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Factor substitution and productivity in New Zealand*

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Abstract

This paper produces aggregate and industry estimates of Total Factor Productivity (TFP) for New Zealand. TFP is estimated based on Constant Elasticity of Substitution (CES) production functions that permit varying assumptions about factor augmentation and that allow for industry-specific values of the elasticity of substitution between inputs. The CES approach simultaneously explains changes in labour share and output over time, and provides estimates of the contribution of capital and labour to productivity in New Zealand. The results suggest that negative capital-augmenting technical change in several industries has weighed on productivity in New Zealand.

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Non-technical summary

It is puzzling that New Zealand's productivity performance has been poor compared to other advanced economies, particularly in light of wide-ranging economic and institutional reforms starting in the mid-1980s. This paper unpacks New Zealand's disappointing productivity growth by taking an industry-level view and estimating the contribution of capital and labour to productivity growth in New Zealand.

Total factor productivity (TFP) is often estimated as a residual from a regression of output against estimates of inputs such as capital and labour. A common assumption when estimating TFP in this way is that capital and labour are substituted one-for-one when their relative prices change. However, this can bias estimates of TFP if the elasticity of substitution is in fact significantly different from one.

Deviating from the assumption that the elasticity of substitution is unity can also help us understand the nature of structural changes in the economy. In a 'traditional' neo-classical growth model, when the elasticity of substitution is one, changes in the capital to labour ratio or the relative price of labour to capital do not cause capital and labour income shares to change since capital intensity and the relative price of labour adjust. However, when the elasticity is different from one, changes in capital and labour productivity and the relative growth rates of capital and labour can generate variation in the share of income received by each factor.

This paper produces TFP estimates based on Constant Elasticity of Substitution (CES) production functions that allow the elasticity of substitution between capital and labour inputs to be estimated. The CES approach simultaneously explains changes in factor share and output over time, and provides estimates of the contribution of capital and labour to productivity.

The results show that the elasticity of substitution is significantly different from one in all industries. Technical change has made capital less productive in many industries, implying that additional increments of capital have tended to weigh on productivity.

1 Introduction

It is puzzling that New Zealand's productivity performance has been poor compared to other advanced economies, particularly in light of wide-ranging economic and institutional reforms starting in 1984 (de Serres et al. 2014). This paper unpacks New Zealand's disappointing productivity growth by taking an industry-level view and distinguishing between the contributions to output growth of changes in New Zealand's endowments of factors of production and the efficiency with which capital and labour are employed.

Total factor productivity (TFP) is often estimated by regressing output against estimates of capital and labour, with TFP computed residually. The exact functional form of these regressions, and in particular the substitutability between capital and labour embodied in the underlying production function, has a material impact on the TFP estimates obtained. Cobb-Douglas type production functions that are commonly used in theoretical models and for the empirical estimation of TFP are characterised by one-for-one substitution of capital and labour when their relative prices change. However, if the elasticity of substitution is not unitary, TFP estimates based on production functions assuming unitary elasticity may be biased. *Ceteris paribus*, as the elasticity falls below unity, there is an increasing downward bias, reflecting the fact that combined inputs tend to change less when relative factor prices shift, and thus measured TFP growth tends to be higher than for a high elasticity.

This paper instead produces TFP estimates based on Constant Elasticity of Substitution (CES) production functions that allow the elasticity of substitution between capital and labour inputs to be estimated. A CES-based approach is likely to be important in a New Zealand context for two reasons. The first is that earlier studies suggest that the elasticity of substitution varies across industries and is below unity at an aggregate level.[1]

The second reason is that more general functional forms that do not assume unitary elasticity can help us understand the nature of structural change. In a 'traditional' neo-classical growth model, for example, when the aggregate elasticity of substitution is less than one, an increase in the capital to labour ratio would tend to be associated with an increase in labour's income share, whereas it would fall if the elasticity is larger than one. This paper shows that there have been significant changes in labour share in many industries in

[1] See Tipper (2012) for both industry and aggregate estimates and Szeto (2001), Hall and Scobie (2005) or Mallick (2012) for aggregate estimates.

New Zealand. Since the approach used to estimate productivity also produces estimates of industry elasticities of substitution, this paper sheds light on the observed changes in factor shares and resource allocations in New Zealand.

This paper estimates CES-based production functions using the 'supply-side system' approach of Klump et al. (2007). There are two main advantages of this approach over the index number approach of Statistics New Zealand (SNZ) and other statistical agencies. The first, as mentioned, is that the elasticity of substitution can be explicitly identified when estimating TFP. The approach also allows for various assumptions about the underlying nature of technological progress, and therefore provides a richer framework for understanding productivity developments.

Three things set this paper apart from most others that estimate CES production functions using the system approach. The first is that this paper produces both aggregate *and* industry-level estimates of TFP. The second is that the annual data used have been aligned to those used by New Zealand's statistical agency, enhancing comparability with official TFP estimates. To investigate the implications of the CES approach for productivity estimates over recent history and understand the contribution of factor augmentation for growth, the annual estimates produced are also compared to estimates based on quarterly data for the total economy.

The results suggest that there has been significant differences in productivity growth at industry-level in New Zealand. In line with official estimates, industries with the weakest productivity performance include mining; electricity, gas, water, and waste services; and professional, scientific, and technical services, administrative and support services. The results suggest decreasing capital productivity in many industries has contributed to New Zealand's poor productivity performance. Estimates based on quarterly data present a similar picture of the contributions of capital and labour to productivity growth.

2 A general CES production function

Consider the following general CES production function incorporating factor-augmenting technology and assuming that there are only two factors of production:

$$Y_t = [\alpha(\Gamma_t^K K_t)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\Gamma_t^L L_t)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where Y_i is real output, K_t is capital, L_t is labour, σ is the elasticity of substitution between K and L, α is a distribution parameter that specifies the relative importance of K and L to production, and $\alpha\epsilon(0,1)$ and $\sigma\epsilon[0,\infty)$.[2] The terms Γ_t^K and Γ_t^L represent K and L-augmenting technological change, respectively. Factor efficiencies are usually assumed to grow as follows: $\Gamma_t^K = e^{\gamma^K}$ and $\Gamma_t^L = e^{\gamma^L}$ where γ denotes growth in percentage terms.[3]

The elasticity of substitution describes how percentage changes in the ratio of capital to labour and percentage changes in the relative cost of labour to capital are related for a given level of output:

$$\sigma = \frac{d(\log(K/L))}{d(\log(F_L/F_K))} = \frac{d(\log(K/L))}{d(\log(w/r))} \tag{2}$$

where equation 2 assumes that markets are competitive and factors of production earn their marginal products.[4]

When $\sigma = 1$, changes in the capital to labour ratio or relative cost of labour do not cause relative factor income shares to change since relative prices and quantities change to offset each other. But when $\sigma \neq 1$, changes in the effective capital-labour ratio (i.e. $\frac{\Gamma_t^K K}{\Gamma_t^L L}$) can generate variation in the share of total income received by each factor. For example, in the general specification in equation 1, when $\sigma < 1$ (i.e. factors are gross complements) improvements in capital-augmenting technology (Γ_t^K) disproportionately reward labour and decreases capital's income share, while labour-augmenting technological progress (Γ_t^L) raises the capital share. When $\sigma > 1$ (factors are gross substitutes), increases in $\Gamma^{K,t}$ would raise the capital share, and Γ_t^L the labour share. The neo-classical explanation of a fall in the labour share is

[2] As $\sigma \to \infty$ production approximates linearity (i.e. perfect substitutability) and as $\sigma \to 0$ production approximates Leontief (i.e. fixed proportions).

[3] Diamond et al.'s (1978) impossibility theorem posits that the nature of technological augmentation needs to be specified for σ to be estimated. Failing to allow for the possibility of factor biases can bias estimates of σ since trends in series may be ascribed to shifts in factors and the elasticity of substitution as opposed to TFP (see for example Antras 2004 for the US). León-Ledesma et al. (2015) also show that estimates of σ will be biased towards one if the economy has been near a balanced growth path or neutrality is imposed when technology is in fact factor-augmenting. A common functional restriction is to assume an exponential growth rate.

[4] This implies that the relative income share is $\frac{rK}{wL} = \frac{\alpha}{1-\alpha}(\frac{\Gamma^K K}{\Gamma^L L})^{\frac{\sigma-1}{\sigma}}$ and $F_K/F_L = \frac{\alpha}{1-\alpha}[(\frac{K}{L})^{-\frac{1}{\sigma}}(\frac{\Gamma^K}{\Gamma^L})^{-\frac{\sigma-1}{\sigma}}]$ and that factor shares will equal the partial elasticities of output with respect to each factor (i.e. $\frac{jf\prime(j)}{f(j)}\epsilon[0,1]$ where $j = K, L$).

either a fall in the capital-labour ratio and/or $\Gamma_t^L > \Gamma_t^K$ when $\sigma < 1$, with reverse effects capable of explaining a fall in the labour share when $\sigma > 1$.[5]

The function form considered in this paper allows assessment of the different factor biases from changes in productivity. Three common neutrality conditions that relate technological changes to changes in factor shares are often imposed on the production function: (a) Solow neutral technology: capital-augmenting technological change with $\gamma^K > 0$ and $\gamma^L = 0$; (b) Harrod neutral technical change: labour-augmenting with $\gamma^K = 0$ and $\gamma^L > 0$, implying that the income distribution is invariant to TFP for a given capital-output ratio; and (c) Hicks neutral technological change where all factors experience the same rate of TFP growth ($\gamma^K = \gamma^L > 0$), and implying that factor shares do not vary. This paper estimates the fully unrestricted version of the system with $\gamma^K \neq \gamma^L$ and tests for such parameter restriction are then applied.

3 Normalisation of CES function with factor-augmenting technology

The estimation of the elasticity of substitution can either be based on single equation regressions of the first order conditions from the system (typically involving a regression of capital intensities on relative factor prices), or joint estimation of the parameters of the CES function. The advantage of the 'systems approach' as applied in this paper is that it implies parameter constraints consistent with the production function and the first order conditions for factor shares implied by neo-classical theory.

'Normalisation' involves expressing the CES function relative to baseline values for the factor shares and other variables in the system of equations. The system approach involves using normalised versions of the aggregate production function along with the first order conditions of profit maximisation to jointly estimate TFP and the elasticity. Klump et al. (2007) and León-Ledesma et al. (2010) show that equation 1 can be normalised to identify σ

[5] Competing explanations of the observed drop in labour income share in many advanced economies hinge on the value of the elasticity σ and the measurement of inputs, outputs and factor costs. For example, Piketty and Zucman (2014) conjecture that $\sigma > 1$, thereby more than offsetting the impacts of the decline in capital's factor share and relative price. Likewise, the model of Karabarbounis and Neiman (2014) can reproduce the decline in the labour share if $\sigma > 1$ and the rental rate of capital falls. In contrast, Acemoglu (2003) argues that $\sigma < 1$ and labour-augmenting growth can account for the fall in the labour share.

for a given baseline period $t = t_0$:

$$Y_t = Y_0[\alpha_0(e^{\gamma^K(t-t_0)}\frac{K_t}{K_0})^{\frac{\sigma-1}{\sigma}} + (1-\alpha_0)(e^{\gamma^L(t-t_0)}\frac{L_t}{L_0})^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where $Y_0 = A\tilde{Y}$, $K_0 = \tilde{K}$, $L_0 = \tilde{L}$, the capital-share is $\alpha_0 = \alpha_K$, $t_0 = \bar{t}$ and $\tilde{}$ denotes geometric mean and $\bar{}$ denotes arithmetic mean. In this general formulation of the CES function, the scaling parameter A is a 'normalisation constant', which is a function of the geometric means used to normalise the data and which has an expected value of around unity (see Klump et al. 2007).

Normalisation serves several purposes.[6] Firstly, the components of the production function are measured in different units, and normalisation expresses the function in index number form. Normalisation involves scaling value added, capital and labour by their means and evaluating the income shares at their average values. This ensures that in steady state factor shares will be constant, but also that TFP estimates are consistent (on average) with observed capital shares (a useful property for approximating steady states in general equilibrium models).[7] Since estimates of TFP and α also depend on the elasticity of substitution and capital and labour income shares, normalisation facilitates interpretation of the parameters at a selected benchmark point. This provides a baseline value for factor income shares useful for comparative statics exercises (such as assessing the impact on factor shares of changes to the elasticity of substitution, *ceteris paribus*). Actual data can be used to set the distribution parameter prior to estimation, reducing the number of parameters to be estimated. This is useful for the economic identification of σ because it provides additional degrees of freedom in estimation.[8]

[6] Normalisation is discussed in more detail in León-Ledesma et al. (2010), Klump et al. (2012) and Cantore et al. (2014). Note that Temple (2012) points out that some of the ratios of the model may not be invariant to the normalisation approach followed.

