, with the slowdown beginning prior to the Great Recession (Figure 1).[1] Although average annual output growth in New Zealand from 2000 to 2008 was somewhat higher than output growth in the 1990s, this growth was due to greater input growth more than compensating for slower productivity growth. Average annual TFP growth from 2000 to 2008 was only 0.6 percent, compared with 1.9 percent between 1990 and 1997, and 1.8 percent between 1997 and 2000. In the aftermath of the Great Recession, both output growth and TFP growth slowed considerably, with average annual TFP growth of just 0.2 percent from 2008 to 2015. This slowdown in TFP growth is concerning given that TFP is a crucial driver of long-run economic growth and a key factor in determining income differences across countries. For instance, Hsieh and Klenow (2010) estimate that between 50 and 70 percent of cross-country income differences are generated by differences in TFP levels, and that TFP also exerts a powerful indirect effect on physical and human capital accumulation.

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Supplemental data for this article can be accessed here. https://doi.org/10.1080/00779954.2019.1573846

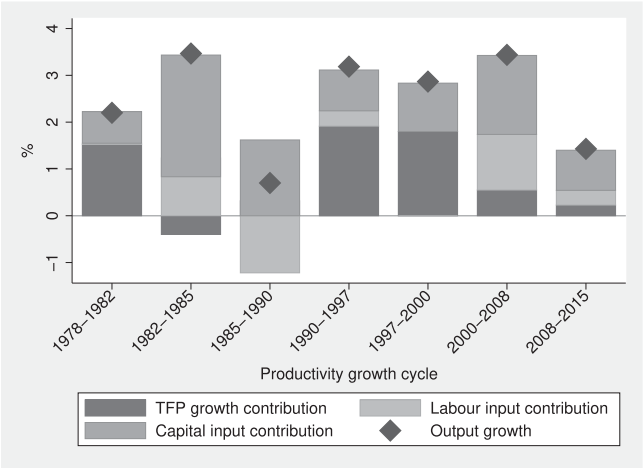

Figure 1. Contributions to output growth over productivity growth cycles. Source: Statistics New Zealand March 2016 Productivity Release.

Notes: The latest full productivity cycle is 2000 to 2008. The most recent period of 2008 to 2015 is an incomplete productivity cycle. Breaking the series into growth cycles allows for average growth rate comparisons that account for variation in capacity utilisation over cycles. Statistics New Zealand calculates these cycles on a 'peak-to-peak' basis using a Hodrick-Prescott filter (for details see Statistics New Zealand , 2007). See endnote 1 for details of industry coverage.

In this paper, I investigate whether changes in within-industry resource misallocation may have contributed to New Zealand's poor productivity growth in the 2000s.[2] I apply a three-factor extension (based on Dias, Robalo Marques, & Richmond, 2016b), which includes intermediate inputs in addition to capital and labour, of Hsieh and Klenow (2009)'s method (henceforth HK) for measuring the efficiency of resource allocation to New Zealand firm-level data from 2001 to 2012. The model estimates the distortions affecting the marginal products of these inputs across firms within the same industry, and the extent to which these distortions lower aggregate TFP and output. This is also the first paper to extend the decomposition method of Chen and Irarrazabal (2015) to three factors in order to examine which distortions have contributed to changes in allocative efficiency over time.

While there is limited relevant New Zealand-specific work in this area, previous work on New Zealand's productivity performance suggests that a slowdown in productivity growth within industries (rather than between-industry resource reallocation) has been the main contributor to the country's slow productivity growth in the 2000s. First, the slowdown in New Zealand's aggregate TFP growth in the 2000s reflects a slowdown in TFP growth within almost all industries (Conway & Meehan, 2013).[3] Also, while there was a shift of employment to industries with below-average labour productivity in the 1990s, this was not the case in the 2000s. Rather, in the 2000s employment shifts across industries made a small but positive contribution to labour productivity growth and resource shifts across industries made a positive contribution to TFP growth (Laws & Meehan, 2015; Maré, Hyslop, & Fabling, 2015; Meehan, 2014). This previous work highlights the importance of slower within-industry productivity growth, and raises the possibility that this could, at least in part, be due to deteriorating within-industry resource allocation.

Moreover, New Zealand is not unique in its experience of a slowdown in productivity growth in the 2000s. While this widespread slowdown in productivity growth preceded the onset of the Great Recession in most countries, growth has been particularly poor in its aftermath. Overseas literature suggests that at least part of the explanation for these trends is that misallocation across firms has increased. For example, Barnett, Broadbent, Chiu, Franklin, and Miller (2014) suggests that an increase in misallocation has made an important contribution to the UK's productivity slowdown. OECD (2015) also notes that net lending in the UK decreased in the aftermath of the Great Recession. Banks were increasingly reluctant to write-down non-performing loans made to unprofitable firms (leading to

an increase in 'zombie' firms) while lending to young but productive firms, which were less likely to have a credit history or collateral, decreased. For southern European economies, Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2015) suggests that the decline in the real interest rate, often attributed to the euro convergence process, led to a decline in TFP as increased capital flows were misallocated towards firms that had higher net worth but that were not necessarily more productive. This is also consistent with Gamberoni, Giordano, and Lopez-Garcia (2016), which finds that capital misallocation increased between 2002 and 2012 in Belgium, France, Italy and Spain (but not in Germany). This work is also part of a wider literature on economic dynamism, such as Decker, Haltiwanger, Jarmin, and Miranda (2014), which finds a secular decline in dynamism in the US.

For New Zealand, this paper finds that if there were no distortions in the allocation of inputs across firms within the same industry then gross output could be about 35 percent higher, and value added could be about 83 percent higher. However, resource allocation has improved somewhat over the 2000s.[4] This overall improvement reflects improvements in the manufacturing and services sectors more than outweighing worsening allocation in the primary and utilities sectors and little change in the construction sector.[5] The level of potential gains from resource allocation also varies by sector, and consistent with international evidence, is higher in the services sector than in manufacturing.

Another implication of the HK model is that many small New Zealand firms are over-producing (i.e. their gross output is higher than optimal) given their relatively low levels of productivity. The general explanation for this result internationally is that small firms are subsidised through size-contingent policies and/or less stringent enforcement of regulations. However, this argument seems less applicable to New Zealand given its policy settings. Instead, it could be argued that this finding is consistent with previous research that highlights the lack of 'up-or-out' dynamics among New Zealand firms (such as Criscuolo, Gal, & Menon, 2014). I also speculate that low-productivity New Zealand firms are able to grow larger than their optimal size due to the limited extent of the market and a lack of competition.

This paper is also the first to extend the decomposition method developed in Chen and Irarrazabal (2015) to the three-factor model. These decompositions highlight that the worsening resource allocation in the primary and utilities sectors mainly reflects increased distortions in the allocation of capital, although output distortions have also contributed.

This next section sets out the methodology. Section 3 discusses the data used, Section 4 presents results and Section 5 concludes.

2. Method

This section outlines the methodology developed by Hsieh and Klenow (2009), with modifications based on Dias et al. (2016b) to incorporate intermediate inputs as a third factor of production. The HK model is based on Melitz (2003), with monopolistic competition among heterogeneous firms. This model is used to estimate distortions affecting the marginal products of inputs across firms within industries, and the extent to which these distortions lower aggregate TFP and output. In the absence of distortions, the model implies that the revenue productivity (TFPR) across firms within the same industry should be equalised, so the variation in TFPR is considered to be a measure of distortion-driven resource misallocation within an industry.

This section also shows how the estimated gross-output gains from optimal resource allocation can be translated into value-added gains. The inclusion of intermediate inputs has the advantage that the estimated value-added gains from optimal resource allocation are consistent with the efficient allocation of intermediate inputs, something that is not guaranteed in the two-factor approach that is often used.[6]

This section then outlines a decomposition method that allows further examination of the individual distortions in capital, labour and output underlying the aggregate level of distortion. To this end, I extend the decomposition method of Chen and Irarrazabal (2015) to the three-factor model.

Finally, this section discusses the implications of the HK method for the size distribution of firms. In doing so, it relates the HK method to another common measure of resource allocation: the Olley and Pakes (1996) covariance.

2.1. Measuring gross-output and TFP gains from reallocation

The basic setup of the model is an economy consisting of hetergeneous firms operating under monopolistic competition. Firms not only have different levels of efficiency, they also face different levels of output, capital and labour distortions.

Starting at the aggregate economy-wide level, a single final good, Y, is produced by a representative firm that combines the output of S industries using Cobb-Douglas production technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} \quad \text{where} \sum_{s=1}^{S} \theta_s = 1 \tag{1}$$

where industry shares, θ_s are given by:

$$\theta_s = \frac{P_s Y_s}{PY} \tag{2}$$

where P_s is the price of industry gross output, Y_s, and P is the price of the final good.

At the industry-level, the gross output of industry s, Y_s, is a constant elasticity of substitution aggregate of N_s differentiated products:

$$Y_s = \left(\sum_{i=1}^{N_s} Y_{si}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)} \tag{3}$$

where Y_{si} is the gross output of firm i and σ is the elasticity of substitution between varieties of differentiated goods. The assumptions of free entry and monopolistic competition at the industry level imply inverse demand equations for each individual variety:

$$Y_{si} = Y_s \left[\frac{P_s}{P_{si}} \right]^{\sigma} \tag{4}$$

$Y_s P_s^{\sigma}$ is not observed, but does not affect relative productivities nor reallocation gains (since this model does not consider inter-industry reallocation gains), so can be set to 1 for each industry s.[7]

Moving to the most disaggregated level, the gross output of firm i in industry s is produced according to a standard Cobb-Douglas technology with constant returns to scale:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} M_{si}^{1-\alpha_s-\beta_s} \tag{5}$$

where A_{si} is firm i's TFP, and K_{si}, L_{si} and M_{si} are firm i's capital, labour and intermediate inputs respectively. Factor shares of capital, labour and intermediate inputs (α_s, β_s and $1 - \alpha_s - \beta_s$ respectively) vary across industries but not across firms within the same industry.

Each firm faces three types of distortions, or wedges: an output distortion ($\tau_{y_{si}}$), a capital distortion ($\tau_{k_{si}}$), and a labour distortion ($\tau_{l_{si}}$). These distortions appear in the firm's profit equation as 'taxes':

$$\pi_{si} = (1 - \tau_{y_{si}}) P_{si} Y_{si} - (1 + \tau_{K_{si}}) R_s K_{si} - (1 + \tau_{l_{si}}) W_s L_{si} - Z_s M_{si} \tag{6}$$

where R_s, W_s and Z_s are the user cost of capital, labour wage and intermediate inputs price respectively.