[7] As discussed by de la Grandville (2009), León-Ledesma and Satchi (2010) and Cantore and Levine (2012), normalisation allows α to be mapped to the measured capital share by addressing the dimension issues associated with using inputs expressed in different units.

[8] Joint identification of σ and the other parameters is improved through use of factor shares in estimating production function parameters (as shown by Klump et al. 2007), while wages and capital rental costs could also be used directly (as shown by León-Ledesma et al. 2010). Alternative results when using the first order conditions for wages and the rental rate as in León-Ledesma et al. (2010) are available on request but are not presented because there are exponential trends in some of the capital rental rates based on unofficial SNZ data. The advantage of the Klump et al. (2007) approach in a New Zealand context is that only official SNZ data are required.

This paper follows the supply system approach of Klump et al. (2007) to estimate the aggregate CES production function. While that paper focuses on the aggregate economy, both industry and aggregate CES production functions are estimated using the same approach in this paper. The system estimated is based on a re-arrangement of equation 3 and the first order conditions under profit maximisation for the capital and labour income shares:

$$\ln(\frac{Y_t}{L_t}) = \ln(\frac{A\tilde{Y}_t}{L_t}) + \gamma^L(t-\bar{t}) - \frac{\sigma}{\sigma-1}\ln[\bar{\alpha}e^{\frac{1-\sigma}{\sigma}(\gamma^L(t-\bar{t})-\gamma^K(t-\bar{t}))}(\frac{K_t/\tilde{K}}{L_t/\tilde{L}})^{\frac{\sigma-1}{\sigma}} + (1-\bar{\alpha})] \tag{4}$$

$$\ln(\frac{R_t K_t}{P_t Y_t}) = \ln(\frac{\bar{\alpha}}{1+\mu}) + \frac{1-\sigma}{\sigma}[\ln(\frac{Y_t/\tilde{Y}}{K_t/\tilde{K}}) - \ln(A) - \gamma^K(t-\bar{t})] \tag{5}$$

$$\ln(\frac{W_t L_t}{P_t Y_t}) = \ln(\frac{1-\bar{\alpha}}{1+\mu}) + \frac{1-\sigma}{\sigma}[\ln(\frac{Y_t/\tilde{Y}}{L_t/\tilde{L}}) - \ln(A) - \gamma^L(t-\bar{t})] \tag{6}$$

where μ is a mark-up reflecting a wedge between GDP and factor payments. Under perfect competition, factor remuneration reflects marginal products and $\mu = 0$. If perfect competition is not assumed, μ can be estimated directly.

Following Klump et al. (2007), additional curvature parameters can be estimated to allow for time-varying TFP growth.[9] To calculate γ_j for $j = K, L$, a Box-Cox transformation can be applied $\gamma^j(t-\bar{t}) = \frac{\gamma_j t_0}{\lambda^j}[(\frac{t}{t_0})^{\lambda^j} - 1]$, where $t > 0$, $t_0 = \bar{t}$ and λ is the curvature parameter.[10] This implies that when $\lambda = 1$ technical progress is linear (i.e. constant), when $\lambda = 0$ it is log-linear and when $\lambda < 0$ it is hyperbolic.

3.0.1 Other functional forms

A more general production function than described above is a 'translog' form that allows for the possibility of non-constant elasticity of substitution across

[9] Allowing time-variation in factor-biased TFP growth allows the short- and long-term factor efficiencies to be compared and for tests of the existence of a balanced growth path (see McAdam and Willman 2013 as an example).

[10] Assuming $e^{\gamma^K} = e^{\gamma^L} = 1$ at the point of normalisation (t_0) ensures that factor shares are exactly equal to $\bar{\alpha}$ and $1-\bar{\alpha}$, respectively, at time t_0 (Klump et al. 2012).

industries or inputs (i.e. 'sigma-augmenting productivity').[11] Statistics New Zealand, like most statistical agencies, use an index number approach to estimate a translog function for New Zealand's official productivity measures. As is typical, Statistics New Zealand imposes Hicks neutrality and do not separately identify the different parameters of the function. Statistical agencies tend to prefer an index number approach over econometric estimation given the complexity of required estimation approaches and increased data requirements.

The reason that this paper estimates CES-based production functions instead of translog functions is that translog functions can be difficult to estimate econometrically given the large number of free parameters involved, and economic interpretability of the parameters is fraught owing to the nonlinearity of the system.[12] The system approach applied in this paper imposes restrictions on the CES function that are useful for the economic identification of σ, while allowing for a variety of forms of technological change.

4 Estimation of CES functions

There are several challenges that need to be overcome when estimating nonlinear CES functions. It can be difficult to obtain global optima and estimates may be sensitive to the initial values used, or suffer from imprecision as the elasticity of substitution approaches zero.[13] Various estimation approaches can be used to estimate a system with endogenous variables and restrictions on parameters. These have different strengths and weaknesses and can produce differing estimates. These differences are discussed in more detail in León-Ledesma et al. (2010) and León-Ledesma et al. (2015), who show using Monte Carlo that a three equation system can identify the true value of σ and the other parameters better than applying OLS estimation of the first order conditions or the Kmenta approximation (a second order Taylor expansion of the production function), and that various estimators produce qualitative similar results. This paper uses non-linear seemingly unrelated

[11] In this paper, returns to scale are ignored since it cannot be separately identified from σ in estimation of the system that will be used (see Fox 2005 for discussion of returns to scale in a New Zealand context).

[12] See Baccar (Baccar) for a general review of problems associated with estimating translog functions. For a systems approach to translog estimation, see Saam (2014).

[13] For example, Henningsen and Henningsen (2012) suggest the use of grid search procedures to alleviate convergence problems and local linear approximations to circumvent rounding errors when σ is near 0.

regression (NLSUR) estimation using Stata's iterative feasible generalized least squares estimators (FGNLS) estimator.[14]

5 Data

This paper uses industry data at a ANZSIC06 one-digit level of disaggregation that closely correspond to the data used to construct New Zealand's official TFP estimates. The data include gross value added, labour and capital income, labour volumes, and productive capital stock.[15] Appendix A describes the annual industry data used in detail.

Studies use a wide variety of definitions of factor volumes, income and output and these have important implications for the estimation of elasticities and the predictions of growth models. Of particular importance is the measurement of the factors shares.[16] The capital income share (α) is often calculated residually as value added less total labour compensation (adjusted for proprietors' income) over nominal value added. However, imperfect competition would imply the existence of profits so that there is a wedge between marginal cost and capital remuneration (and therefore an aggregate mark-up). To account for profits, capital share can be alternatively calculated as the rental price of capital times the nominal capital stock (as in Klump et al. 2007).[17]

In calculating the capital share for New Zealand industries, this paper deviates from other papers in the literature. Statistics New Zealand assume that all

[14] This involves non-linear least squares regressions on the equations in the system to construct the variance-covariance matrix using the estimated errors and then estimating the system using GLS. The benefit of using the FGNLS estimator is that it controls for any cross equation correlation between innovations. More generally, SUR estimation is appropriate when there are contemporaneous correlation between the error terms of the equations in the system. As pointed out by Luoma (2010), the results from FGLS in estimating CES production functions can be sensitive to starting values used, so any sensitivity to initial values is discussed.

[15] New Zealand is not included in datasets that are commonly used to compare industry output and productivity data across countries as some New Zealand industry data cannot be harmonized with international equivalents. In particular, the EU KLEMS dataset provide comparable measures of TFP estimated using a index numbers with a larger number of inputs than used in this paper. New Zealand is not in this database as detailed industry data of gross output or taxes and subsidies are not currently available.

[16] For example, Muck et al. (2015) show that different definitions of capital-labour share have very different time series properties.

[17] In addition, some (like the OECD) use cost shares instead. See Aiyar and Dalgaard (2005) for more on measurement for international comparisons.

profits accrue to capital when calculating capital income and industry data on profits are not available. As a result, capital income share is calculated as its share in combined labour and capital income, after mixed income and net taxes have been attributed to labour and capital, respectively, and mark-up μ is therefor assumed to be zero.

Data availability prevents estimation of the system for the total economy in New Zealand. The 'aggregate economy' grouping used in this paper covers about 89 percent of total GDP. This aggregate includes the 'hard to measure sectors': education and training, healthcare and social assistance, and excludes government and owner-occupied housing (see Appendix A for more details). Statistics New Zealand provides two industry aggregations in its productivity data and results are also produced for these aggregations in this paper. The first is called the 'former measured sector' and includes industries for which data is available back to 1978: agriculture, forestry, and fishing; mining; manufacturing; electricity, gas, water, and waste services; construction; wholesale trade; retail trade, accommodation and food services; transport, postal, and warehousing; information media and telecommunications; and financial and insurance services. The 'measured sector' aggregation is only available from 1996 and adds the rental, hiring and real estate industry (excluding owner-occupied property operation) to the former measured sector.

The benchmark estimates for the aggregate economy are based on the sample 1996 to 2012 on account of data availability and the structural shifts that occurred following the economic reforms initiated in the mid-to-late 1980s. The reform period involved a series of 'big bang' economic reforms that rapidly changed the economy from one of the most insulated and regulated among western advanced economies to one of the most flexible. This deregulation was accompanied by substantial factor reallocations across industries as the economy rapidly moved to more market-determined relative prices. Following the reforms, there was a significant downward pressure on wages (Figure 17 in the Appendix) as employment shifted from previously sheltered, subsidised or state-controlled sectors and the unemployment rate increased - from below 5 percent 1984 to over 11 percent in 1992. Factor reallocations were large: in manufacturing, employment fell by 40 percent between 1984 and 1991. Rapid structural change and corporatisation/privatisation reforms also implied big changes to the areas where capital was employed and to the industries attracting new investment. Including the reform period in the estimation causes some of the swings in factor shares and output to factor ratios, particularly in restructured formerly state-dominated industries, to be attributed to changes in technology and σ.

Bearing this caveat in mind, full sample (1978-2012) estimates for the former measured sector are provided in Appendix C for comparison to official TFP estimates, which are available from 1978 for several industries.

Measurement of capital services and capital income in public sectors is fraught. The lack of a market for public capital services means that it is difficult to estimate the rate of return on public capital, and capital income include a very low factor payments to capital in such industries (see Figure 18 in the Appendix). Although estimates from public sector-dominated industries are provided for comparisons to official TFP estimates, conclusions about public sector productivity are not drawn in this paper.

Figures 1 to 3 present key ratios for the aggregate economy data used in this paper. The output-capital ratio was relatively flat through the 1990s, before beginning to decline in the late 2000s. Labour productivity (the output-labour ratio) and capital intensity (the capital-labour ratio) have strong upward trends. New Zealand's labour share has fallen from around 65 percent in 1978 to around 55 percent in 2012 in the former measured sector, while being relatively stable in the aggregate economy over the benchmark sample (see Figure 3).[18] The aggregate labour share picture masks significant divergences at an industry level. Labour shares have fallen in all industries, except professional scientific, technical and adminstration and support services, education and training and health care. Since 1978, factor income shares have fallen most in information, media and telecommunications, electricity, gas and water and in mining (Figure 21 Appendix). Labour shares have been largely flat in agriculture (at around 50 percent) and manufacturing (at about 60 percent). The labour share in service-orientated industries ranges from about 44 percent in information media and telecommunications to about 87 percent in the health sector.[19]

[18] See Figure 13 in the Appendix for a backdate of the labour share for the aggregate economy and a comparison to other measures. Bridgman and Greenaway-McGrevy (2016) discuss the impact of the reforms on the labour share in New Zealand.

[19] There have been quite different trends in labour productivity and real wages and these differ markedly by industry (Figure 20 in the Appendix). In most goods-producing industries, labour productivity has outstripped real wage growth, with the opposite observed in most service-orientated industries.

Figure 1: Great ratios

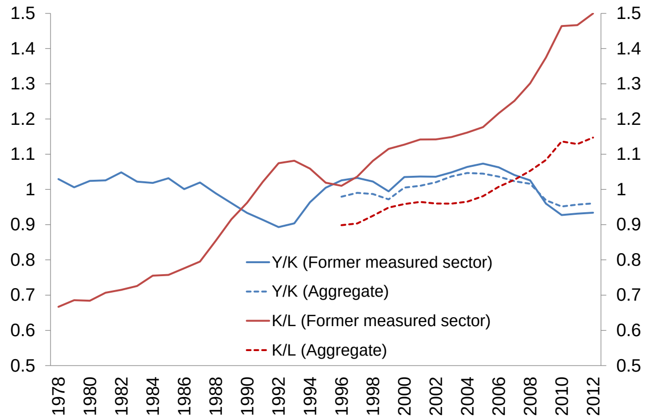
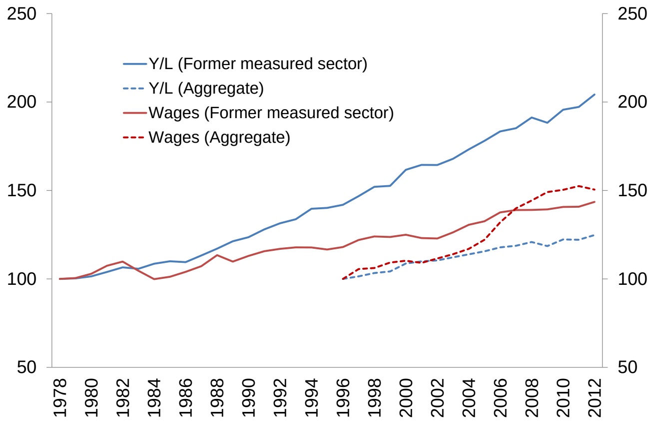
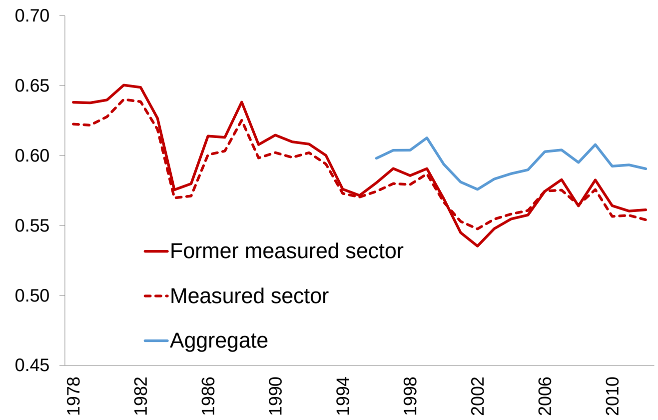


Figure 2: Labour productivity and real wages



These figures differ from estimates for the US, as well as many other developed economies. For the US for example, Herrendorf et al. (2015) estimate the labour share to be 70 percent in aggregate; 40 percent for agriculture; 70 percent in an aggregation of construction; mining and manufacturing and 65 percent in services. They also show that agriculture and manufacturing experienced larger falls in labour share than services (see also Alvarez-Cuadrado et al. 2014).

Figure 3: Labour share



6 Estimation results

Several sets of estimates of industry elasticities and TFP growth are produced based on alternative restrictions to the parameters of the production function. In addition, this paper separately estimates industry and aggregate TFP and substitution elasticities, allowing assessment of the economic reasonableness of different restrictions on factor augmentation.

The benchmark values used for parameters at the point of normalisation are as follows: α, γ_K and γ_L are based on the sample averages of α, and the average growth rates of $\frac{Y}{K}$ and $\frac{Y}{L}$, respectively. The scaling parameter A is initialized at 1 as suggested by Klump et al. (2007). When non-constant growth is assumed for productivity, the starting values of the curvature parameters (λ_K and λ_L) are selected based on the fit of trend lines to $\frac{Y}{K}$ and $\frac{Y}{L}$: 1 if a linear fit is best, 0.95 if a logarithmic line has the highest R^2 or -0.05 for hyperbolic. The initial condition for σ is based on the long run estimates from Tipper (2012) for industries in the former measured sector. For other industries, and aggregations, OLS estimates from the first order conditions for capital and labour are used as in León-Ledesma et al. (2015) and models minimising the determinant selected. Since profits are included in the capital share for New Zealand industries, the mark-up μ is fixed at zero in all specifications.[20]

Data availability prevents estimation of a total economy measure of TFP back to 1978 when industry data are available on consistent industry classification

[20] When μ is left unrestricted, it is estimated to be close to zero, as expected given the way capital share is constructed, although other parameter values change.

for selected industries. The sample period reflects data availability for the largest possible number of industries. Appendix C.1 presents estimates for various specifications for other measures of the aggregate economy for alternative samples. For the full sample results, the following specifications are tested: time varying factor-augmenting technical growth (λ estimated, Columns 1); constant factor-augmenting technical growth ($\lambda = 1$ imposed, Column 2); Hicks neutrality with time-varying technical growth ($\gamma_L = \gamma_K$ and $\lambda_L = \lambda_K$ imposed, Column 3); and Hicks neutrality with constant technical growth ($\gamma_L = \gamma_K$ and $\lambda = 1$ imposed, Column 4).[21] For each of the specifications, parameter starting values are varied to check that coefficient estimates are stable, and final specifications selected based on the lowest determinant of residual covariance. For results based on a short sample of 1996 to 2012, the number of data points per parameter to be estimated is maximised by assuming constant growth rates of technological change and by fixing the capital share α in estimation at its calibrated level.[22] For results based on longer samples, α is estimated directly.

6.1 Aggregate economy

Results for the aggregate economy for 1996-2012 are presented in Table 1 (and the underlying data summarised in Figures 14 to 16 in the Appendix). The scale parameter is close to unity in both cases, as expected. The elasticity σ measures the ease with which the economy can adjust its capital to labour ratio to match changes in the relative prices of labour and capital. Estimates of σ are 0.86 in the general specification and 1.13 when assuming Hicks neutrality.[23] For both specifications, Wald tests reject the unity restriction,

[21] For the full sample results in the Appendix, likelihood ratio tests are used to select the benchmark specification, but these are omitted for the estimates from 1996 owing to the small sample size. In Appendix Table 5, the tests reject the null that restrictions to the factor-augmenting specification in Columns 2 to 4 are appropriate. This suggests that the general specification produces parameter estimates that best fit the data. Harrod neutral and Solow neutral specifications were also tested but Hicks neutral specifications were generally preferred on the basis of likelihood ratio tests. León-Ledesma et al. (2010) describe likely biases from imposing certain neutrality conditions should these differ from the data generating process.

[22] Based on the five series used, this implies 85 data points for the three parameters in the restricted Hicks neutral case in the shortest annual sample, compared with 175 datapoints in the full sample.

[23] Full sample estimates in Appendix Table 5 from different models for the former measured sector vary between 0.84 and 1.92, depending on the restrictions placed on the nature of productivity growth and the value of the curvature parameter.

and the estimate of σ is always more than three standard deviations away from unity.

Table 1
Estimates for the Aggregate economy (1996-2012)

	1	2
	Factor-augmenting	**Hicks neutral**
ξ	0.999***	1.000***
	(0.004)	(0.004)
σ	0.862***	1.133***
	(0.002)	(0.004)
γ_K	-0.013**	
	(0.005)	
γ_L	0.022***	
	(0.003)	
γ		0.007***
		(0.001)
λ_K	1	1
λ_L	1	1
$\sigma = 1$	[0.0000]	[0.0000]
Nested in Model 1	-	[0.7214]
TFP growth	0.011	0.007
Determinant	3.23E-14	2.90E-14

Note: All estimations reported are based on NLSUR estimated in Stata. *, ** and *** indicate the 10, 5 and 1 percent level of significance. ( ) denotes standard errors and [ ] denotes p-values. Wald tests used to test the restriction that $\sigma = 1$, while likelihood ratio tests are used to compare restricted and unrestricted models. TFP growth is calculated using the Kmenta approximation.

When using a general factor-augmenting specification (Column 1), capital-augmenting growth ($\hat{\gamma}_K$) is negative at 1.3 percent per annum, while labour-augmenting growth ($\hat{\gamma}_K$) is 2.2 percent. In Column (2), where technical progress is assumed to be symmetric for labour and capital, factor-augmenting technical progress is estimated to be 0.7 percent.[24] In the general specification, net labour augmentation and $\hat{\sigma} < 1$ explains the slight downward trend in labour share and the upward trend in the capital share in aggregate over the sample (Figure 15).[25] Specifically, the estimates of γ_K and γ_L suggests that although the measured capital-labour ratio has risen, in effective terms, that ratio has actually fallen.[26] This suggests that labour-augmenting technical change has been sufficiently fast to offset the incentives to substitute capital for labour given the rise in real wages relative to user costs (see Figure 16).[27] However, the Hicks neutral specification, with $\hat{\sigma}$ slightly above unity, has a superior determinant. The preferred Hicks neutral estimate of σ suggests that capital and labour are gross substitutes and that improvements in productivity affect capital and labour symmetrically. Table 2 shows that a Hicks neutral specification is also supported for alternative aggregations of New Zealand industry data.

Using the Kmenta approximation,[28] implied TFP growth is 1.1 percent per annum in the general specification and 0.07 percent in the preferred Hicks neutral specification.[29] For the general specification, this can be decomposed into average capital-augmenting growth of around -1.8 percent and about

[24] For the full sample, the estimates of labour and capital-augmenting technical progress differ substantially depending on the specification used in Appendix Table 5. In the general factor-augmenting specification, $\hat{\gamma}_L$ is not statistically different from zero, while $\hat{\gamma}_K$ is 3.5 percent. In Column (1), $\hat{\lambda}_L < 0$ and $\hat{\lambda}_K > 0$ imply that that labour augmenting growth is hyperbolic and rapidly dissipating, while capital-augmenting growth is exponential but decelerating. Column (2) assumes $\lambda_K = \lambda_L = 1$ (constant growth). In this case, $\hat{\sigma}$ is below unity, and labour-augmenting technical progress dominates capital-augmenting technical change ($\hat{\gamma}_L > \hat{\gamma}_K$). When assuming Hicks neutrality in Columns (3) and (4), the average growth rate of factor-augmenting technical change is estimated to be 1.3.

[25] ADF tests are omitted for the short sample results but the stationarity of the full sample model residuals were checked using Dickey-Fuller GLS tests in Stata, as well as bootstrapped critical values since the limiting distribution of the test under the null is not known in this non-linear system.

[26] As discussed in León-Ledesma et al. (2010), the condition governing the relative capital-labour share under competitive profit maximisation can be used to interpret the contributions of observed changes in capital intensity and factor shares and the estimates obtained, where $\frac{\Gamma_t^K K}{\Gamma_t^L L}$ are the effective capital-labour ratio: $\frac{r_t K_t}{w_t L_t} = \frac{\alpha_t}{1-\alpha_t}(\frac{\Gamma_t^K K_t}{\Gamma_t^L L_t})^{\frac{\sigma-1}{\sigma}}$.

[27] These estimates are also consistent with the findings of Lawrence (2015) for the US, which suggest that a fall in the effective capital-labour ratio and $\hat{\sigma} < 1$ together explain the decline in US labour share.

[28] That is, $\frac{dTFP}{dt} = (\tilde{\alpha})\gamma_K + (1-\tilde{\alpha})\gamma_L - \frac{1-\sigma}{\sigma}(\tilde{\alpha})(1-\tilde{\alpha})(\gamma_K - \gamma_L)(\frac{d\gamma_L}{dt} - \frac{d\gamma_K}{dt})$.

[29] By way of comparison, Klump et al. (2007) estimate aggregate TFP for the US to be about 1.3 percent on average between 1953 and 1998 for the US and 1.1 percent when assuming Cobb-Douglas in Herrendorf et al. (2015) between 1947 and 2010.

3 percent for labour. As discussed, in the general specification, net labour augmentation implies, *ceteris paribus*, that capital deepening will have a tendency to raise the labour share.

Studies using the same approach generally suggest that σ is below one in the US. Klump et al. (2007) estimate it to be between about 0.5 and 0.6, León-Ledesma et al. (2010) find it to be between 0.4 and 0.7 depending on the specification used and Herrendorf et al. (2015) estimate it to be 0.84. For Canada, on the other hand, Stewart and Li (2014) estimate σ to be 0.90, which in that paper is within two standard deviations of unity.

Several other studies have also produced negative estimates of γ_K at an aggregate level. Stewart and Li (2014) and Herrendorf et al. (2015) use a systems approach to estimate CES functions and estimate γ_K to be negative for Canada and the US, respectively.[30] The results for the general specification are also in line with estimates from OECD (2016), which suggests that aggregate capital productivity growth has been negative in all advanced economies (except Finland) between 1995 and 2014.