In Equation (6), the output wedge denotes any distortion that changes the marginal products of capital, labour and intermediate inputs by the same proportion. Firms that face restrictions on size

would have high τ_y and firms that benefit from subsidies would have low τ_y. These output distortions could be driven by things such as subsidies to specific producers, regulatory or tax collection enforcement activities that are focussed on the largest firms, or restrictions on firm size due to limitations in the extent of the market.[8] The capital (labour) wedge denotes any distortion that raises the marginal product of capital (labour) relative to the marginal product of intermediate inputs. For example, τ_k would be high for firms that do not have access to credit and low for firms with access to cheap credit. These situations may arise due to a non-competitive banking system that provides favourable loan conditions to certain producers, or due to financial institutions that are unable or unwilling to provide credit to firms that are highly productive but have no credit history or lack tangible assets for use as collateral.[9]

From the first-order conditions, we have the marginal revenue products of each input:

$$\begin{aligned} MRPK_{si} &= R_s \frac{1+\tau_{k_{si}}}{1-\tau_{y_{si}}} \\ MRPL_{si} &= W_s \frac{1+\tau_{l_{si}}}{1-\tau_{y_{si}}} \\ MRPM_{si} &= Z_s \frac{1}{1-\tau_{y_{si}}} \end{aligned} \tag{7}$$

Intuitively, in the absence of distortions, the marginal revenue products of each input would be equal to their respective input prices.[10] So, if all firms within an industry face the same input prices, in the absence of distortions, the marginal revenue products of capital, labour and intermediate inputs would equalise across firms within the same industry. However, if there are distortions then the 'after-tax' marginal revenue products of each input will equalise across firms. The 'before-tax' marginal revenue products must be higher in firms that face disincentives and can be lower in firms that benefit from subsidies.

The first-order conditions also allow estimation of the three wedges from information on gross output, input costs, elasticity, and factor shares:

$$\begin{aligned} (1+\tau_{k_{si}}) &= \frac{\alpha_s}{(1-\alpha_s-\beta_s)} \frac{Z_s M_{si}}{R_s K_{si}} \\ (1+\tau_{l_{si}}) &= \frac{\beta_s}{(1-\alpha_s-\beta_s)} \frac{Z_s M_{si}}{W_s L_{si}} \\ (1-\tau_{y_{si}}) &= \frac{\sigma}{\sigma-1} \frac{1}{(1-\alpha_s-\beta_s)} \frac{Z_s M_{si}}{P_{si} Y_{si}} \end{aligned} \tag{8}$$

That is, the distortions are expressed in terms of output, capital and labour relative to intermediate input distortions. For instance, the presence of a capital distortion involves a ratio of intermediate consumption to capital costs that is high relative to what would be expected from the output elasticities with respect to capital and intermediate outputs. Similarly, for output and labour distortions.

Hsieh and Klenow (2009) distinguish between physical productivity (TFPQ) and revenue productivity (TFPR). This distinction is important because it is usual to use revenues when estimating production functions since a measure of physical output is typically not available. Therefore, firm-level revenue is deflated using industry-level price deflators, which neglects price variation across firms. The use of firm-specific deflators would yield TFPQ, whereas using an industry deflator gives TFPR. In the situation where firms have a degree of market power, the use of revenues instead of physical output means that measured firm productivity is a mix of true productivity and demand factors. The HK method infers the physical output, Y_{si} from the observed output, $P_{si}Y_{si}$, by assuming a CES

elasticity of demand. Thus firm-level TFPQ and TFPR are defined as:

$$TFPQ_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{\beta_s} M_{si}^{(1-\alpha_s-\beta_s)}} = \frac{(P_{si}Y_{si})^{\sigma/(\sigma-1)}}{K_{si}^{\alpha_s} L_{si}^{\beta_s} M_{si}^{(1-\alpha_s-\beta_s)}} \tag{9}$$

$$\begin{aligned} TFPR_{si} &= P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s} L_{si}^{\beta_s} M_{si}^{(1-\alpha_s-\beta_s)}} \\ &= \frac{\sigma}{\sigma-1}\left(\frac{MRPK_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{MRPL_{si}}{\beta_s}\right)^{\beta_s}\left(\frac{MRPM_{si}}{1-\alpha_s-\beta_s}\right)^{1-\alpha_s-\beta_s} \end{aligned} \tag{10}$$

From the definition of TFP (taking industry inputs K_s, L_s and M_s to be the sum of respective firm-level inputs) and using Y_s from Equation (3), industry TFP can now be calculated as:

$$TFP_s = \left[\sum_{i=1}^{N_s}\left(A_{si}\frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right]^{1/(\sigma-1)} \tag{11}$$

where N_s is the number of firms in industry S, and $\overline{TFPR_s}$ is industry average TFPR, calculated as:

$$\begin{aligned} \overline{TFPR_s} &= \frac{\sigma}{\sigma-1}\left[\frac{R_s}{\alpha_s\sum_{i=1}^{N_s}\frac{1-\tau_{Y_{si}}}{1+\tau_{K_{si}}}\frac{P_{si}Y_{si}}{P_sY_s}}\right]^{\alpha_s}\left[\frac{W_s}{\beta_s\sum_{i=1}^{N_s}\frac{1-\tau_{Y_{si}}}{1+\tau_{L_{si}}}\frac{P_{si}Y_{si}}{P_sY_s}}\right]^{\beta_s} \\ &\times\left[\frac{Z_s}{(1-\alpha_s-\beta_s)\sum_{i=1}^{N_s}1-\tau_{Y_{si}}\frac{P_{si}Y_{si}}{P_sY_s}}\right]^{1-\alpha_s-\beta_s} \\ &= \frac{\sigma}{\sigma-1}\left(\frac{\overline{MRPK_s}}{\alpha_s}\right)^{\alpha_s}\left(\frac{\overline{MRPL_s}}{\beta_s}\right)^{\beta_s}\left(\frac{\overline{MRPM_s}}{1-\alpha_s-\beta_s}\right)^{1-\alpha_s-\beta_s} \end{aligned} \tag{12}$$

Equation (10) shows that TFPR does not vary across firms within the same industry unless firms face some type of distortion. Intuitively, in the absence of distortions, more inputs would be allocated to firms with higher TFPQ up to the point where their higher output would lower price and result in the same TFPR as in firms with lower TFPQ. However, in the presence of distortions, a high (low) TFPR is a sign that the firm confronts barriers (enjoys benefits) that raise (lower) the firm's marginal products of the different factors of production, rendering the firm smaller (larger) than optimal.

In the absence of distortions, the 'efficient' industry TFP is given by the CES aggregate of each individual firm's TFPQ:

$$TFP_s^* = \bar{A}_s = \left(\sum_{i=1}^{N_s} A_{si}^{\sigma-1}\right)^{1/(\sigma-1)} \tag{13}$$

Thus, industry output gains from improving efficiency are given by:

$$\frac{Y_s^*}{Y_s} = \left(\sum_{i=1}^{N_s}\left(\frac{\bar{A}_s}{A_{si}}\frac{TFPR_{si}}{\overline{TFPR_s}}\right)^{\sigma-1}\right)^{1/(\sigma-1)} \tag{14}$$

To calculate aggregate efficiency gains, it is assumed that the output of each industry is aggregated using a Cobb-Douglas production technology, implying:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} = \prod_{s=1}^{S}\left(TFP_s K_s^{\alpha_s} L_s^{\beta_s} M_s^{1-\alpha_s-\beta_s}\right)^{\theta_s} \tag{15}$$

where Y is aggregate value added, S is the number of industries and θ_s is the share of industry s in aggregate output.

And aggregate TFP is:

$$TFP = \prod_{s=1}^{S} TFP_s^{\theta_s} = \prod_{s=1}^{S} \left[\sum_{i=1}^{N_s} \left(A_{si} \frac{\overline{TFPR_s}}{TFPR_{si}} \right)^{\sigma-1} \right]^{\theta_s/(\sigma-1)} \tag{16}$$

Finally, the relative gains from efficiency improvements within industries can be expressed as the ratio of 'efficient' and actual output:

$$\frac{Y^*}{Y} = \prod_{s=1}^{S} \left[\sum_{i=1}^{N_s} \left(\frac{\bar{A}_s}{A_{si}} \frac{TFPR_{si}}{\overline{TFPR_s}} \right)^{\sigma-1} \right]^{\theta_s/(\sigma-1)} \tag{17}$$

2.2. Measuring value-added gains from reallocation

While Equations (14) and (17) allow the estimation of the industry and aggregate gains in gross output from reallocation, we may also be interested in how the gross-output gains translate into value-added gains, as these are more closely related to welfare gains. Following Dias et al. (2016b), for industry s, value-added gains are given by:

$$\frac{V_s^*}{V_s} = \frac{(P_s Y_s)\frac{Y_s^*}{Y_s} - Z_s M_s}{P_s Y_s - Z_s M_s} = \frac{\left(\frac{Y_s^*}{Y_s}\right) - m_s}{1 - m_s} \tag{18}$$

and aggregate value-added gains are calculated as:

$$\frac{V^*}{V} = \frac{(PY)(\frac{Y^*}{Y}) - ZM}{PY - ZM} = \frac{(\frac{Y^*}{Y}) - m}{1 - m} \tag{19}$$

where Y_s^*/Y_s and Y^*/Y are given by Equations (14) and (17), and m_s and m are the industry-level and aggregate intermediate input shares, respectively.

As mentioned, this method of estimating value-added efficiency gains has at least two advantages. First, it provides estimates of value-added efficiency gain that are consistent with the efficient allocation of intermediate inputs, something that is not guaranteed with the two-factor HK approach. Second, firms with legitimately negative value added are excluded from analysis using the two-factor model, which is a potential source of bias. However, firms with negative value added can be included in this three-factor model.

2.3. Decomposition analysis: relative importance of distortions

In order to better understand the forces driving aggregate misallocation, I extend the decomposition method of Chen and Irarrazabal (2015) to three factors. This subsection briefly outlines this method.[11]

First, TFP_s is re-written as:

$$\begin{aligned} TFP_s = & \left[\left(\sum_{i=1}^{N_s} \frac{A_{si}(1-\tau_{ysi})}{(1+\tau_{ksi})^{\alpha_s}(1+\tau_{lsi})^{\beta_s}} \right)^{\sigma-1} \right]^{\sigma/(\sigma-1)} \left[\sum_{i=1}^{N_s} \frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}(1+\tau_{lsi})^{\beta_s(\sigma-1)}} \right]^{-\alpha_s} \\ & \times \left[\sum_{i=1}^{N_s} \frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}(1+\tau_{lsi})^{\beta_s(\sigma-1)+1}} \right]^{-\beta_s} \\ & \times \left[\sum_{i=1}^{N_s} \frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}(1+\tau_{lsi})^{\beta_s(\sigma-1)}} \right]^{-(1-\alpha_s-\beta_s)} \end{aligned} \tag{20}$$

Then assuming that A_{si}, $(1-\tau_{ysi})$, $(1+\tau_{ksi})$ and $(1+\tau_{lsi})$ are jointly log normal, the gains from efficient resource allocation can be approximated by applying the Central Limit Theorem to Equation (20):

$$\begin{aligned}\log TFP_s^* - \log TFP_s = &\frac{\sigma}{2}\text{var}[\log TFPR_{si}] \\ &+ \frac{\alpha_s(1-\alpha_s)}{2}\text{var}[\log(1+\tau_{ksi})] + \frac{\beta_s(1-\beta_s)}{2}\text{var}[\log(1+\tau_{lsi})] \\ &- \alpha_s\beta_s\text{cov}[\log(1+\tau_{ksi}), \log(1+\tau_{lsi})] \end{aligned} \tag{21}$$

The left-hand side of Equation (21) represents the gains in Equation (14). On the right-hand side, the variation of TFPR, var[log $TFPR_{si}$], captures resource misallocation across firms, and the variation of capital distortions, var[log$(1+\tau_{ksi})$] captures the distortions that drive the capital-intermediate inputs ratio away from the first-best outcome, and similarly for the variation of labour distortions, var[log$(1+\tau_{lsi})$].