6.2 Industry estimates

Most studies that use a systems approach to estimate TFP focus on the aggregate economy. A disaggregated focus may be helpful in explaining shifts in resource allocations and industry output shares that are usually ruled out by Cobb-Douglas production functions. In addition to shifts in factor shares, multi-sector growth models show that industry variation in σ could drive reallocations of factors across industries, with sectors with easier substitutability tending to use the abundant factor more intensely. Herrendorf et al. (2015) estimate sectoral CES functions for the US and conclude using a multi-sector model that the estimated sectoral productivity

[30] On the other hand, Antras (2004), Klump et al. (2007) and León-Ledesma et al. (2010) find $\hat{\gamma_K} > 0$ for the US, which León-Ledesma et al. (2010) note could reflect the use of private non-residential capital stock instead of capital inputs data which are generally preferred for productivity analysis. Indeed, León-Ledesma and Moro (2016) show that there has been a fall in the output-capital ratio (and marginal product of capital) in the US when using capital services for the private business sector from the BLS (see also Gourio and Klier 2015).

differences can account for the observed structural change in the US.[31] The estimates produced in this paper therefore informs the debate about the underlying nature of productivity growth in New Zealand.

Table 2 summarises the benchmark estimates of σ by industry for the period 1996 to 2012, for which comprehensive data is available for all industries except government.[32] For all but four industries, the preferred specification is the general factor-augmenting specification. Five industries have $\hat{\sigma}$ above unity.[33] Table 2 also compares the benchmark estimates to the confidence interval across the specifications from Tipper (2012) for selected New Zealand industries (where his sample spans 1978 to 2009).[34] Estimate of σ are generally higher than those based on a single equation approach by Tipper (2012).

Mechanisation has resulted in a significant fall in the labour share in agriculture in other advanced economies. Since 1996, the labour share in agriculture, forestry and fishing in New Zealand declined by almost 20 percent.[35] The industry's capital-labour ratio increased by over 50 percent between 1996 and 2012, while its output-capital ratio fell by 3 percent. The benchmark estimate of σ for agriculture, forestry and fishing is substantially below unity. This suggests that capital and labour are gross complements and therefore that an increase in capital per worker would, by itself, tend to be associated with a increase in the labour share in this industry. However, the fall in the industry's labour share over the 1996 to 2012 period reflects estimates of factor augmentation consistent with a fall in its effective capital-labour ratio.

Although $\hat{\sigma}$ for electricity, gas, water and waste services and construction, transport, postal and warehousing and financial and insurance services are higher than in Tipper (2012) or similar studies for other advanced economies,

[31] In a similar vein, Acemoglu and Guerrieri (2008) show how sector-specific technological change and differences in capital intensity can generate reallocations of capital. In their model, a sector will see an increase in labour share if there is an increase in its capital-labour ratio and fall in its rental rate-wage rate ratio. Labour thus shifts to the slower growth sector(s) while keeping aggregate capital share constant. Alvarez-Cuadrado et al. (2014) provide a two-sector model that shows that dominance of labour-augmenting technology and $\sigma < 1$ would imply a fall in the aggregate labour share from a rise in the relative abundance of effective labour (i.e. outweighing the rise in effective capital).

[32] Appendix C.1 also presents estimates for former measured sector industries for a sample from 1978.

[33] That said, many industries have estimates from at least one specification considered that is within three standard deviations of unity or exceeded one.

[34] Note also that Tipper's (2012) estimates are based on ANZSIC96 industrial classification data.

[35] That said, New Zealand stands out if viewed over a long sample starting in 1978, since the labour share in agriculture, forestry and fishing has been relatively flat (Figure 19).

the benchmark specifications for these industries capture factor share and output developments.[36] In these industries, $\hat{\gamma_K}$ are either negative or not statistically different from zero. The negative tehcnological change coefficients for electricity, gas, water and waste services reflect the substantial increase in its capital-labour ratio in the late 1990s following deregulation and its falling output to capital ratio. Wald tests reject the restriction that $\hat{\sigma} = 1$ for all industries.

Labour-augmenting technical change has been higher than capital-augmenting technical change in seven out of the 11 industries with factor-augmenting preferred specifications. Estimated γ_K is highest in the professional, scientific, and technical services, administrative and support services category at 6 percent per annum. This might seem surprising given the decline in the output-capital ratio for this industry. But unlike most industries, the output-labour ratio also declined for professional services, while its labour share rose. Higher capital-labour ratios in industries such as agriculture, forestry and fishing; and manufacturing, reflect not only higher levels of productive capital, but also substantial falls in employment. The implausible $\hat{\gamma}$ for financial and insurance services reflects the difficulty in fitting the factor share equations for this industry, given the hump-shaped profile of the capital-output ratio and rising output-labour ratio over the sample.[37] Labour-augmenting technical change is estimated to be lowest in mining and education and training, but implausibly high in rental, hiring and real estate, financial services and insurance and arts and recreation given the convexity in the great ratios and concavity of the labour share for latter industry over the sample.[38]

[36] In the US for example, estimates by Herrendorf et al. (2015) suggest that factor substitutability is easiest in US agriculture, with $\hat{\sigma}$ of about 1.6 in agriculture, 0.8 in manufacturing (an aggregation of mining, electricity and gas, manufacturing and construction) and 0.75 in aggregated service industries). On the other hand, estimates from various estimation approaches are generally significantly below unity for these industries for US data in papers by Young (2013) and Lawrence (2015).

[37] For financial and insurance services, Harrod or Solow neutral specifications have larger determinants than the preferred specification, while there are local optima for the factor augmented and Hicks neutral specifications have very large $\hat{\sigma}$ and lower implied TFP estimates.

[38] There are very few papers that use a similar approach to estimating industry-level TFP. For the US, Herrendorf et al. (2015) estimate that $\hat{\gamma_K}$ is 0.023 in agriculture, -0.045 in good-producing industries (an aggregation of construction, mining and manufacturing) and -0.00 (not statistically significant) in services, whereas $\hat{\gamma_L}$ is 0.05, 0.044 and 0.016, respectively in these sectors.

Table 2
Estimates of σ

	σ	**95% Confidence interval**	γ_K	γ_L	**Benchmark specification**	**Tipper (2012) σ interval**
Agriculture, forestry and fishing	0.676	0.641-0.711	-0.053	0.059	Factor-augmenting	0.10-0.21
Mining	0.932	0.918-0.945	-0.030	-0.030	Hicks neutral	-0.37-0.91
Manufacturing	0.478	0.470-0.486	0.008	0.008	Hicks neutral	0.08-0.82
Electricity, gas water, and waste services	3.555	3.470-3.640	-0.026	-0.008	Factor-augmenting	0.24-1.29
Construction	0.590	0.582-0.597	-0.010	0.007	Factor-augmenting	0.15-0.42
Wholesale trade	0.638	0.626-0.650	0.020	0.020	Hicks neutral	0.08-0.34
Retail Trade and Accommodation	0.218	0.217-0.220	-0.007	0.013	Factor-augmenting	0.03-0.19
Transport, postal and warehousing	1.567	1.487-1.648	0.006	0.006	Hicks neutral	0.02-0.30
Information media and telecommunications	1.767	1.718-1.816	-0.008	0.077	Factor-augmenting	-8.64-15.21
Financial and insurance services	0.911	0.882-0.941	-0.270	0.233	Factor-augmenting	0.07-0.39
Rental, hiring, and real estate services	0.937	0.918-0.956	-0.086	0.443	Factor-augmenting	
Prof, Scien, Tech, Admin and Support Services	0.853	0.825-0.880	0.061	-0.028	Factor-augmenting	
Arts, Recreation and Other Services	1.528	1.463-1.593	0.014	-0.001	Factor-augmenting	
Education and training	0.919	0.918-0.920	0.019	-0.028	Factor- augmenting	
Healthcare and social assistance	1.132	1.130-1.134	-0.093	0.026	Factor-augmenting	
Former measured sector	1.597	1.564-1.629	0.009	0.009	Hicks neutral	0.38-1.27
Measured sector	1.537	1.521- 1.553	0.009	0.009	Hicks neutral	
Aggregate*	1.133	1.124-142	0.007	0.007	Hicks neutral	

Note: All estimations reported are based on NLSUR estimated in Stata. * The benchmark estimate excludes local and central government and public safety and owner-occupied housing. See Appendix A for more details on industry classification and comparability with official statistics. The confidence interval limits for Tipper's (2012) estimates are for the long run elasticity from an AR1 model.

The finding of capital regress for many industries is surprising given the sense in policy institutions in New Zealand that 'capital shallowness' is weighing on labour productivity (Hall and Scobie 2005 or Conway et al. 2015).[39] There are many possible explanations for negative capital productivity when observed over a long period of time (as in the 1996-2012 benchmark sample). One possibility is that there has been mis-allocation of capital.[40] In a New Zealand context, inefficient allocation of capital could reflect factors such as a high proportion of small, owner-run firms, weak links to global value chains, poor management practices, or under-investment in intangible assets such as information and communications technology (ICT) (see, for example, de Serres et al. 2014, Conway et al. 2014 or Meehan 2016).

Another possibility is mis-measurement of real value added growth or of inputs. Quality adjustment is difficult for ICT related goods and service, and it may be that price deflators are overestimated and real value added therefore underestimated. Likewise, a shift away from expenditure on physical capital towards pay-as-you-go services (such as cloud computing) could therefor cause the contribution of TFP to output growth to be understated (see Hatzius and Dawsey 2015). The fall in relative price of equipment and ICT goods and services might also have accelerated obsolescence, implying that productive capital stock figures may be overstated (see Musso 2006 or Pessoa and Van Reenen 2014). Currently, data availability prevents assessment of the extent to which changes in the composition of capital or quality of inputs and outputs have impacted measured capital stock and output in New Zealand.[41]

6.3 Comparison to other TFP estimates for New Zealand

Table 3 compares the CES-based industry estimates to New Zealand's official TFP statistics. Statistics New Zealand calculate TFP as a Cobb-Douglas type production function assuming Hicks neutrality, and use inputs and output in index form.[42] According to the benchmark specifications over the 1996 to

[39] In contrast however, labour productivity decompositions in Conway and Meehan (2013) suggest that New Zealand's recent poor labour productivity performances reflects low TFP growth and not slow capital deepening.

[40] Recent international studies providing evidence of mis-allocation include Gopinath et al. (2015) and Gamberoni et al. (2016).

[41] In a similar vein, York (2011) suggests that missing inputs are a major issue in New Zealand (e.g. water in the case of the agriculture industry).

[42] Specifically, SNZ uses as a Tornqvist index, weighting capital and labour exponentially by their income shares (see Statistics New Zealand 2012 for more detail).

2012 sample, implied TFP growth has been fastest in finance and insurance, information, media and telecommunications, and rental, hiring and real estate. This is also the case based on official estimates. Implied TFP growth has been negative in mining; electricity, gas, water, and waste services; education and training; and professional, scientific, and technical services, administrative and support services. For several industries (such as mining and electricity, gas and water) TFP estimate are lower than the Statistics New Zealand estimate. These estimates reflect the falls in the labour share and output to capital ratios, despite substantial increases in capital-labour ratios and substantial decline in user costs relative to wages. Industries that have higher TFP estimates, such as finance and insurance and rental, hiring and real estate, have similar $\hat{\sigma}$ but experienced opposing changes in their great ratios that the model is capturing. Finance and insurance experienced substantial increases in the capital-labour ratio, while output to capital remained largely flat and labour share fell. In rental, hiring and real estate, the labour share also fell, but the capital to labour ratio fell and output-capital ratio rose. Recall that the benchmark specifications for the aggregate measures implies a TFP estimate of 0.7 percent per annum between 1996 and 2012. According to Statistics New Zealand's estimates, 'measured sector' TFP rose by 0.65 percent per year, whereas a CES function suggests that TFP growth was slightly higher at 0.89 percent. Lastly, bearing in mind the impacts of the reform period on the estimates of technology, the full sample (1978-2012) TFP estimate for the former measured sector aggregate is higher than the official estimate, at 1.29 percent compared with 0.88 percent per annum as estimated by Statistics New Zealand (Tables 5 and 7).

Table 3

TFP estimates compared to official estimates (percent)

	Benchmark estimates	**SNZ***
Agriculture, forestry and fishing	1.63	1.13
Mining	-2.77	-1.38
Manufacturing	0.82	0.52
Electricity, gas water, and waste services	-3.18	-2.41
Construction	0.43	0.49
Wholesale trade	1.89	1.63
Retail Trade and Accommodation	1.25	0.83
Transport, postal and warehousing	0.63	0.69
Information media and telecommunications	2.96	1.87
Financial and insurance services	6.70	1.52
Rental, hiring, and real estate services	5.30	1.68
Prof, Scien, Tech, Admin and Support Services	-0.71	-0.62
Arts, Recreation and Other Services	0.47	0.44
Education and training	-2.19	-1.91
Healthcare and social assistance	1.17	0.76
Former measured sector	0.83	0.71
Measured sector	0.89	0.65
Aggregate**	0.73	-

* Compound annual average, weighted using current price GVA when combining industry data where necessary. ** The benchmark estimate excludes local and central government and public safety and owner-occupied housing. See Appendix A for more details on industry classification and comparability with official statistics.

There are several alternative estimates for New Zealand that are not shown in the Table 3 as other studies use different industrial classifications and slightly different underlying data compared with current official estimates and those in this paper. At an aggregate level, estimates using a Tornqvist index for the total economy in New Zealand suggest that TFP growth averaged -0.34 percent between 1996 and 2012 according to Inklaar and Timmer (2008)[43], compared to -0.71 percent based on estimates by The Conference Board (2016).

Earlier index number-based estimates by Diewert and Lawrence (1999) and Black et al. (2003) suggest that compound annual TFP growth in the 'market sector' averaged 1.2 percent between 1978 and 1998, while Black et al. (2003) estimate that TFP averaged 0.9 percent between 1988 and 2002.[44] Given the short samples used by these studies, TFP estimates cannot be produced for comparable sample periods in this paper.[45]

6.4 Implications of the industry estimates

Theory suggests that sectoral productivity developments and relative prices should be related. According to the Balassa-Samuelson hypothesis, sectors producing 'tradeables' may be expected to exhibit faster productivity growth and falling relative prices compared with 'non-tradables'.

Figure 4 is based on the benchmark TFP estimates for each industry and illustrates that since 1996, large industries such as rental, hiring and real estate;

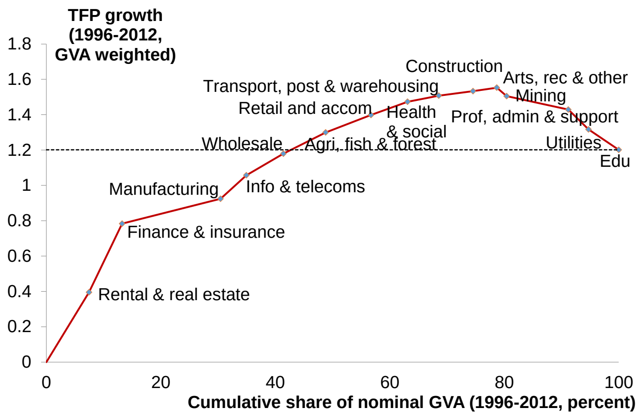
[43] Steenkamp (2015) discusses differences in data construction in official statistics and the approach used by Inklaar and Timmer (2008).

[44] Diewert and Lawrence (1999) show that there was negligible aggregate TFP growth for several years after the reform period began, which was followed by a strong pick-up. Whereas market sector TFP averaged near zero between 1988 and 1993, it averaged 1.7 percent between 1993.

[45] Diewert and Lawrence (1999) estimate that TFP grew at a compound annual rate of 3.9 percent in agriculture, -0.3 for fishing and hunting, 5.1 for forestry, 2.4 in mining, 3.7 in electricity, gas an water, 0.7 in construction, -0.7 in trade, restaurants and hotels, 3.3 percent in transport and storage, 5.0 in communications, -1.7 in finance services and 0.4 in community services between 1978 and 1998. The industry estimates of Black et al. (2003) cover the period 1988 to 2002, and are -0.2 percent for mining and quarrying, -1.5 for construction, 0.0 for manufacturing, -0.2 for electricity, gas and water, 5.9 for transport and communications, -0.4 for business and property services, 1.2 percent for personal and community services and 0.8 percent for retail and wholesale trade.

and finance and insurance services have shown the fastest TFP growth.[46] Industries that experienced declines in TFP include mining; electricity, gas, water and waste services; professional, scientific, technical, administrative and support services; and education and training. These estimates suggest that industries often thought of as more tradable (such as manufacturing or mining) have not out-performed industries producing relatively non-tradable products (such as service-oriented sectors).[47]

Figure 4: Output share weighted aggregate TFP



Note: Sectors ordered by weighted contribution to aggregate TFP calculated when aggregating industry TFP using average gross value added shares over the sample.

The estimates presented here suggest that there is some evidence that the New Zealand economy may be suffering from 'Baumol's cost disease'. Baumol (1967) suggested that the relative prices of goods from low labour productivity industries may be expected to rise for activities where labour cannot easily be substituted for capital. In the context of the estimates produced here, the prices of the goods and services produced by low productivity industries tended to rise by more than those produced by high productivity industries for the 1996 to 2012 sample (Figure 5). That said, industries that experienced relatively high TFP growth are a mix of what might be thought of as labour

[46] The aggregate TFP estimate from Table 3 is slightly lower than the weighted average of industry TFP estimates based on value added shares. Likewise, the weighted average of industry $\hat{\sigma}$ is 0.93, lower than the aggregate Hicks-neutral based $\hat{\sigma}$ and slightly higher than the estimate based on the general specification in Table 1.

[47] For US data, León-Ledesma and Moro (2016) argue that that a TFP growth differential between goods and service producing sectors can explain the fall in the output-capital ratio, as well as the decline in real return on capital.

intensive and non-labour intensive industries. Official TFP estimates tell the same story (Figure 6).

Figure 5: Benchmark TFP estimates

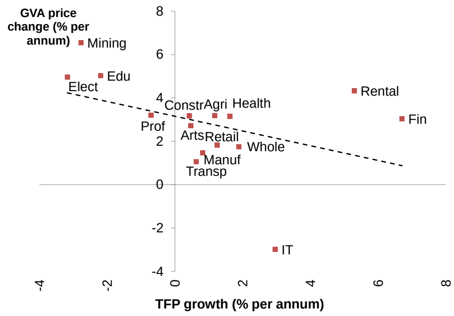
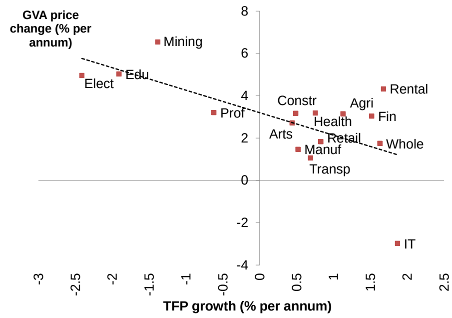


Figure 6: SNZ TFP estimates



Baumol's prediction does not imply that society will necessarily be worse off because of relative price shifts. Relative prices simply provide signals of the relative costs and benefits of producing different goods and welfare will be enhanced if labour is allocated across sectors according to its relative scarcity. If real wage equalisation occurs, wages will also rise in industries with low productivity growth. Indeed, in New Zealand, real wage growth does not display a clear pattern by relative TFP growth (Figures 7 and 8). Unfortunately, data availability prevents assessment of the extent to which labour share changes themselves have reflected changes in profits or shifts in the skill mix of those employed in each industry.[48] While some industries (such as finance, healthcare and mining) have experienced relatively fast wage growth, real wages have risen economy-wide.

Of course, such upward pressure on wage levels can reinforce real exchange rate appreciation. A stronger exchange rate tends to lower the costs of consumption for consumers by reducing the cost of imports, implying lower tradable prices relative to non-tradables, all else equal. There have long been concerns about the high level of the New Zealand dollar and the stress this

[48] Conway et al. (2015) provide estimates of industry contributions to decline in 'the measured sector' labour share and suggests that the change in New Zealand's labour share has not been associated with productivity growth: real wage developments have largely tracked productivity growth. Note that whereas real wages in this paper are deflated by the aggregate price level, Conway et al. (2015) define wages as the real product wage (labour compensation over industry output prices) and the labour income share as labour cost over income in order to decompose the labour income share into contributions from the cost of labour and labour productivity.

places on the tradables sector of the economy. A key puzzle related to New Zealand's economic performance is why the real exchange rate has defied the economy's deteriorating relative productivity. Figure 9 shows that while the ratio of tradable-to-non-tradble TFP has been relatively flat over recent years, New Zealand's real exchange rate has appreciated strongly, implying that other important factors have been influencing relative prices.[49]

Figure 7: Benchmark TFP estimates

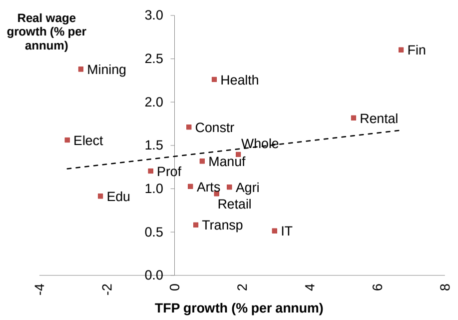
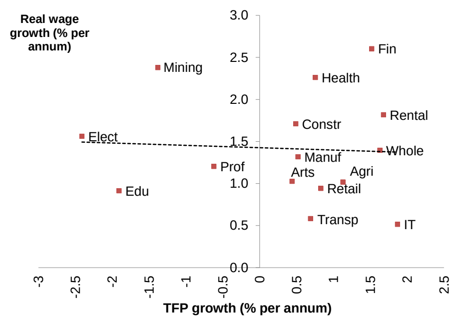
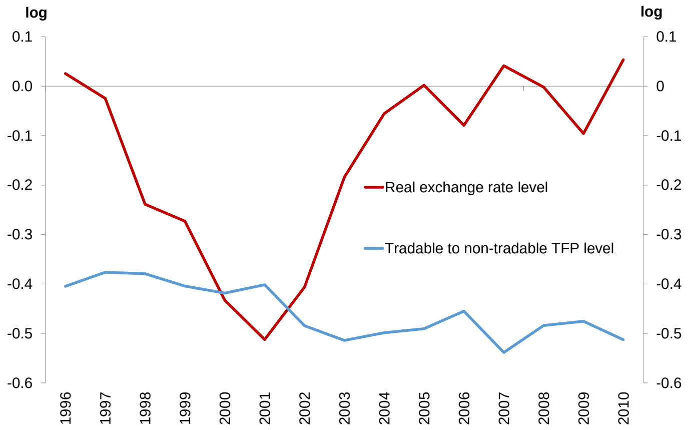


Figure 8: SNZ TFP estimates



[49] Although empirical support for the 'textbook' Balassa-Samuelson relationship between sectoral price and productivity differentials and real exchange rates is fairly weak, models are able to explain more of the cross-country differences in relative prices and their changes over time when controlling for structural labour market differences (see Berka et al. 2014 and Berka and Steenkamp 2017, *forthcoming*).

Figure 9: Real exchange rate and relative TFP *levels* (vs United States)



Source: Berka and Steenkamp 2017, *forthcoming*. The real exchange rate is the logarithm of the nominal exchange rate to the United States (US) dollar (defined as the US dollar price of one New Zealand dollar so that an increase represents appreciation), deflated by relative aggregate consumer price *levels* in each country. The latter are calculated using aggregate CPI and relative price levels in 2011 from The World Bank (2011). TFP levels are constructed by aggregating industry TFP levels from the Groningen Growth and Development Centre Productivity Level database (EU KLEMS Growth and Productivity Accounts 2014) for the US and Mason 2013 for New Zealand and linking these to time series TFP estimates from EU KLEMS (O'Mahony and Timmer 2009), with construction detailed in Steenkamp (2015). Tradable to non-tradable TFP levels are expressed relative to the US and calculated as $\log TFP_{NZ,T} - \log TFP_{NZ,NT} - (\log TFP_{US,T} - \log TFP_{US,NT})$.

7 Estimates based on quarterly data

To investigate the implications of the CES approach for productivity estimates over recent history, this section estimates TFP using CES production functions but using quarterly data available for the total economy. To understand the contribution of factor augmentation for growth, the estimates produced using the CES approach are compared to those from the Reserve Bank of New Zealand.

The Reserve Bank estimates TFP using a Cobb-Douglas approach with an adjustment for capacity utilisation, and uses data in levels as follows: $Y_t = A_t(C_tK_t)^{\alpha}(H_tL_t)^{1-\alpha}$, where real production GDP is Y_t, C_t denotes capacity utilisation, K_t the productive capital stock, H_t hours worked per employee, L_t is the number of employed (constructed as the product of the employment rate, participation rate and working age population) and α is capital share in output (assumed to be $\frac{1}{3}$).