In order to further investigate the driving forces of the time variation in the TFPR dispersion, I decompose var[log $TFPR_{si}$] into:

$$\begin{aligned}\text{var}[\log(TFPR_{si})] = &\text{var}[\log(1-\tau_{ysi})] + \alpha_s^2\text{var}[\log(1+\tau_{ksi})] + \beta_s^2\text{var}[\log(1+\tau_{lsi})] \\ &- 2\alpha_s\text{cov}[\log(1-\tau_{ysi}), \log(1+\tau_{ksi})] - 2\beta_s\text{cov}[\log(1-\tau_{ysi}), \log(1+\tau_{lsi})] \\ &+ 2\alpha_s\beta_s\text{cov}[\log(1+\tau_{ksi}), \log(1+\tau_{lsi})] \end{aligned} \tag{22}$$

where the first term captures resource misallocation due to output distortions, the second term captures capital distortions, the third term captures labour distortions, and the remaining terms capture the covariance between the distortions.

Plugging Equation (22) into Equation (21) gives a decomposition of TFP gains into the variation in output, capital and labour distortions as well as the covariance between the distortions:

$$\begin{aligned}\log TFP_s^* - \log TFP_s = &\frac{\sigma}{2}\text{var}[\log(1-\tau_{y_{si}})] \\ &+ \frac{\alpha_s^2(\sigma-1)+\alpha_s}{2}\text{var}[\log(1+\tau_{k_{si}})] + \frac{\beta_s^2(\sigma-1)+\beta_s}{2}\text{var}[\log(1+\tau_{l_{si}})] \\ &- \sigma\alpha_s\text{cov}[\log(1-\tau_{ysi}), \log(1+\tau_{ksi})] - \sigma\beta_s\text{cov}[\log(1-\tau_{ysi}), \log(1+\tau_{lsi})] \\ &+ (\sigma-1)\alpha_s\beta_s\text{cov}[\log(1+\tau_{ksi}), \log(1+\tau_{lsi})] \end{aligned} \tag{23}$$

2.4. The size distribution and the Olley-Pakes covariance measure

As outlined in Chen and Irarrazabal (2015), TFPQ and firm-level distortions jointly determine the distribution of firm size (where, in the three-factor model, a firm's size is its level of gross output). This has implications for the size distribution of firms. These calculations also shed some light on the relationship between the HK measure and another common measure of allocation: the Olley and Pakes (1996) covariance term. In essence, both methods imply that more productive firms should be larger than less productive firms within the same industry.

In the HK model, the distribution of firm size translates into a distribution of firm output. From Equation (4):

$$P_{si}Y_{si} = Y_{si}^{1-1/\sigma}P_sY_s^{1/\sigma} \tag{24}$$

Since $\sigma \geq 1$, this implies that larger firms should have higher output. Moreover:

$$Y_{si} = \frac{A_{si}^{\sigma}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s\sigma}(1+\tau_{lsi})^{\beta_s\sigma}}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{\alpha_s}{R_s}\right)^{\alpha_s\sigma}\left(\frac{\beta_s}{W_s}\right)^{\beta_s\sigma}\left(\frac{1-\alpha_s-\beta_s}{Z_s}\right)^{\sigma(1-\alpha_s-\beta_s)}P_s^{\sigma}Y_s \tag{25}$$

Substituting Equation (25) into Equation (24) gives:

$$P_{si}Y_{si} \propto \left[\frac{A_{si}(1-\tau_{y_{si}})}{(1+\tau_{k_{si}})^{\alpha_s}(1+\tau_{l_{si}})^{\beta_s}}\right]^{\sigma-1} \tag{26}$$

In words, if there are no distortions, more productive firms tend to be larger. If A_{si} and $1-\tau_{y_{si}}$ are negatively correlated, more productive firms tend to be smaller than their efficient size. Similarly, if A_{si} and $1+\tau_{k_{si}}$ are positively correlated, more productive firms tend to be smaller than their efficient size (and likewise for A_{si} and $1+\tau_{l_{si}}$). This implies that when there are distortions, the efficient size distribution is more dispersed than the actual size distribution.

In reality, apart from firm distortions, the distribution of TFPR may result from other frictions, such as overhead labour, quasi-fixed capital, firm-level demand and cost factors. Therefore, I also compute the Olley-Pakes covariance between TFPR and activity share as an alternative measure of misallocation as the prediction that more productive firms should be larger is robust to a wide range of models (Bartelsman, Haltiwanger, & Scarpetta, 2013). The presence of firm capital, labour and output wedges, as implied by Equation (24), essentially adds noise to the profitability of firms and thus reduces the correlation between productivity and size.

3. Data

This section describes New Zealand's Longitudinal Business Database, the parameters used to estimate the gains from resource reallocation derived in Section 2 and provides some basic descriptive statistics.

3.1. Statistics New Zealand's longitudinal business database

The Longitudinal Business Database (LBD) component of Statistics New Zealand's Integrated Data Infrastructure (IDI) contains a wide range of administrative and survey information on New Zealand businesses.[12]

The population of the LBD is all economically significant businesses.[13] I use an annual panel of firms, using financial information provided on a New Zealand tax year basis (April-March). I therefore refer to years by their end date (e.g. 2001 refers to the year ending March 2001).

I restrict the analysis to industries that are part of what Statistics New Zealand refers to as the 'measured sector'. The measured sector includes industries which are identified as mainly containing firms that are market producers (Statistics New Zealand, 2016), and in particular excludes government administration, education and training and healthcare and social assistance industries. I further restrict the analysis to private sector, for-profit firms.

The analysis is run on 45 industries. The level of industry disaggregation is chosen based on the availability of suitably disaggregated industry price indices and an adequate number of firms for each industry-year combination. I follow Fabling (2011) and repair firm identification links using plant-level employment information. I also assign each firm to one predominant permanent industry over its lifetime as outlined in Fabling and Maré (2015b).

Although the population of the LBD is all economically significant firms, the resulting dataset is not necessarily representative of all firms in the measured sector. This is due to limitations of data availability and coverage, especially for smaller firms (for details see Fabling & Maré, 2015b; Fabling & Sanderson, 2016).

I draw information from two main sources within the LBD: the Annual Enterprise Survey (AES) and IR10 tax forms. The preferred source of production measures is AES as this information is collected by Statistics New Zealand for the purpose of the production of National Accounts. The AES is a postal sample survey, supplemented with administrative data from tax sources. I use postal returns from AES to provide annual gross output and factor inputs for each firm's financial year. This information is available for around 10% of firms, but these are disproportionately larger firms, accounting for

around 50% of total employment in New Zealand. Where AES information is not available, I derive comparable measures from annual tax returns (IR10s).

Measures of gross output, capital input, labour input and intermediate input are used. I take the widely used approach in the HK literature of measuring labour input as the firm's total wage bill. Unfortunately, this information does not include non-wage labour compensation. However, in New Zealand, this is likely to be less problematic than in other countries as labour compensation tends to include a comparatively small non-wage component due to a relatively neutral labour income tax system.[14] An additional, and likely larger issue, is that labour compensation may not adequately account for the labour input of working proprietors. New Zealand has a high proportion of small firms with working proprietors. While some working proprietors pay themselves a wage/salary which will be captured in the wage bill measure, many receive other forms of working-proprietor income. Moreover, regardless of their form, these payments are most likely to be structured to minimise tax liabilities rather than reflecting working-proprietor labour input to the firm.

Hsieh and Klenow (2009) argues that the approach of using wages to measure labour input adjusts for differences across firms in hours worked and worker skill levels. However, they also note that firm-level wage differences could reflect rent sharing between the firm and its workers. If this is the case then differences in TFPR across firms (and therefore the HK measure of misallocation) could be understated because the most profitable firms have to pay higher wages. Indeed, there is empirical evidence for New Zealand and internationally that more successful firms do pay a firm-wage premium (over and above the worker-wage premium) (for example, see Card, Cardoso, Heining, & Kline, 2016; Maré, Sanderson, & Fabling, 2014). Surprisingly, Hsieh and Klenow (2009) find that using employment as the labour input measure tends to decrease the reallocation gains in China and India, suggesting that wage differences tend to amplify TFPR differences rather than limit them. Therefore, as a robustness test, I also use the sum of full-time-equivalent employees (FTEs) and working proprietors as an alternative labour input measure (see Appendix 1).[15]

For the calculation of capital input, I depart somewhat from most existing studies using the HK method, which typically measure capital input as capital stock net of depreciation. Instead, I use the approach of Fabling and Maré (2015b), which measures capital services as the average of opening and closing book value multiplied by a 10% user cost of capital plus reported depreciation, plus rental, hiring and leasing costs.[16] The inclusion of rental, hiring and leasing costs reflects that, ideally, all capital services, whether derived from rented or owned capital, should be included.

Each output and input component is deflated to 2007 prices. Gross output is deflated using industry producer output prices, intermediate inputs are deflated using industry producer input prices, wages are deflated using private sector labour costs and capital is deflated using the capital goods price deflator.[17]

The issue of working-proprietor labour input discussed above reflects a broader issue with working-proprietor-only firms, where measured capital and labour input are likely to reflect tax rules and suffer from greater measurement error. Due to these issues, only firms with non-zero employment are included in the analysis (i.e. working-proprietor-only firms are excluded). Despite this restriction, the data includes much smaller firms than much of the existing international literature in this area, where the analysis is often restricted to firms with more than 10 or 20 employees.

I also undertake two stages of data trimming. In the first stage, firms with non-positive values for gross output, capital inputs, labour input or intermediate inputs are dropped. In addition, observations with log changes in gross output, capital, labour or intermediate inputs of greater than 4 that arise from value changes of more than $50,000 for financial variables and more than 20 for employment (to allow for plausibly large growth rates for small firms).

In the second stage, most existing literature trims the 1% tails of the distributions of $\log(TFPR_{si}/\overline{TFPR}_s)$ and $\log(A_{si}/\bar{A}_s)$ for each year and then recalculates the relevant variables. However, this approach would eliminate about a quarter of the annual gross output for my dataset. This large proportion of gross output is because firms in the top 1% of the distribution are on average, several times larger than the other firms.[18] This also suggests that these firms' high productivity may

not simply be due to measurement error. Therefore, I take an approach which is closer to the method of Oberfeld (2013) and trim the 1% tails of each of the output, capital and labour distortions for each year.[19] All relevant variables are then recalculated.

Although the analysis is undertaken for 45 industries, most results are aggregated up to the total or sector level. Five main sectors are examined: primary, manufacturing, utilities, construction and services.[20]

It is important to note that due to different industry, firm and time coverage as well as differences in the trimming method, the results from this paper are not directly comparable to the results of other papers using the HK method. As discussed in Fabling and Sanderson (2014), international comparisons of firm-level analysis can be problematic and should be interpreted with caution.[21] However, where appropriate, some broad comparisons to existing international literature are drawn.

3.2. Key parameters

In order to measure the effects of resource misallocation, some key parameters need to be set. First, the elasticity of substitution parameter, σ, is set to 3, following the standard approach in the HK literature. However, empirical estimates of industry markups usually suggest higher values of σ. For example, Christopoulou and Vermeulen (2012) suggest higher values for σ for both the Euro area and the US, which implies that using $\sigma = 3$ will give conservative estimates of the potential gains from improving allocative efficiency. Moreover, robustness tests using different values for this parameter result, as expected, in changes in the level of estimated efficiency gains, but does not qualitatively change the trends over time or the differences across sectors.

Another potential issue is the possibility of industry-specific elasticities of substitution. If σ differs across industries, this may be problematic for comparisons of the efficiency of resource allocation across industries. Due to this issue, Benkovskis (2015) departs from other HK literature and estimates σ for each industry, and finds that σ for a typical Latvian industry is close to 6.5, but that this value varies considerably across industries. In contrast, Dias, Robalo Marques, and Richmond (2016a) (using evidence from an early version of Amador and Soares (2018)) concludes that while σ varies across industries, there is no significant difference between the average estimates of σ for the manufacturing and services sectors in Portugal, and therefore assumes that σ is constant across industries.

Applying the same approach as Amador and Soares (2018) to New Zealand firm-level data, MBIE (2016) suggests that New Zealand is similar to Latvia, with manufacturing industries tending to have, in general, higher elasticities of substitutions and lower markups. While estimating and applying industry-specific σ is left for future work, the possible implications of this assumption for the interpretation of sector-level misallocation are discussed in Section 4.

An additional issue relating to σ is that it may vary over time, therefore affecting the interpretation of temporal changes in misallocation. While this does not appear to have been addressed in the HK literature to date, evidence from Amador and Soares (2018) suggests that the elasticity of substitution in some Portuguese industries (particularly non-tradable ones) decreased during the 2000-2009 period. However, this consideration may be less of a concern in New Zealand as MBIE (2016) finds relatively stable elasticities over the 2000–2010 period.

As discussed, I use the total wage bill in my baseline calculations, that is, $L_{si} = W_{si}H_{si}$ and $W_s = 1$, where H_{si} stands for the number of workers, and W_{si} is the firm-specific average wage rate. For intermediate inputs, I take a similar approach and assume that the price of intermediate products, Z_s is equal to 1, so that the expenditure on intermediate inputs reflects not only the amount of inputs but also their quality. While we cannot observe the equivalent of the total wage bill or total intermediate input spending for capital, we do observe firm-level depreciation and rental, hiring and leasing costs, so in this sense, each firm does face a firm-level rental price of capital. Thus, I take the same approach as with labour and intermediate inputs, and set $K_{si} = R_{si}S_{si}$, where $R_{si}S_{si}$ is set equal to the average

of opening and closing book value multiplied by a 10% user cost of capital less reported depreciation plus rental, hiring and leasing costs, and R_s is set to one.

The capital and labour factor shares, α_s and β_s, are set to the relevant industry-level factor shares for the United States. As discussed in Hsieh and Klenow (2009), it is not possible in the model used to separately identify the average input distortions (i.e. the average wedges) and the input elasticities in each industry. Thus, using factor shares from the US economy is a simple way to control for distortions that could affect the input shares in the New Zealand economy, while the US is taken as a benchmark of a relatively undistorted economy.[22]

As is evident from Equation (5), I follow the usual approach of assuming constant returns to scale, so the intermediate input share is $(1 - \alpha_s - \beta_s)$. Extending the method to allow for non-constant returns to scale, and using Levinsohn and Petrin (2003)'s method to estimate production functions, Gong and Hu (2016) estimate that manufacturing industries in China have, on average, decreasing returns to scale. They find that relaxing the constant-returns-to-scale assumption in the HK model lowers the estimates of the extent of misallocation in China. For New Zealand, Cobb-Douglas fixed-effects production function regressions estimate returns to scale of about one on average, which suggests this may not be a large issue. However, for New Zealand, returns to scale estimates do vary somewhat by industry, and may differ if alternative production estimation methods are used.[23] Future work may involve estimating production functions using structural approaches to obtain factor shares rather than using US factor shares, and applying Gong and Hu (2016)'s extension of the HK method.

3.3. Basic descriptives

The final sample has about 87,000 to 101,000 firms a year (Table 1). The services sector accounts for the majority of the firms in the sample, with the share rising from about 56 percent in 2001 to 60 percent in 2012. However, the services sector accounts for a lower share of gross output due to the smaller average size of these firms (about 44 percent of gross output in 2001, increasing to 46 percent in 2012) (Table 2). The primary sector accounted for about 22 percent of firms in 2001, dropping to 17 percent in 2012. However, the primary sector's share of gross output increased over this period (from about 6 percent to about 7 percent). Construction accounted for a growing share of firms - 11 percent in 2001 and rising to 14 percent in 2012 - as well as a growing share of gross output. The share of firms in the manufacturing sector dropped from about 10 percent in 2001 to about 9 percent in 2012, as did its share of gross output (from 37 percent in 2001 to 31 percent in 2012). Utilities accounted for only a very small share of firms, at around 0.3 percent, but a greater share of gross output (about 5 percent).

Table 1. Number of firms by year and sector.[a,b]

Year	Primary	Manufacturing	Utilities	Construction	Services	Total
2001	18,930	9,012	297	9,915	48,684	86,838
2002	18,960	9,051	312	10,023	49,128	87,474
2003	18,981	9,411	303	11,007	51,609	91,311
2004	18,393	9,549	315	11,952	52,860	93,069
2005	17,685	9,684	318	13,056	54,870	95,610
2006	17,028	9,813	321	14,208	56,028	97,398
2007	16,815	9,711	318	14,877	57,000	98,718
2008	16,614	9,744	348	15,726	58,722	101,157
2009	16,341	9,369	348	15,222	57,873	99,150
2010	16,125	8,991	324	13,827	55,902	95,169
2011	15,468	8,739	324	13,428	55,728	93,684
2012	15,198	8,256	312	13,083	54,207	91,053

[a] All figures are randomly rounded to base 3, in accordance with Statistics New Zealand confidentiality requirements. Columns may not add to the totals due to rounding.
[b] See endnote 20 for details of the industries included in each of the sectors.

Table 2. Sector share of gross output by year (%).[a]

Year	Primary	Manufacturing	Utilities	Construction	Services
2001	5.71	37.04	5.25	8.30	43.69
2002	5.91	38.19	4.87	8.15	42.88
2003	6.57	36.21	5.23	8.81	43.19
2004	6.19	36.48	4.77	9.08	43.48
2005	6.14	34.54	5.40	9.95	43.97
2006	5.84	34.55	5.03	10.62	43.96
2007	5.84	32.96	5.33	10.88	44.98
2008	6.52	31.93	5.71	10.52	45.32
2009	6.23	32.48	5.78	10.73	44.77
2010	6.43	32.41	5.44	9.50	46.22
2011	6.44	32.17	5.65	9.65	46.09
2012	6.81	31.35	5.58	10.01	46.25

[a]See endnote 20 for details of the industries included in each of the sectors.

Table 3. Gross-output gains from optimal resource allocation by sector.[a,b]

Year	Primary	Manufacturing	Utilities	Construction	Services	Total
2001	44.20	34.98	17.70	29.01	54.17	42.03
2002	42.67	34.44	20.40	31.58	44.69	38.24
2003	55.42	15.40	23.85	30.98	43.56	31.25
2004	39.89	23.54	24.91	40.13	60.09	41.02
2005	48.56	16.01	16.62	34.17	41.46	30.43
2006	42.97	41.17	18.45	32.20	45.92	41.10
2007	75.28	14.45	15.94	37.37	41.30	31.68
2008	77.23	17.51	18.51	31.44	42.57	33.38
2009	96.77	18.62	29.28	27.96	43.50	35.08
2010	87.91	14.79	27.45	29.88	43.64	33.74
2011	69.37	15.78	35.66	30.48	42.54	33.29
2012	61.82	15.71	41.10	34.73	41.01	33.18

[a]Calculated as $(Y^*/Y - 1) * 100$ where (Y^*/Y) is given in Equation (17).
[b]Results use the wage bill as the labour input measure (as defined in Section 3).

4. Results

This section presents the results from applying the three-factor HK method to New Zealand data. First, it presents the main results over time and by sector. It then looks at the Olley-Pakes covariance as an alternative measure of allocation. Then, some implications of the HK results for the firm-size distribution are drawn. Finally, the HK results are decomposed into contributions from output, capital and labour distortions.

4.1. Main HK results

This sub-section provides the main results from applying the three-factor HK method to New Zealand firm data. In aggregate, the potential gross-output gains from optimal within-industry resource allocation are around 35 percent on average (Table 3, 'Total' column). The potential value-added gains are much larger, at about 83 percent on average (Table 4, 'Total' column). The large difference between gross-output and value-added gains is unsurprising given Equation (18), which implies that even small gains in terms of gross output may imply large value-added gains, particularly in industries where intermediate inputs are a large proportion of gross output. The differences between gross-output and value-added results are similar in magnitude to those found in Dias et al. (2016b) using Portuguese data, where an economy-wide gross-output gain of 28 percent translated into value-added gains of 79 percent.

Table 4. Value-added gains from optimal resource allocation by sector.[a,b]

Year	Primary	Manufacturing	Utilities	Construction	Services	Total
2001	104.12	104.50	36.31	99.33	110.96	102.16
2002	101.70	104.92	45.75	108.60	86.84	91.88
2003	127.47	50.99	53.83	104.54	83.18	75.61
2004	91.67	77.07	49.93	141.71	114.09	98.40
2005	108.18	54.11	35.97	120.79	78.39	73.25
2006	93.07	128.11	41.08	109.39	83.49	94.78
2007	161.73	48.62	42.29	117.20	75.62	74.44
2008	173.59	60.03	45.64	97.48	75.70	76.89
2009	259.96	59.47	94.47	82.66	79.70	82.82
2010	215.23	48.06	75.06	83.42	78.30	77.10
2011	192.05	48.53	105.15	85.74	74.29	74.76
2012	160.18	52.39	124.23	95.15	71.12	75.07

[a]Calculated as $(V^*/V - 1) * 100$ where (V^*/V) is given in Equation (19).
[b]Results use the wage bill as the labour input measure (as defined in Section 3).