The benchmark TFP estimate based on annual data for the aggregate economy (excluding owner-occupied housing and government) from Table 1 is lower than that obtained based on the Reserve Bank of New Zealand's approach for the total economy of 1.2 percent compound annual average growth between 1996Q1 and 2012Q1. If the CES approach used in this paper is applied to the same quarterly data as used by the Reserve Bank (described in detail in Lienert and Gillmore 2015) from 1996Q1 to 2016Q2, estimates of implied TFP growth vary between 0.5 to 0.7 percent per annum, compared to an estimate of about 0.9 percent when using the Reserve Bank approach over the same sample period (Table 4).[50]

The estimates in Table 4 are based on specifications assuming constant growth rates to simplify the growth accounting to follow. In the factor augmenting specification (which is preferred based on its determinant), $\hat{\sigma}$ is above unity, while it is below unity when imposing Hicks neutrality.[51] In line with the aggregate estimates based on aggregated annual industry level productivity data, $\hat{\gamma}_L > 0 > \hat{\gamma}_K$ in the general specification.

It might appear surprising that $\hat{\gamma}$ based on the quarterly data are similar to those obtained based on industry-data when there are difference in $\hat{\sigma}$. But there is a stark difference in the labour shares obtained when aggregating official industry productivity statistics compared with those based on total economy quarterly national accounts data for New Zealand (Figure 13 Appendix). While the aggregate labour share falls slightly according to the annual productivity data (Figure 3), it rises based when calculated using national-accounts based data (Figure 15 Appendix). This difference reflects, in large part, the attribution of mixed income and net taxes to labour in the official productivity statistics. The quarterly national accounts-based labour share presented here, on the other hand, is based only on labour compensation after adjustment for taxes and subsidies. As discussed earlier, a rise in the national-accounts measured labour share can be explained in a CES framework by labour-augmenting technical change if $\hat{\sigma} > 1$.

[50] Bearing caveats around the impact of economic reforms on the technology parameters in mind, full sample estimates produce $\hat{\sigma}$ slightly below unity in the factor-augmenting specification, and well below unity in the Hicks neutral specification. Full sample TFP estimates are 2.1 percent and 1.1 per annum, respectively, compared to 0.8 percent based on the RBNZ approach. Note that as in the short sample case, there is a local optimum for the general specification with $\hat{\sigma} > 1$, which in that case implies a TFP estimate of 1.1 percent.

[51] The estimates in Column 1 represent a local optimum but is selected since the global optimum for this specification does not produce plausible parameter estimates.

7.1 Potential output and the output gap

Production functions are often used to identify the structural determinants of the economy's growth performance. This section produces estimates of potential output (usually defined as the level of output consistent with stable inflation) and the output gap (defined as the difference between actual output and its potential level) from CES production functions using quarterly data, and provides comparisons to estimates from the Reserve Bank. The Reserve Bank estimates potential output by extracting trends from the input series using a Kalman filter and combining these in a Cobb-Douglas function. Under the Reserve Bank approach, potential output is defined as the level of output consistent with inputs and productivity being at their trend levels based on the given production function. The output gap is constructed as the difference between the actual level of GDP and the estimate of potential, expressed as a percentage of potential.

Performing growth accounting is more complex when using CES production functions owing to the non-linearity of the system. This paper constructs potential using the fitted values of equation 3 and decomposes $\hat{Y}$ using a first order Taylor expansion (as described in Flix and Almeida 2006) as:

$$\ln \Delta Y_t = w_t^K \ln \Delta \hat{\Gamma_t^K} + w_t^L ln \Delta \hat{\Gamma_t^L} + w_t^K ln \Delta K_t + w_t^L \ln \Delta L_t \tag{7}$$

where

$$w_t^K = \frac{\alpha(\hat{\Gamma^K}_{t-1} K_{t-1})^{(\hat{\sigma}-1)/\hat{\sigma}}}{\alpha(\hat{\Gamma^K}_{t-1} K_{t-1})^{(\hat{\sigma}-1)/\hat{\sigma}} + (1-\alpha)(\hat{\Gamma^L}_{t-1} L_{t-1})^{(\hat{\sigma}-1)/\hat{\sigma}}} \tag{8}$$

and

$$w_t^L = \frac{(1-\alpha)(\hat{\Gamma^L}_{t-1} L_{t-1})^{(\hat{\sigma}-1)/\hat{\sigma}}}{\alpha(\hat{\Gamma^K}_{t-1} K_{t-1})^{(\hat{\sigma}-1)/\hat{\sigma}} + (1-\alpha)(\hat{\Gamma^L}_{t-1} L_{t-1})^{(\hat{\sigma}-1)/\hat{\sigma}}} \tag{9}$$

Table 4
Estimates based on quarterly data (Total economy 1996Q1-2016Q2)

	1	2
	Factor-augmenting	**Hicks neutral**
ξ	0.994***	0.997
	(0.001)	(0.002)
α	0.539***	0.545***
	(0.000)	(0.001)
σ	1.407***	0.491***
	(0.006)	(0.001)
γ_K	-0.003***	
	(0.000)	
γ_L	0.006***	
	(0.000)	
γ		0.001***
		(0.000)
$\sigma = 1$	[0.0000]	[0.0000]
Nested in Model 1	-	[0.0000]
TFP growth (annualised)	0.005	0.007
Determinant	1.22E-13	1.45E-13

Note: All estimations reported are based on NLSUR estimated in Stata. *, ** and *** indicate the 10, 5 and 1 percent level of significance. ( ) denotes standard errors and [ ] denotes p-values. Wald tests used to test the restriction that $\sigma = 1$, while likelihood ratio tests are used to compare restricted and unrestricted models. TFP growth is calculated using the Kmenta approximation and then annualised.

Figure 10 compares the published output gap of the Reserve Bank to implied output gaps based on CES-based estimate when assuming constant growth over alternative sample periods.[52] The factor-augmenting CES model suggest that the output gap was larger than the Reserve Bank estimate during the late 1990s to late 2000s.[53] For the most recent period, CES models estimated from 1996 onwards produce estimates of potential that are closer on average to actual output than if estimated over the full sample period. The CES model

[52] For comparability with RBNZ estimates, the growth accounting estimates are presented in annual average percentage change terms instead of percentage terms as in the rest of the paper. Note that the official RBNZ output gap estimates incorporate an adjustment to TFP for the impact of the earthquakes in 2011 and judgement to the starting point and forecasts for the output gap, while the CES-based models do not.

[53] Since $\hat{\sigma}$ is significantly different from unity, it is not surprising that the CES models produce different estimates of the output gap to the Cobb-Douglas production function approach. The CES approach also simultaneously explains the changes in aggregate labour share in New Zealand according to the quarterly data and the rise in the capital to labour ratio over the sample period (Figures 14 and 15).

with factor augmentation (the preferred specification) produces a positive output gap estimate for the most recent data point, which is higher than the estimate from the Reserve Bank. CES models with factor augmentation have therefore pointed to stronger inflationary pressures than implied by the Reserve Bank estimates. For the sample 1996Q1-2016Q2, the estimate of potential from the factor-augmenting CES model is around 2.5 percent annual average growth, compared to 2.75 percent based on the Reserve Bank's approach.[54] A Hicks neutral specification, on the other hand, produces a similar profile for the output gap to the factor-augmenting one, although it is notable that it is negative over the recent period. Over recent history, a higher estimate of potential based on a CES approach reflects the strong growth in labour supply and capital stock, since the CES model used assumes factor-augmenting technical change to be constant over time.

The CES approach used in this paper cannot readily inform the debate about whether potential growth has fallen in recent years. Since the approach used is based on normalised data and given the short sample of data available, the growth accounting exercise is focused on the entire 1996Q1-2016Q2 period instead of assessments of different cycles. Figure 11 compares growth decompositions based on the Reserve Bank Cobb-Douglas approach and CES specifications assuming constant growth. Over the 1996Q1 to 2016Q2 sample, the contribution of trend growth in labour to potential in Reserve Bank model was around 1.05 percent on average, while that of trend growth in capital was around 0.85 percent and trend growth in TFP contributed 0.85 percent. The preferred factor-augmenting CES model instead suggests that capital contributed around 1.3 percent, labour supply approximately 0.85 percent, labour productivity around 1.4 percent and capital regress subtracted 0.8 percent. The strong growth in capital inputs almost entirely reflects an increase in capital stock (as opposed to a shift in trend capacity utilisation), while the increase in labour supply reflects a strong increase in working age population and small increases in the employment and participation rates.

In the context of the estimation approach used, the negative estimate of capital-augmenting technical change reflects the fall in the output to capital ratio, despite the increase in capital-labour ratio (Figure 14). These estimates are also consistent with the estimates from the same approach when applied to annual data aligned to those used by Statistics New Zealand to estimate TFP for the period 1996 to 2012 in Table 1.

[54] Based on the full sample model, on the other hand, annual average potential growth is estimated to be around 2.8 percent, which is slightly higher than the estimate of 2.65 based on the RBNZ's estimates for the sample 1990Q1-2016Q2.

Based on both the Reserve Bank and CES approaches, the estimates suggest that factor accumulation has played an important role in the growth of potential output. The advantage of the CES approach is that the contributions of factor productivity can be assessed. In line with the results based on annual industry-level productivity data, estimates based on quarterly national-account data suggest that while labour productivity growth has added meaningfully to potential, a decline in capital productivity has weighed on potential over recent years.

Figure 10: Output gap comparison

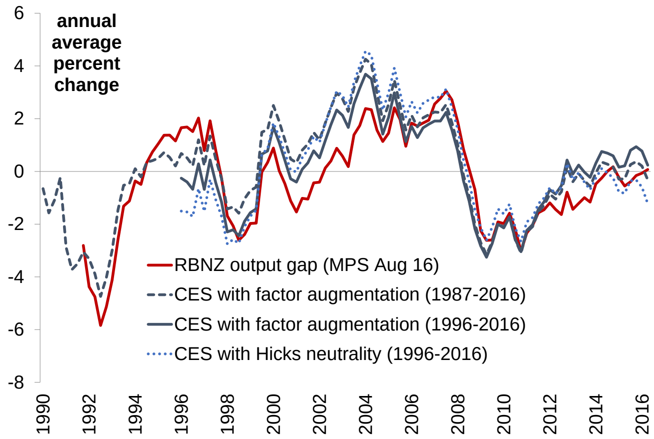
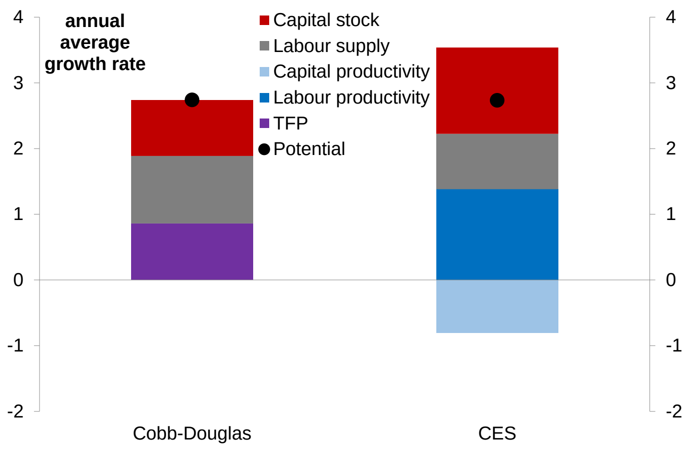


Figure 11: Contribution to potential output



8 Conclusion

This paper uses a variety of CES production functions to estimate the relationship between factor shares, productivity and the ease with which factors can be substituted. Estimates of productivity growth are produced at both an aggregate and industry-level for New Zealand. Few a priori restrictions are placed on the nature of technical change, allowing assessment of the impact on estimates from imposing different neutrality assumptions. The data used in this paper closely correspond to the data used to construct New Zealand's official TFP estimates, enhancing comparability to the estimates produced by Statistics New Zealand.

Data constraints make it impossible to estimate of productivity and factor substitutability of the aggregate economy over a long period of time for New Zealand. For industries that have data available back to 1978, the estimates presented here suggest that TFP growth was higher than implied by New Zealand's official estimates. But structural changes brought on by the reforms in the mid-1980s are likely to make these estimates unreliable. Focusing instead on the period from 1996, for which data for more industries are available, New Zealand's aggregate TFP growth is estimated to have been below 1 percent per annum.

The benchmark estimates suggest that the elasticity of substitution is significantly different from one in all industries. The benchmark estimates suggest that there has been regress in capital-augmenting technology, implying that additional increments of capital have tended to weigh on productivity. Providing a more detailed explanation for New Zealand's negative capital technical change requires more detailed data, in particular information on the composition and quality of capital at industry-level, which are not currently available. Additional research into the efficiency with which capital is employed in New Zealand is warranted.