4.1.1. Trends over time

The economy-wide potential gains from optimal resource allocation have fallen over time, suggesting that the overall allocation of capital, labour and intermediate inputs across firms within the same industry has improved somewhat over time. Therefore, it appears that worsening within-industry resource allocation has not contributed to New Zealand's slowing aggregate productivity growth over the 2000s.[24] For gross-output, the gains fell from around 42 percent in 2001 to 33 percent in 2012, while the value-added gains fell from 102 percent in 2001 to 75 percent in 2012.[25]

However, the overall decrease in aggregate potential gains over time does not reflect an improvement in allocation across all sectors. Rather, the decrease in aggregate potential gains reflects improved resource allocation in the two largest sectors: manufacturing and services. Potential gains in the manufacturing sector have decreased from 35 percent in 2001 to less than half this initial amount in 2012 (16 percent). In the services sector, output gains have fallen from 54 percent in 2001 to 41 percent in 2011. In contrast, potential output gains in the primary sector have increased over time, reaching a peak of 97 percent in 2009, suggesting that resource allocation has worsened over time in this sector. Similarly, potential gains in the utilities sector have increased, more than doubling from about 18 percent in 2001 to over 40 percent in 2012, although with a significant amount of fluctuation over time (which could be, at least in part, due to the relatively small number of firms in this sector). Therefore, worsening within-industry resource allocation may have contributed to the productivity slowdown in the primary and utilities sectors. There is no clear trend for the construction sector, with the trend oscillating around an average of about 33 percent.

It is difficult to explain the changes in potential gains from resource allocation over time. There may be a cyclical element to the trends, especially given the relatively short timeframe examined.[26] However, it is an open question whether or not reallocation dynamics following recessions generally have a 'cleansing' effect. Recessions could accelerate the pace of productivity-enhancing reallocation by increasing the exit rate of low-productivity firms and allowing those resources to shift towards higher-productivity firms, or they could extend the life of low-productivity 'zombie' firms and thereby hinder reallocation. The existing empirical evidence generally suggests that misallocation tends to be pro-cyclical. For example, Foster, Grim, and Haltiwanger (2016) finds that downturns are periods of accelerated productivity-enhancing reallocation, although reallocation in the Great Recession was less productivity-enhancing than in prior recessions. In addition, examining five large euro area countries, Gamberoni et al. (2016) finds that misallocation tends to increase during upturns.

The cyclical explanation does not appear to be particularly applicable to the case of the New Zealand manufacturing and services sectors, as misallocation was decreasing even before the Great Recession in these sectors. However, it may be more applicable to the primary sector, where misallocation was increasing in the lead up to the Great Recession, and decreased subsequently. It is

also notable that agricultural credit increased markedly before the Great Recession, accompanied by falling real interest rates and increasing rural land prices.[27] International work, such as Gopinath et al. (2015), suggests that expanding credit can result in an increase in capital misallocation if, for example, it means that the credit going to low-productivity but high-collateral firms increases relative to the credit going to high-productivity but low-collateral firms.

Looking to international studies for possible explanations of the New Zealand time trends, those that examine transition countries such as the Ukraine (Ryzhenkov, 2015) and developing countries such as China (Hsieh & Klenow, 2009) and Costa Rica (Alfaro Ureña & Garita Garita, 2018) generally find improved resource allocation over time. This is perhaps unsurprising given liberalisation, improvements in regulatory settings and financial sector development in these countries.[28] However, this explanation is less applicable to New Zealand, where the estimated improvement in resource allocation over the 2000s is generally smaller than that of developing countries and major economic reforms occurred prior to the period under investigation.

The results for developed countries are more mixed, although worsening allocation over time seems to be the more common finding. For example, García-Santana, Moral-Benito, Pijoan-Mas, and Ramos (2016) and Dias et al. (2016b) find worsening resource allocation across all sectors in Spain and Portugal respectively, and Calligaris (2015) finds worsening allocation in Italy's manufacturing sector. Korea exhibits a pattern consistent with the general trends for both developing and developed country, with misallocation decreasing during the 1980s and early 1990s, as the economy exhibited strong income per capita convergence, but misallocation increasing in more recent years (Kim, Oh, & Shin, 2017).

However, the reasons behind these trends for developed countries are generally less clear. For example, Dias et al. (2016b) states that it is not easy to identify the reasons behind increasing within-industry misallocation among Portuguese firms. However, Kim et al. (2017), Dias et al. (2016b), García-Santana et al. (2016) and Calligaris (2015) all find that distortions are greater among small and young firms. In addition, these papers find that the importance of capital distortions has increased among Portuguese and Spanish firms, suggesting that the financial sector may have contributed to the survival of many small and relatively inefficient firms. As discussed in Section 1, this is also consistent with other strands of literature such as Barnett et al. (2014) and Gopinath et al. (2015).

For New Zealand, the decompositions presented in Section 4.4 are a first pass at addressing the question of what factors might be driving the changes in the efficiency of resource allocation over time. Future work may provide more insights into this question by looking at the relationship between distortions and firm- and industry-level characteristics.

Another possibility in the case of New Zealand that could be explored in subsequent work is the role of input prices. For example, Sandoz (2017) extends the three-factor HK model to include imported intermediate goods in order to study the effect of falling intermediate input prices, particularly due to increased imports from China, on resource allocation in France. The paper finds that that a one percentage point increase in intermediate inputs from China raises TFP growth in France by 0.2 percentage points due to improved resource allocation. New Zealand has also experienced growth in imports from China, which have been particularly strong since 2000 (see, for example, Carroll, 2012). While this is a possibility that would need to be investigated further, it could have contributed to the improving resource allocation in New Zealand.

4.1.2. Misallocation by sector

The level of potential gains in New Zealand also vary by sector. Potential gains in the primary and services sectors are generally higher than in the manufacturing, utilities and construction sectors. These cross-sector differences in magnitude should be interpreted with some caution, however, since the possibility that the value of σ varies across industries is not taken into account here. In particular, available evidence suggests that the elasticity of substitution is higher on average in manufacturing than the services sector (MBIE, 2016). Assuming that σ is constant across industries may, therefore, underestimate misallocation in the manufacturing sector relative to the services sector.

Despite this limitation, the results seem sensible and in line with international evidence. Although the vast majority of studies using the HK method examine the manufacturing sector only, those that do examine both the manufacturing and non-manufacturing sectors find that the opportunities for resource allocation improvements are greater in non-manufacturing sectors, and in particular, the services sector. For example, studies on Spain (García-Santana et al., 2016) and Portugal (Dias et al., 2016b) find that misallocation is higher in the services sector than manufacturing. An exception to this general finding is Alfaro Ureña and Garita Garita (2018) for Costa Rica. However, as that paper notes, this may be due to the exclusion of informal firms from the analysis - at 41% of the labour market, informality in Costa Rica is high by developed-country standards, and is more prevalent in the services sector, which likely means that misallocation in that sector is underestimated relative to manufacturing.

These results are also consistent with the idea that market distortions are likely to have a stronger impact in terms of resource misallocation in the services sector than in the manufacturing sector. Duarte and Restuccia (2010) suggest that this is because the degree of competition is lower in the services sector than in manufacturing. Services are less tradable (both within a country as well as internationally) than manufactured products, which limits the extent of the market and therefore competition in the services sector. Moreover, service industries are often more heavily regulated.

4.1.3. International comparisons

Keeping in mind the issues of international comparisons discussed in Section 3, the results from applying the three-factor HK model to New Zealand data are similar (albeit slightly higher) to those found for Portugal. As mentioned, the average gross-output gains for New Zealand are 35 percent, compared 28 percent for Portugal; and average value-added gains for New Zealand are 85 percent versus 79 percent for Portugal.

It is difficult to compare the magnitude of potential gains for New Zealand to other international findings as these tend to look at potential value-added gains using the original two-factor version of the HK model. As discussed in Dias et al. (2016b), the three-factor model tends to deliver higher value-added gains than the two-factor model. However, as a reference point, Hsieh and Klenow (2009)'s original paper found that potential within-industry allocative efficiency gains in US manufacturing were about 36 percent in 1998, growing to about 43 percent in 2005, and that China and India had significantly higher levels of misallocation, with potential gains of 100–128 percent for India and 87–115 percent for China. Indeed, perhaps unsurprising, studies that examine transition and developing economies using the HK method generally find that these countries have considerably higher misallocation than the US. For example, Latin American economies (Busso, Madrigal, & Pagés, 2013), the Ukraine (Ryzhenkov, 2015), Bolivia (Machicado & Birbuet, 2012) and Thailand (Dheera-Aumpon, 2014). However, this is not generally the case for studies that look at developed countries, with some studies finding a higher degree of misallocation than the US (such as Calligaris, 2015, for Italy), while others find a similar or even somewhat lower degree of misallocation. For instance, Bellone and Mallen-Pisano (2013) finds that the level of measured misallocation in France is similar to the US. As a result, they suggest that the HK method may be useful for detecting large efficiency gaps between developing and developed countries, but may not do a good job at discriminating among developed countries.[29] For this reason, as well as the more general difficulties of making international comparisons, it is important not to read too much into the slightly higher potential gains in New Zealand compared with Portugal.

4.2. Olley-Pakes: an alternative measure

An issue with the HK method is that changes in the dispersion of TFPR might arise from other frictions apart from idiosyncratic distortions. For instance, differences in firm TFPR can arise due to overhead labour or quasi-fixed capital (see Bartelsman et al., 2013). An additional advantage of the

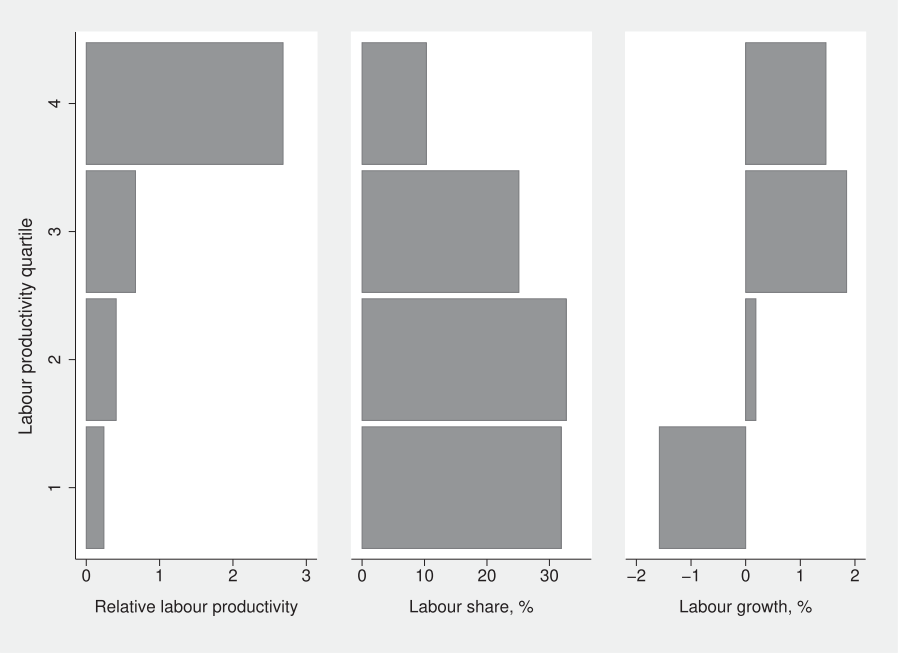

Figure 2. OP allocation by labour productivity quartile.

Notes: The highest productivity quartile is '4', the lowest is '1'. 'Relative labour productivity' is the average productivity for firms within each quartile in the industry relative to the industry unweighted mean, summed over industries using industry labour input weights, and averaged across years. 'Labour shareï£¡ï£¡ is the share of total labour input in each quartile. 'Labour growth' is labour growth by quartile less total labour growth.

Olley-Pakes method is that it can be used to investigate both labour productivity and TFP. Therefore, this subsection presents (Olley & Pakes, 1996) covariances as an alternative measure of misallocation.

The Olley-Pakes method involves computing the covariance between firm-specific production shares and productivity. As discussed in Section 2, there is a link between the HK and Olley-Pakes measures as both methods imply that under an efficient allocation of resources, more productive firms should be larger than less productive firms.

The first two columns of Figures 2 and 3 are graphical representations of the Olley-Pakes measures for labour productivity and TFPR. These columns show the productivity differences across quartiles of the productivity distribution and production shares by productivity quartile. The production shares are measured using labour input in the case of labour productivity and gross output in the case of TFPR.[30] More specifically, for each quartile of the productivity distribution, the first column shows the average productivity of firms within that industry and quartile relative to the overall average firm productivity for that industry. The second column shows the share of labour input (gross output) for firms in each labour productivity (TFPR) quartile. As discussed, the Olley-Pakes measure suggests that the labour input (gross output) shares should be larger for higher labour productivity (TFPR) quartiles.

However, the Olley-Pakes measure is static in the sense that it only looks at whether more productive firms are larger at a particular point in time. Intuitively, if there are few or no impediments to resource reallocation, economies should exhibit the tendency for more productive firms to have faster-than-average growth over time, and for less productive firms to shrink or exit. To get a more dynamic view of these developments, Figures 2 and 3 also show the growth rates of firms by productivity quartiles. Specifically, the third column shows the growth of labour input (gross output) for firms in each quartile of lagged labour productivity (TFPR).

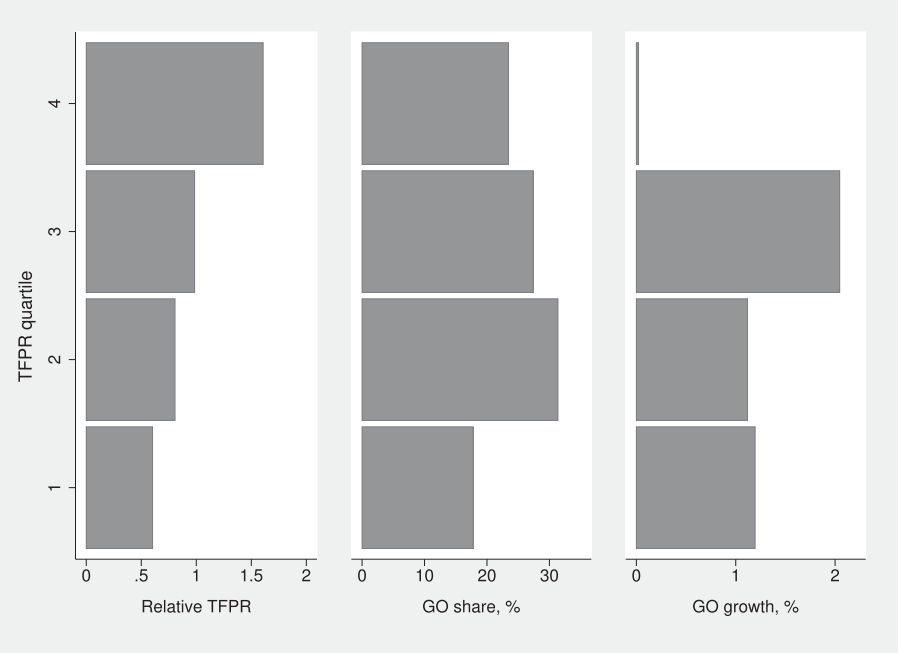

Figure 3. OP allocation by TFPR quartile.

Notes: The highest productivity quartile is '4', the lowest is '1'. 'Relative TFPR' is the average productivity for firms within each quartile in the industry relative to the industry unweighted mean, summed over industries using industry gross-output weights, and averaged across years. 'GO share' is the share of total gross output in each quartile. 'GO growth' is GO growth by quartile less total GO growth.

The first column of Figure 2 shows that there is a wide distribution of labour productivity. The top quartile of firms in the labour productivity distribution are about 2.7 times more productive than the average firm in the same industry, while those in the bottom quartile have productivity that is only about 0.24 of the average. Although it is not possible to compare this distribution directly with results for other countries due to differences in data and coverage, this pattern also appears in other countries, albeit to varying degrees (for example, see Bartelsman, 2013).

Turning to the second column of Figure 2, as mentioned, the intuitive interpretation of the Olley-Pakes measure is that more productive firms should have greater market share. Bartelsman (2013) shows that this holds empirically for many countries, although for some countries such as the UK, the lowest labour productivity quartile actually accounts for the largest share of labour input. In this respect, New Zealand appears to have similar characteristics as the UK, with the bottom two quartiles accounting for the majority of the labour input (about 65 percent), and the highest productivity quartile accounting for the smallest share (about 10 percent). Conway (2018) suggests that this result reflects weak competition that allows low-productivity firms to survive, in addition to the size constraints for relatively productive firms operating in New Zealand's small domestic market.

The third column of Figure 2 shows the labour input growth by productivity quartiles, and this presents a most positive view on reallocation within the New Zealand economy. The top two quartiles of the productivity distribution have the fastest growth in labour input, while the labour input of firms in the lowest quartile is shrinking.

Figure 3 shows that average TFPR by TFPR quartile follows the same general pattern as labour productivity, although the differences across the quartiles are less stark. The TFPR of the top quartile is about 1.6 times larger than the average TFPR, and the bottom quartile is about 0.60 of the average. Turning to the share of gross output by TFPR quartile, the bottom quartile has the lowest share of gross output. However, both the second and third quartiles have larger shares than the top quartile.

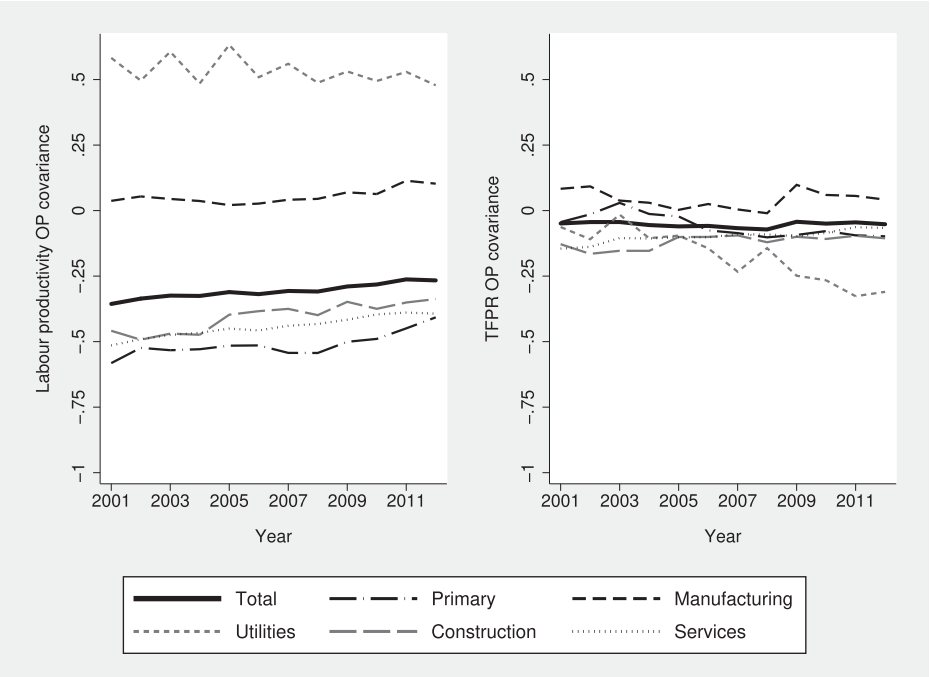

Figure 4. Olley-Pakes covariance over time.

Notes: See endnote 31 for details.

Figure 3 also shows that the top quartile has much lower gross output growth than the other quartiles, with the second highest quartile exhibiting the fastest output growth.

A more formal way to present the results in Figures 2 and 3, as well as investigate changes over time, is via the Olley-Pakes covariance measure. Figure 4 shows the labour productivity and TFPR Olley-Pakes covariances over time and by sector. This measure is calculated as the covariance between firm-specific production shares and productivity. These covariances are calculated at the industry level and aggregated up to the sector level.[31]

For the total measured sector, both the labour productivity and TFPR Olley-Pakes covariance are negative. The labour productivity covariance is particularly negative, reflecting the relationship seen in Figure 2 whereby firms with lower labour productivity had a higher share of labour input. However, the labour productivity covariance has become less negative over time, suggesting an improvement in resource allocation over time. The TFPR covariance has been flat over time, which suggests little change in resource allocation over time (whereas the HK measure suggested a small improvement over time).

Looking across sectors, according to the Olley-Pakes labour productivity covariance, allocation is worst in the primary sector, followed by the services sector and manufacturing, then construction and best in the utilities sector. According to the TFPR covariance measure, allocation is best in the manufacturing sector. The better allocation in the manufacturing sector compared with other sectors is consistent with the HK measure discussed above. However, allocation in the primary sector looks better relative to the other sectors by the Olley-Pakes TFPR covariance measure compared with the earlier HK results.