At an industry-level, estimates of the elasticity of substitution and factor-augmenting technical change vary significantly. These results have several implications for the calibration of business cycle and endogenous growth models of the New Zealand economy. Firstly, the findings from this paper support the use of a general factor-augmenting functional form over more restricted specifications of the production function for New Zealand industry data. Secondly, the significant amount of heterogeneity between industries highlights the importance of modeling at a disaggregated level. This study also provides estimates of the elasticity of substitution that are consistent with the evolution of factor shares at industry level. Just as the estimates presented suggest that there are substantial differences in substitutability between capital and labour across industries, there may be considerable differences between different types of labour and capital, and further disaggregation could be a topic for future study.

Future work could also test whether the stylised facts alluded to in this paper (i.e. non-unitary substitution elasticity, industry differences in factor-augmenting technology and capital deepening) are able to explain the observed structural changes in New Zealand in the context of a neo-classical growth model.

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A Data Appendix

The annual industry-level data used have been constructed as follows:

- Output is measured as gross value added (gross output less intermediate consumption).[55]
- Labour inputs are based on industry hours paid (ordinary time plus overtime) for all employed and self-employed.[56]
- Capital inputs are based on the productive capital stock.[57] The capital stock estimates are the sum of national accounts-based chain-volume capital stock series, land and inventory (including livestock and timber). The calculation of the productive capital stock accounts for a decline in the efficiency of assets as they age.[58]
- Labour income is based on compensation of employees, net of taxes on production attributable to labour and the labour income of working proprietors. As income is value added-based, all non-labour income is attributed to capital.
- Nominal wages are calculated as labour income over total employed hours and converted to real values using the aggregate implicit GVA deflator.
- Real capital rental rates are constructed as $R_t = \frac{U_t}{K_t}$ using SNZ user costs of capital (where $U_t = R_t K_t$).[59] Industry user cost is aggregated additively using current price user cost instead of GVA weights (which

[55] Gross output is preferred for industry level productivity analysis, gross output data is not available at the required level of disaggregation for use in this paper.

[56] Changes in human capital will affect embodied technological change. See Statistics New Zealand (2008) for discussion of quality adjusted in a New Zealand context.

[57] SNZ use the volume of capital services from the productive capital stock, which in turn is calculated using a perpetual inventory method incorporating efficiency adjustments by asset class and a 4 percent discount rate. SNZ aggregate capital services for each industry using asset-specific user cost-based weights.

[58] Improvements in the quality of capital volume measures now available for New Zealand enhances the measurement of the real value of capital services compared to using net capital stock, as is common in other papers. Statistics New Zealand (2014) discusses the measurement of capital in New Zealand, and the treatment of land.

[59] The user cost of capital is based on SNZ data and is interpretable as the marginal revenue or marginal cost per unit of capital services. The SNZ data are calculated by inferring an implicit rental rate based on an exogenous real rate of return of 4 percent, a constant assumed depreciation rate, and average non-income tax rate on production for each industry (see MacGibbon 2010).

would overstate the contribution from labour) and then deflated using the implicit price deflators from industry productive capital stock. The rental rate of capital is expressed relative to productive capital stock volumes.

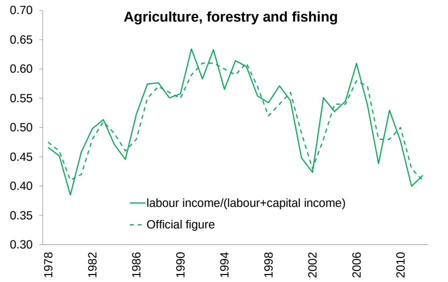
- Capital income is based on gross operating surplus (adjusted for the labour income of working proprietors) and net taxes on production attributable to capital. Profits are implicitly treated as a return to capital, implying that the factor of production exhaust total income.

- Official factor income shares are only published from 1996 onwards for several industries, so factor income shares are calculated as ratios to total factor income. The differences between this approach and the official shares are small (as demonstrated by Figure 12), although it produces a higher measure than using national-accounts data or alternative estimates for New Zealand (Figure 13).

- For consistency with the SNZ approach, national aggregates are created using chain-linked Laspeyres indices for capital and outputs.[60] The 'former measured sector' includes agriculture, forestry, and fishing; mining; manufacturing; electricity, gas, water, and waste services; construction; wholesale trade; retail trade; accommodation and food services; transport, postal, and warehousing; information media and telecommunications; and financial and insurance services. The rental, hiring and real estate industry data used exclude owner-occupied property operation, allowing an equivalent to SNZ's 'measured sector' category to be created by adding this industry to the former measured sector. The benchmark results are based on an aggregation that adds the 'hard to measure sectors' education and training, and healthcare and social assistance to the measured sector. The following industries are excluded from this study on account of data availability: local and central government and public safety (together representing about 4.5 percent of GDP).

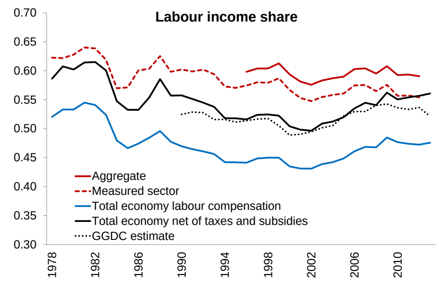
[60] See Diewert and Lawrence (1999) or Black et al. (2003) for more on the impact of indexing methods in a New Zealand context.

Figure 12: Labour share calculation



Source: Author calculations, SNZ (unofficial backdate), Inklaar and Timmer (2008)

Figure 13: Labour share measures



Source: Author calculations, SNZ (unofficial backdate), Inklaar and Timmer (2008)

Figure 14: Great ratios: Total economy (quarterly national accounts)

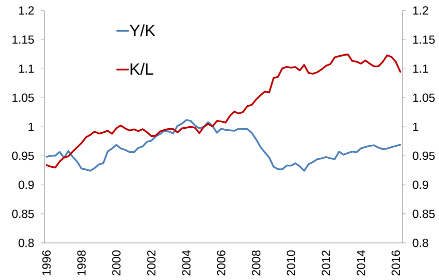


Figure 15: Labour share: Total economy (quarterly national accounts)

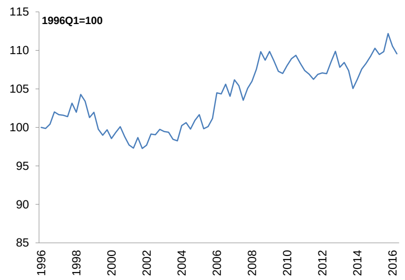


Figure 16: Relative returns: Aggregate economy (Annual data)

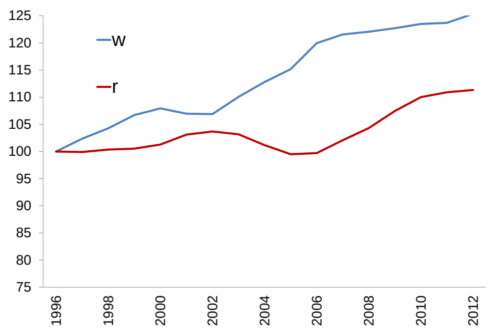
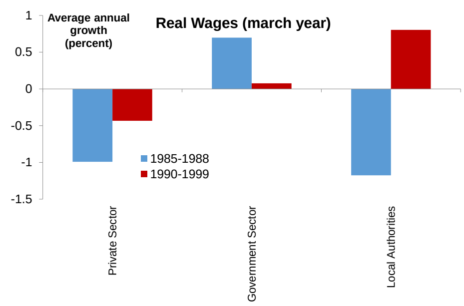
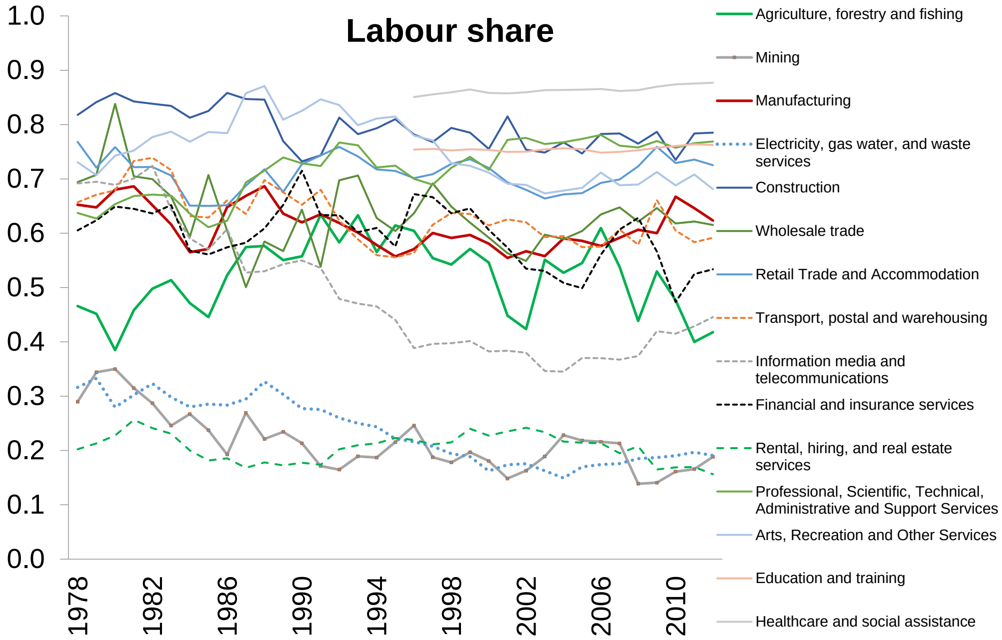


Figure 17: Real wages by sector



Source: EMP (Avg Hr Rates by Sector), QES (Avg Earnings by sector), SNZ, author's calculations.