4.3. Implications for the firm size distribution

As discussed, Equation (26) suggests that, over time, a shift in the size distribution is driven by changes in the distribution of both physical productivity and idiosyncratic distortions. The distribution of

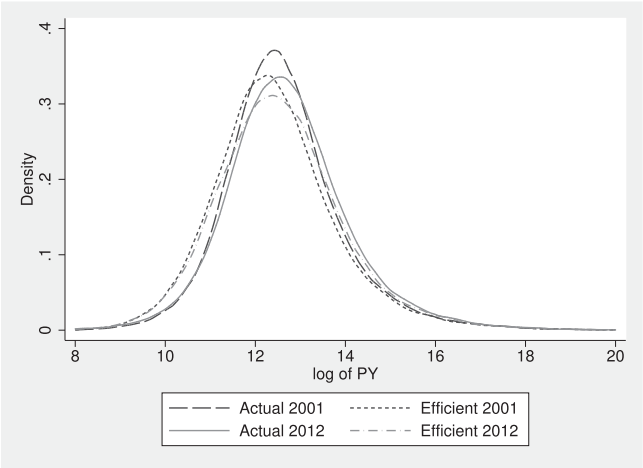

Figure 5. Firm size: Actual versus efficient size distributions, 2001 and 2012.
Notes: Extreme tails of the distribution have been truncated for confidentiality reasons.

physical productivity determines the efficient size distribution, and the idiosyncratic distortions determine the gap between the actual and efficient size distribution.[32]

Looking first at the efficient size distribution, Figure 5 shows that the efficient size distribution for the total economy has become wider over time. This appears to be mostly due to a stretching of the right tail, which suggests that firms with initially higher productivity (relative to the industry average) grew faster.[33]

Turning to the gap between the actual and efficient firm size distribution, as discussed in Section 2, with the HK method, when there are distortions, the efficient size distribution is more dispersed than the actual size distribution, and this is indeed what we observe in Figure 5. An interesting feature of Figure 5 is that it suggests that small firms are generally too large given their level of TFPR (or equivalently, that their level of TFPR is too low given their size). That is, given their level of TFPR, small firms tend to over-produce relative to their efficient level. This result is also found for Chile (Chen & Irarrazabal, 2015), the Ukraine (Ryzhenkov, 2015), Colombia, El Salvador and Mexico (Busso et al., 2013). The general explanation given for this result is that small firms are subsidised (either implicitly or explicitly), for example, through size-contingent policies or less stringent enforcement of tax collection or of other regulations. This argument is more difficult to make for New Zealand, which lacks explicit size-contingent policies and where the case that enforcement is more lax for small firms is harder to make.[34]

It is possible, however, that there are other distortions (or frictions) that result in small firms being larger than their efficient size.[35] For instance, some commentators note that many small firms in New Zealand are closely-held businesses that may be financed by securing a mortgage against the owners' residential property. That is, small, closely-held businesses may be able to borrow at mortgage rates which are likely to be lower than business rates due to the differences in the risk premia. Or it may be that firms that have low TFPR are able to grow bigger than optimal due to a limited extent of the market and a lack of competition. This ability for firms to grow larger than their TFPR levels would dictate also seems to be consistent with the comparatively poor 'up-or-out' dynamic among New Zealand firms. For example, Criscuolo et al. (2014) finds that New Zealand has a high proportion of small, old firms which suggests that the competitive pressure to improve and grow, or shrink and eventually exit, may not be strong in New Zealand as it is in most other OECD countries.

As a first step in investigating these possibilities further, these distributions are broken down by sector, with a particular focus on comparing the manufacturing and services sector (Figure 6). First,

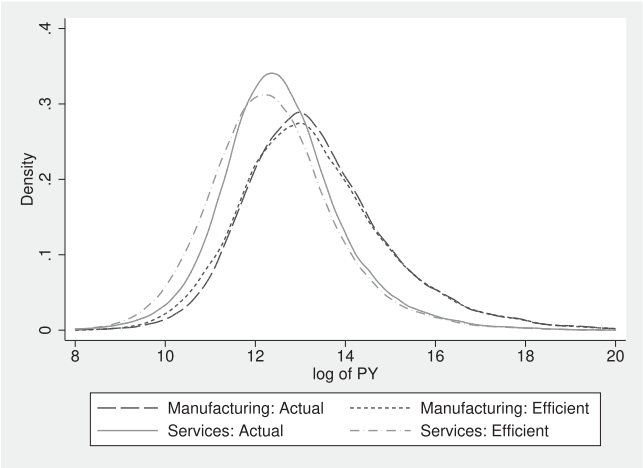

Figure 6. Firm size: Actual versus efficient size distributions, manufacturing and services (all years).
Notes: Extreme tails of the distribution have been truncated for confidentiality reasons.

the average manufacturing firm is larger in terms of both actual and efficient size than the average service firm. This is to be unsurprising given that manufacturing firms serve a larger market given the more tradable nature of their output.[36] More interestingly, there are very few manufacturing firms that are larger than their efficient size. That is, the overall gap between actual and efficient size is mainly driven by non-manufacturing firms, and in particular, those in the services sector.[37] In order to investigate the possible reasons for these sector differences, future work could look into sector and industry differences in more detail, for example, by assessing whether there is a relationship between industry characteristics (such as the degree of tradability) and the differences between actual and efficient size.

In addition, to gain more insights into the contribution of firms with different characteristics, including small firms, to the overall level of misallocation, future work may look at the relationship between distortions and firm characteristics. For example, García-Santana et al. (2016) finds that young and small firms are potential sources of the increase in misallocation in Spain. Similar, Calligaris (2015) finds that misallocation in Italy is higher among small and young firms, as well as firms located in southern Italy and firms that operate at low-technology intensity. In contrast, Dheera-Aumpon (2014) finds that mid-sized firms face higher distortions than small firms in Thailand.

4.4. Decomposing the HK results

I now decompose the HK measure of misallocation into the contribution of various components. Figure 7 decomposes the approximate TFP gains from efficient resource allocation into output distortion variance, capital distortion variance, labour distortion variance and the covariances between each of the distortions using Equation (23).

Output distortion variance and labour distortion variance are the largest components of the total distortion. The output distortion variance has increased a little over time while the labour distortion variance has decreased. While the capital distortion variance component is much smaller than the output and labour distortion variance components, it is steadily increasing over time. The covariance between output and labour distortions is positive, meaning that high output distortions are usually accompanied by high labour distortions. The covariance between output and capital distortions is also positive, but much smaller than the covariance between output and labour distortions. The covariance between output and labour distortions is positive but small.

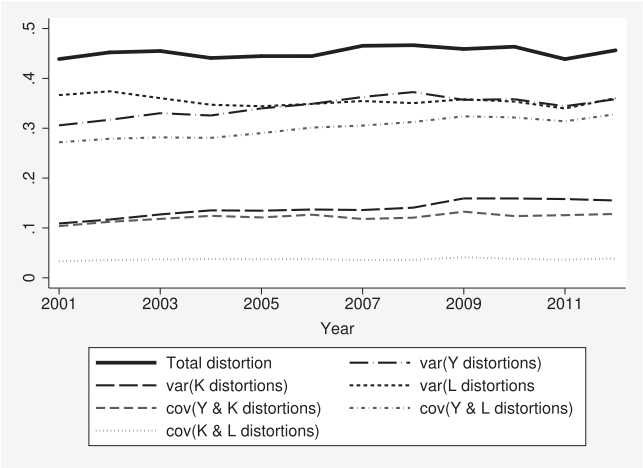

Figure 7. Decomposition of potential TFP gains: Total economy.

Notes: Calculated using Equation (23). var(Y distortions) $= (\sigma/2)\text{var}[\log(1-\tau_{y_{si}})]$; var(K distortions) $= ((\alpha_s^2(\sigma-1)+\alpha_s)/2)\text{var}[\log(1+\tau_{k_{si}})]$; var(L distortions) $= ((\beta_s^2(\sigma-1)+\beta_s)/2)\text{var}[\log(1+\tau_{l_{si}})]$; cov(Y & K distortions) $= \sigma\alpha_s\text{cov}[\log(1-\tau_{y_{si}}), \log(1+\tau_{k_{si}})]$; cov(Y & L distortions) $= \sigma\beta_s\text{cov}[\log(1-\tau_{y_{si}}), \log(1+\tau_{l_{si}})]$; cov(K & L distortions) $= (\sigma-1)\alpha_s\beta_s\text{cov}[\log(1+\tau_{k_{si}}), \log(1+\tau_{l_{si}})]$. Components are the weighted mean across industries, where θ_s is used for the weights.

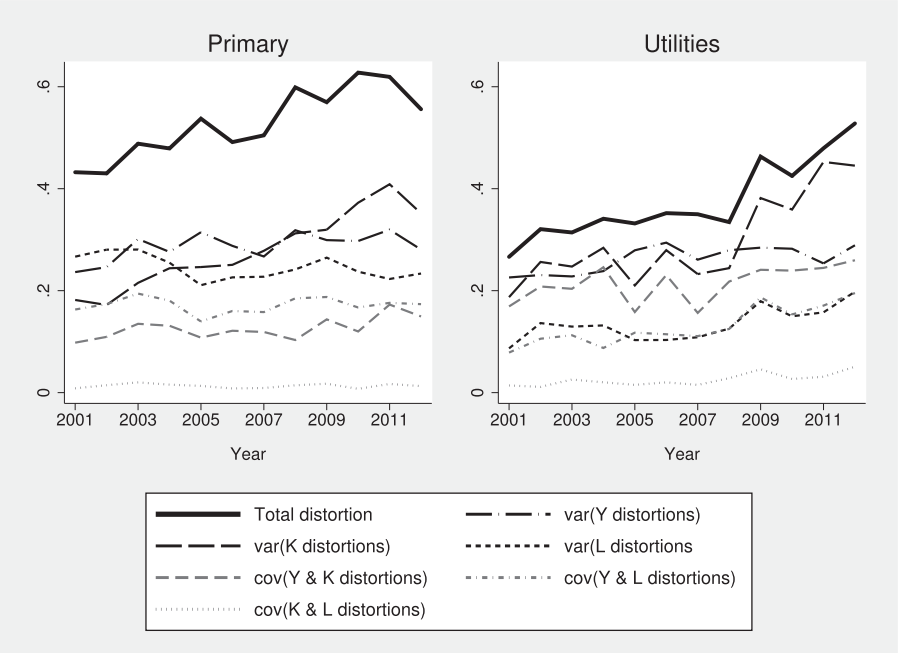

Figure 8. Decomposition of potential TFP gains: Primary and utilities sectors.

Notes: See notes to Figure 7.

As noted above, potential output gains in the primary and utilities sectors have increased over time. Decomposing the HK measure of misallocation for these two sectors shows that the variance in capital distortions is a large and growing component (Figure 8), suggesting a potentially important role of increased capital misallocation in these sectors. Output distortions have also increased in both of these sectors, but to a less extent than the increase in capital distortions. Some of the covariances between

distortions have also increased, for example, the covariance between output and capital distortions has increased in both sectors, suggesting that distortions have become more interdependent over time.

5. Conclusion

TFP growth in many countries, including New Zealand, has slowed in recent years, with this slowdown preceding the onset of the Great Recession. Some international studies suggest that worsening resource allocation may be one of the culprits behind this slowdown. To investigate this possibility for New Zealand, this paper applies a three-factor extension of the Hsieh and Klenow (2009) (HK) model to firm-level data from 2001–2012. This model measures the efficiency of within-industry resource allocation and the extent to which output, capital and labour distortions lower aggregate TFP and output.

This paper finds that gross output could have been about 35 percent higher if there were no distortions in resource allocation. However, total resource allocation does not appear to have worsened over time. Rather, resource allocation actually improved slightly over the period examined.

It also finds that potential output gains from improved resource allocation are greater in the services sector than in manufacturing, which is consistent with international studies using the HK method. However, allocation has improved over time in both the manufacturing and services sectors, while it has worsened in the primary and utilities sectors, resulting in the overall slight improvement for the total economy.

A comparison of the actual and efficient size distributions suggests that many small firms are too large. That is, given their level of TFPR, many small firms tend to over-produce relative to their efficient level of output. The general explanation given for this result internationally is that small firms are subsidised through vehicles such as size-contingent policies and less stringent enforcement of tax and regulations. Given the policy environment, this argument is harder to make for New Zealand. Instead, I speculate that low-productivity New Zealand firms are able to grow larger than their optimal size due to the limited extent of the market and a lack of competition. In order to investigate this possibility further, future work could look the relationship between industry characteristics (such as the degree of tradability) and the HK distortion measures. It could also be argued that this finding is consistent with previous research that highlights the lack of 'up-or-out' dynamics among New Zealand firms. This possibility could be investigated further by looking at the relationship between the HK measures and firm characteristics. For example, this could shed light on the role of capital distortions among young, credit-constrained firms.

Notes

1. Statistics New Zealand productivity data are available for the 'former measured sector' (which includes ANZSIC06 industries AA-LL1) from 1978 onwards, and for the 'measured sector' (which includes ANZSIC06 industries AA-LL1, MN and RS) from 1996 onwards (for details see Statistics New Zealand, 2014). The data presented here are spliced series for the former measured sector up to 1995 and the measured sector from 1996. However, the general trends are similar if the former measured sector is used for the entire period.
2. See Conway (2018) for a broader discussion of New Zealand's productivity underperformance, the economic reasons behind this underperformance, and policy directions for improvements.
3. However, it should be noted that the productivity slowdown discussed above and examined in Conway and Meehan (2013) uses Statistics New Zealand official industry and aggregate productivity series. These official series are based on value-added productivity, whereas the current paper uses gross-output productivity (official gross-output productivity series for New Zealand are not available currently).
4. While it would have been preferable to examine misallocation and productivity over a longer time period, and in particular, to compare the 1990s with the 2000s, at the time of writing, appropriate firm-level data were only available from 2001 to 2012.
5. Throughout this paper, I use the Statistics New Zealand convention of referring to a broad grouping of industries as a sector.

6. An additional advantage is that it allows for firms with legitimately negative value added to be included in the analysis. The exclusion of these firms in the two-factor model is a potential source of bias.
7. This is equivalent to Hsieh and Klenow (2009) setting the scaling factor $\kappa_s = (P_s Y_s)^{-1/(\sigma-1)}/P_s$ to 1.
8. This point is relevant for goods and services that are less tradable, particularly for New Zealand as a small and remote economy. See Conway and Zheng (2014) for a discussion of the degree of trade over distance across different industries in New Zealand.
9. Besides distortions on the prices of inputs, wedges may also be interpreted as a proxy for all of the costs of hiring factors beyond the market price of the factor itself (i.e. frictions). Thus, they may also capture the presence of adjustment costs, for example. Distortions cannot be identified separately from more general frictions with the current empirical strategy, thus I generally use the term distortion to refer to a combination of the two.
10. In this sense, the HK method is similar in spirit to the Petrin and Levinsohn (2012) measure of allocative efficiency. However, as discussed in Chen and Irarrazabal (2015), in the Petrin and Levinsohn (2012) measure, the reallocation term is measured by the weighted average of *changes* in factor inputs across firms, where weights are the gaps between the firm's marginal product of an input and its cost. Hence, this measure would miss the change in allocative efficiency when both TFPQ and idiosyncratic distortions move in the same direction, so that there are no changes in individual firms' inputs. The HK method focuses on the gaps and their changes, thus nesting the changes in allocative efficiency measured by Petrin and Levinsohn (2012).
11. A full derivation is available as an online appendix.
12. For further information about the LBD, see Fabling and Sanderson (2016). For more information about the derivation of production variables from LBD, see Fabling and Maré (2015b).
13. A business is economically significant if it (a) has annual Goods and Services Tax (GST) turnover of more than $30,000; (b) has paid employees; (c) is part of an enterprise group; (d) is part of a GST group; (e) has more than $40,000 income reported on tax form IR10; *or* (f) has a positive annual GST turnover and has a geographic unit (i.e. plant) classified to agriculture or forestry.
14. However, it may be that the non-wage compensation component has increased modestly over time due to the introduction of a subsidised voluntary superannuation scheme (KiwiSaver) in 2007.
15. Information on hours worked is not available in LBD, and the measure of FTEs is therefore derived from the number of employees and information on wages and the number of jobs held by each employee using the method developed by Fabling and Maré (2015a). That is, the FTE measure partially, but not completely, adjusts for the likely hours worked.
16. For New Zealand, the use of book values can be justified on the basis that asset-specific tax depreciation rates are intended to align with economic depreciation rates (Fabling & Sanderson, 2016).
17. Whole-economy labour costs and capital goods price deflators are used as industry-level deflators are not available for capital goods, and only available from 2009 for labour costs.
18. This issue is likely to be larger in the case of New Zealand than in overseas studies because of the inclusion of much smaller firms in my dataset.
19. The trimming was done at a 1-digit industry level to mitigate the issue of the trimming falling unevenly on particular industries.
20. The primary sector consists of agriculture, forestry, fishing and mining industries (ANZSIC06 A and B). The manufacturing sector is ANZSIC06 C, utilities is ANZSIC06 D, and construction is ANZSIC06 E. The services sector consists of market services (ANZSIC06 F-LL1, M, N, R and S).
21. The growth of international distributed firm microdata projects reflects the desire to make cross-country firm microdata as comparable as possible while adhering to individual country's data confidentiality requirements. Examples include the OECD's MultiProd project and the European Central Bank's Competitiveness Network Research.
22. Due to differences in industry classification in the two countries, I make an approximate concordance between the two classifications.
23. In particular, structural models such as Ackerberg, Caves, and Frazer (2015) or Levinsohn and Petrin (2003).
24. However, this should be interpreted with some caution as the official productivity statistics which show slowing productivity growth are based on value-added productivity measures. The current analysis is based on gross-output measures. Indeed, an early version of this paper using the HK two-factor model of value-added productivity showed worsening resource allocation over the 2000s (see Meehan, 2016).
25. Results using an estimate of full-time equivalent workers as an alternative measure of labour input are provided in Appendix 1. Under this alternative measure, the magnitude of the potential gains increase, as expected (see Section 3 for a discussion). However, this alternative labour input measure yields similar patterns over time and by sector as the baseline model.
26. Indeed, the period 2001–2012 encompasses only one full productivity growth cycle (see Figure 1).
27. Based on the Reserve Bank of New Zealand's 'C27 Agricultural credit by registered banks' series, total agricultural loans increased from $18.9b in 2003 to $45.4b in 2009 (in nominal terms) with much flatter growth between 2009 and 2012. In addition, Allan and Kerr (2014) shows the large increase in rural land sale price per hectare in New Zealand in the 2000s leading up to the Great Recession.

28. An exception to the general trend of improving resource allocation in developing countries is Mexico, where high misallocation has been increasing over time. Levy Algazi (2018) links these trends to specific issues with labour regulation, the tax system, contract enforcement and product market competition that favour low-productivity firms (particularly informal firms) over high-productivity firms, with many of the policy biases favouring low-productivity firms increasing over time.
29. Bellone and Mallen-Pisano (2013) note that an alternative explanation is that the allocative efficiency is indeed close in France and the US, which would challenge the established view that continental European economies have higher input and output distortions than the US economy.
30. The use of gross output for TFPR is for presentational simplicity. The calculation of the Olley-Pakes covariance, as presented in Figure 4, uses firm-specific production share weights, as described below.
31. To be more precise, for industry s and year t, the covariance for labour productivity is calculated as:

$$OP_{st} = \sum_i (\theta_{ist} - \bar{\theta}_{st})(\omega_{ist} - \bar{\omega}_{st})$$

where i is the firm index, ω_{ist} is firm-specific productivity, θ_{ist} is firm-specific labour input share and $\bar{\omega}_s t$ and $\bar{\theta}_{st}$ are the unweighted averages of industry s. Industry-level results are then weighted up to the sector/total results using industry labour input shares. The same covariance is computed for TFPR using firm-specific production shares, i.e. $K_{ist}^{\alpha_s} L_{ist}^{\beta_s} M_{ist}^{1-\alpha_s-\beta_s}$. However, gross-output weights are used to weight up from the industry level to the sector level due to the difficulty of comparing combined inputs across industries due to industry differences in α_s and β_s.
32. The efficient size is calculated as the level of gross output that a firm would have if it had an efficient level of TFPR (where the efficient level of TFPR is the average industry TFPR given in Equation (12)).
33. Using LBD data over the same period, Zheng (2016) also finds that New Zealand firms with the highest levels of TFP grew faster than other firms in their industry.
34. It also appears to contradict the conventional wisdom that New Zealand's productivity performance is hampered by an abundance of small firms and a lack of large firms. However, this is not necessarily the case as this method only examines the efficient size of a firm given its TFPR, and this relative measure does not necessarily rule out this possibility.
35. As discussed, in the HK model, any factor that result in a distribution of TFPR is a distortion. That is, it does not allow for the possibility of other frictions that would result in a distribution of TFPR, such as adjustment costs.
36. Of course, there are also likely to be other reasons for this, such as generally higher fixed costs among manufacturing firms.
37. Although not shown here, many firms in the primary and construction sectors, and to a lesser extent, the utilities sector, are also larger than their efficient size.

Acknowledgements

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 New Zealand, the New Zealand Productivity Commission, the New Zealand Government or the OECD. Access to the anonymised data used in this study was provided by Statistics New Zealand 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 wwww.stats.govt.nz. The results are based in part on tax data supplied by Inland Revenue to Statistics New Zealand under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes. Any person wo has had access to the unit record data has certified that they have been show, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

Disclosure statement

No potential conflict of interest was reported by the author.

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Appendix 1. Alternative labour input measure

Table A1. Gross-output gains from optimal resource allocation by sector: Alternative labour input measure.[a,b]

Year	Primary	Manufacturing	Utilities	Construction	Services	Total
2001	38.48	40.65	20.00	31.56	45.59	40.67
2002	45.73	47.69	25.37	31.12	42.51	42.80
2003	61.00	17.86	28.13	32.85	44.13	33.28
2004	43.57	26.43	29.28	38.23	62.00	43.33
2005	38.92	18.86	20.37	38.71	43.18	32.33
2006	46.09	25.85	22.06	35.24	44.79	35.88
2007	77.27	17.23	18.34	42.16	42.24	33.85
2008	79.42	20.01	20.88	36.38	43.64	35.43
2009	107.40	21.75	30.72	31.67	47.50	38.88
2010	100.22	17.62	27.50	33.94	44.93	36.74
2011	72.84	17.60	35.34	32.30	42.94	34.78
2012	65.41	16.84	44.83	32.88	43.45	35.16

[a]Calculated as $(Y^*/Y - 1) * 100$ where (Y^*/Y) is given in Equation (17).
[b]Results use estimated full-time equivalent workers (see Section 3) as the labour input measure.