Figure 18: Labour share by industry



B Industry charts

Figure 19: Great ratios

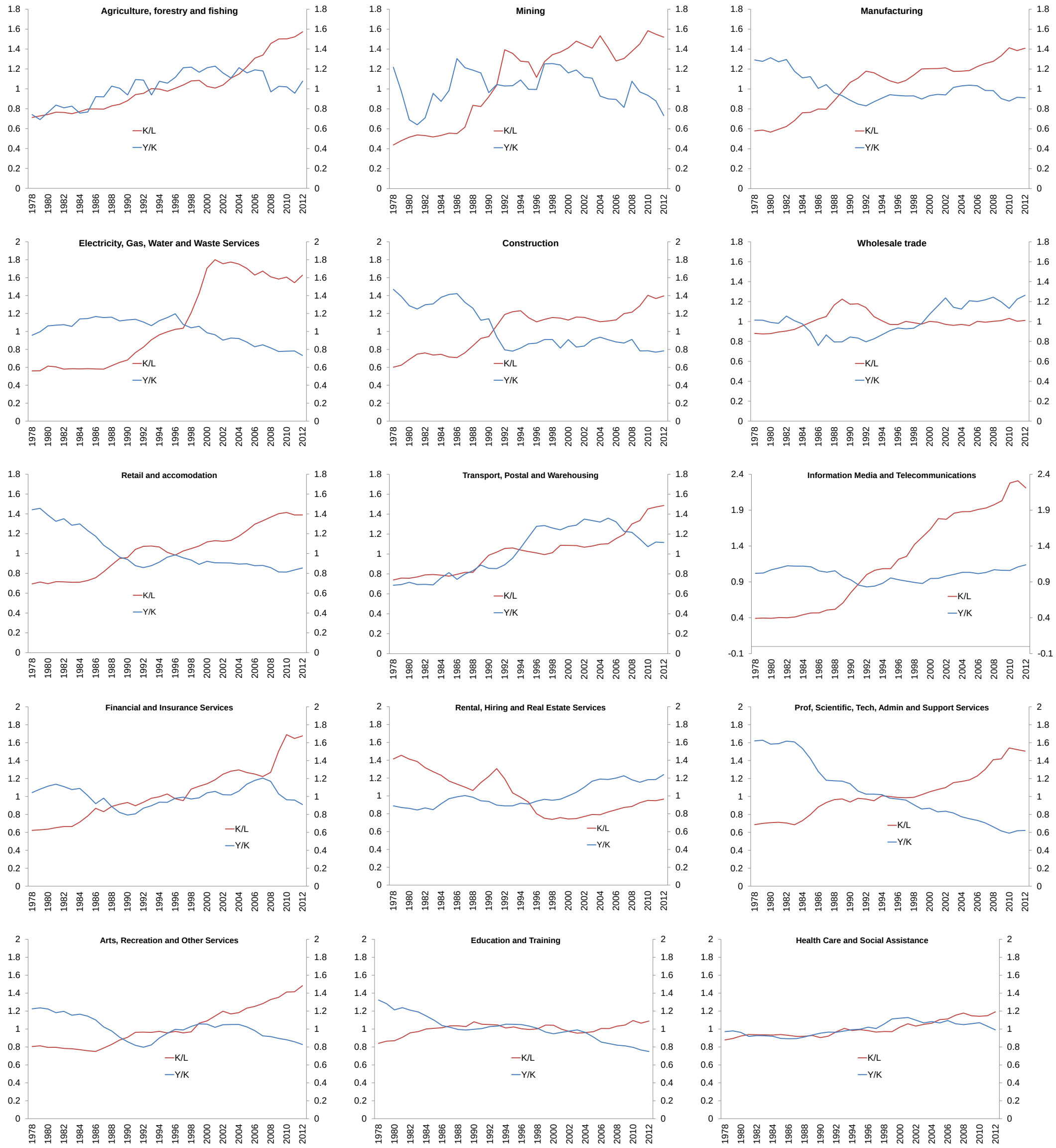


Figure 20: Labour productivity and real wages

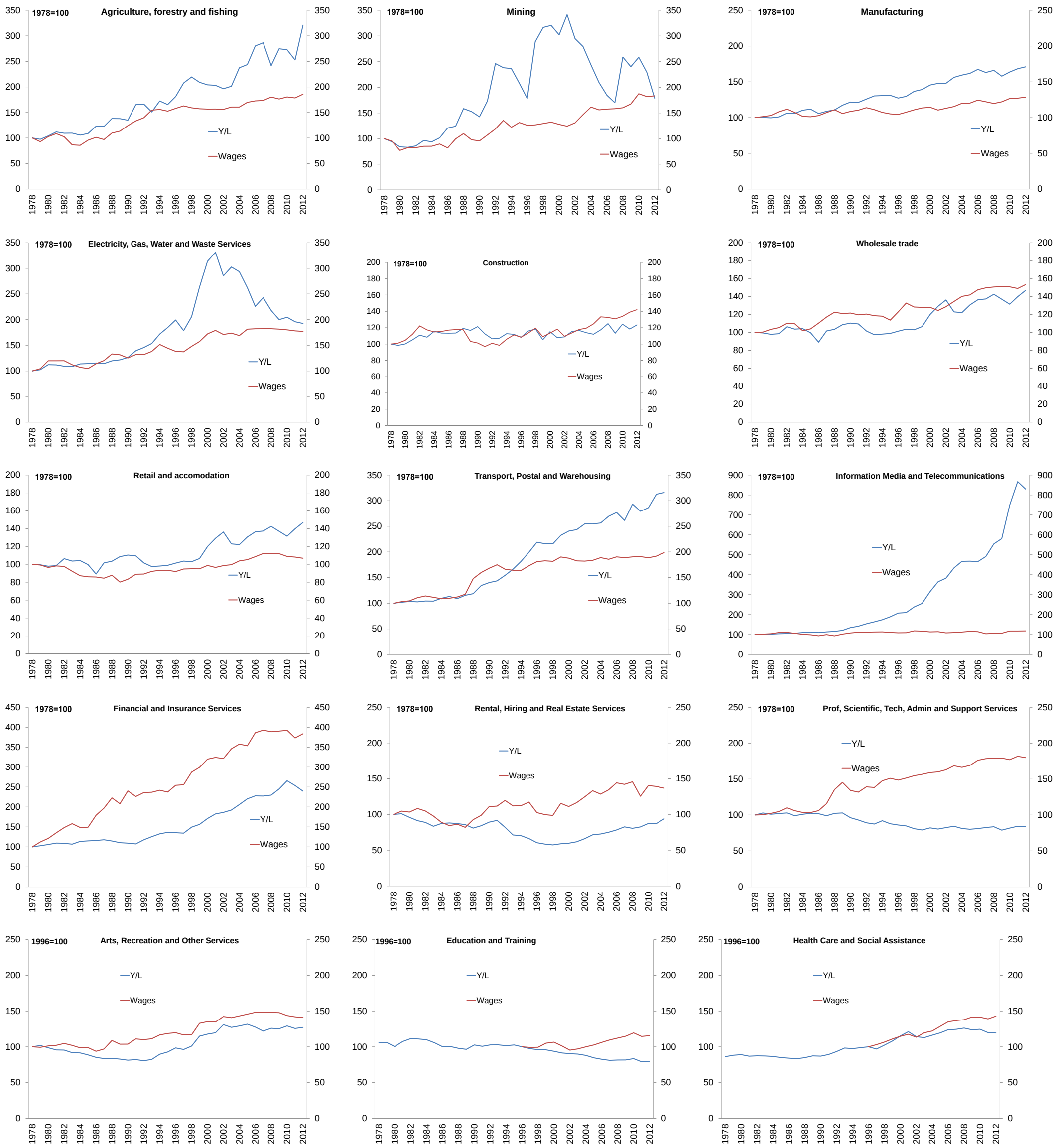
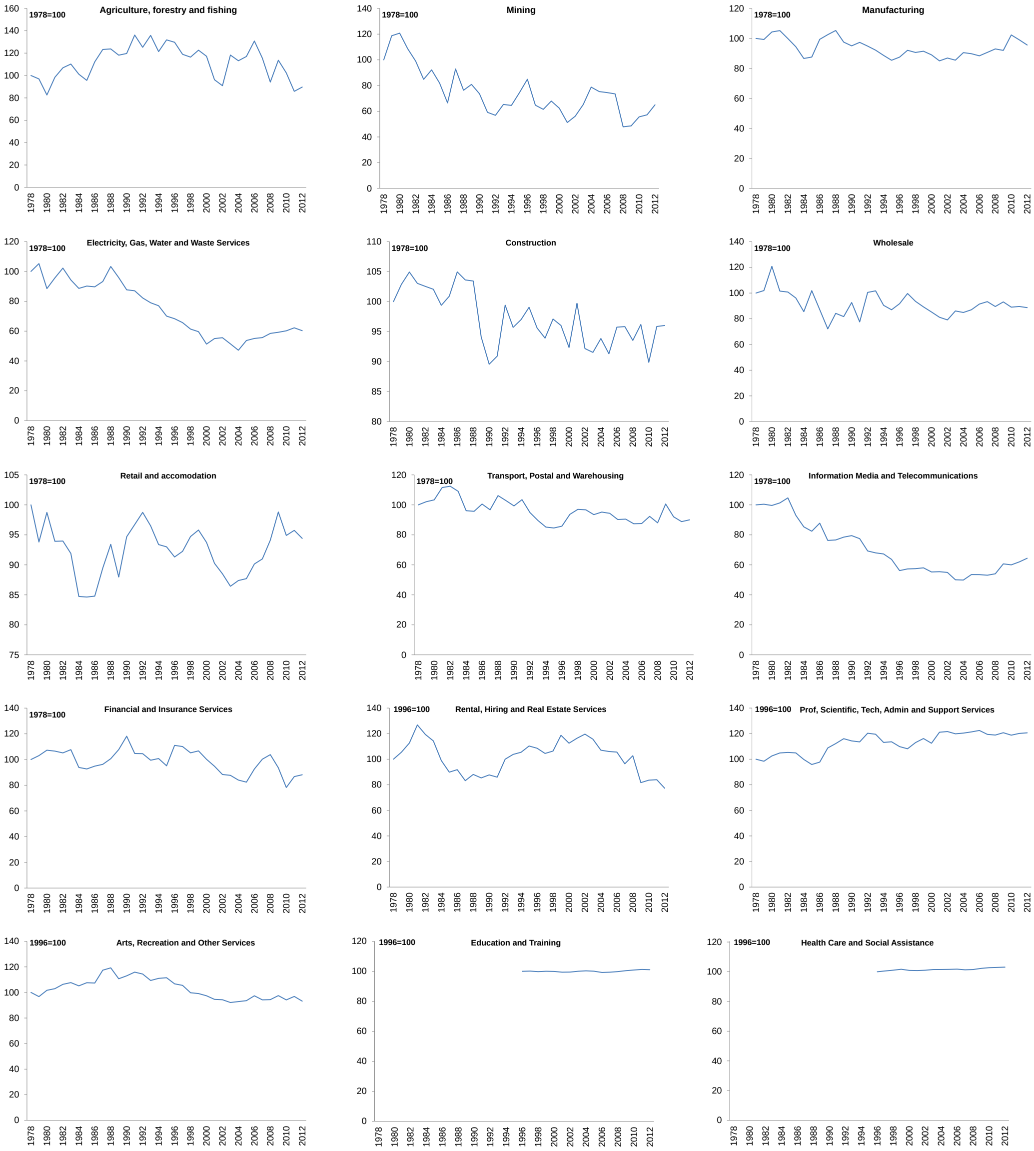


Figure 21: Labour share



C Robustness

C.1 Estimation over alternative samples

Table 5

Former measured sector (1978-2012)

	1	2	3	4
	Factor-augmenting		**Hicks neutral**	
ξ	0.998***	1.004***	0.995***	0.992***
α	0.409***	0.403***	0.405***	0.405***
σ	1.195***	0.844***	1.900***	1.927***
γ_K	0.035***	-0.036***		
γ_L	-0.002	0.047***		
γ			0.013***	0.013***
λ_K	0.583***	1	0.925***	1
λ_L	-0.402	1	0.925***	1
$\sigma = 1$	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Nested in Model 1		[0.046]	[0.054]	[0.082]
TFP growth	0.013	0.031	0.013	0.022
Determinant	1E-11	1.25E-11	1.2E-11	1.3E-11

Note: All results are based on NLSUR estimated in Stata. *, ** and *** indicate the 10, 5 and 1 percent level of significance. [ ] denotes p-values. Wald tests are used to test the restriction that $\sigma = 1$. TFP growth is calculated using the Kmenta approximation. Seem Appendix A for more details on industry classification and comparability with official statistics. Likelihood ratio tests are used to compare restricted (nested) and unrestricted models.

Table 6
Industry estimates of σ (1978-2012)

	σ	**95% Confidence interval**	γ_K	γ_L	**Benchmark specification**	**Tipper σ interval**
Agriculture, forestry and fishing	0.337***	0.333-0.341	0.009***	0.035***	Factor-augmenting	0.10-0.21
Mining	1.194***	1.172-1.217	0.0294***	-0.0726***	Factor-augmenting	-0.37-0.91
Manufacturing	2.613***	2.340-2.886	-0.000	0.013***	Factor augmenting	0.08-0.82
Electricity, gas water, and waste services	3.441***	3.267-3.615	-0.000	-0.000	Hicks neutral	0.24-1.29
Construction	3.424***	3.116-3.733	-0.0007	-0.0007	Hicks neutral (constant technical growth)	0.15-0.42
Wholesale trade	0.969***	0.899-1.038	-0.0138	0.0269	Augmenting (constant technical growth)	0.08-0.34
Retail Trade and Accommodation	0.386***	0.325-0.327	-0.010***	0.006***	Factor-augmenting	0.03-0.19
Transport, postal and warehousing	1.084***	1.052-1.116	0.0945***	-0.00795	Factor-augmenting	0.02-0.30
Information media and telecommunications	5.128***	2.570-7.688	0.024***	0.036***	Factor-augmenting	-8.64-15.21
Financial and insurance services	1.04***	0.998-1.092	0.094***	-0.015	Factor-augmenting	0.07-0.39
Former measured sector	1.195***	1.162-1.228	0.035***	-0.002	Factor-augmenting	0.38-1.27

Note: All estimations reported are based on NLSUR estimated in Stata. *, ** and *** indicate the 10, 5 and 1 percent level of significance. Model specification selected based on likelihood ratio test. See Appendix A for more details on industry classification and comparability with official statistics. The confidence interval limits for Tipper's (2012) estimates are for the long run elasticity from an AR1 model.

Table 7

TFP estimates compared to official estimates (percent, 1978-2012)

	Benchmark estimates*	**SNZ****
Agriculture, forestry and fishing	2.51	2.41
Mining	1.48	-0.54
Manufacturing	0.60	0.18
Electricity, gas water, and waste services	0.46	0.11
Construction	-0.12	0.12
Wholesale trade	1.22	0.53
Retail Trade and Accommodation	0.09	-0.06
Transport, postal and warehousing	3.30	3.15
Information media and telecommunications	3.38	2.22
Financial and insurance services	0.88	0.95
Former measured sector	1.29	0.88

* Model specification selected based on likelihood ratio test. ** Compound annual average, weighted using current price GVA when combining industry data where necessary. See Appendix A for more details on industry classification and comparability with official statistics.