A Richer Understanding of Australia's Productivity Performance in the 1990s: Improved estimates based upon firm-level panel data

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Abstract

Australia's productivity performance is characterized by important differences across continuing firms, frequent entry of new firms, and substantial exit of firms which, for one reason or another, decide to cease production. These basic facts call into question the appropriateness of measuring productivity using an aggregate production function that is based upon a representative firm. This study relaxes the standard assumptions that industries are comprised of a set of homogeneous firms, the set of which are constant over time. Instead, we apply a semi-parametric production function estimation technique that explicitly models the firm's decision to continue production. The model controls for the relationship between productivity shocks and input choices and the inter-relationship between these and the decision to continue production. Using the Business Longitudinal Survey, we estimate an improved set of production functions for twenty-five two-digit industries in Australia. We use these results to examine aggregate industry-level productivity performance. We use a new aggregation method in calculating these changes which allows us to separate productivity changes and output composition changes which sheds new light on industry-level productivity performance in Australia.

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1 Introduction

Many studies of productivity focus on the average productivity performance of an industry or industries. While useful in understanding overall trends, such a focus generally hides a great deal of mixed results at the firm level. Some firms do very well in productivity terms while others falter. Some may even cease operation. Meanwhile new entrants put pressure on incumbent firms and those incumbents are themselves innovating and investing to stay ahead of their competitors. Some succeed in this effort while others fail.

Differing productivity performance across firms (firm heterogeneity) and firm entry and exit (dynamics) have received widespread and systematic substantiation in recent years via a number of international studies using large-scale longitudinal micro data sets, the availability of which is a fairly recent phenomenon (see review in Bartelsman and Doms (2000)). These data have allowed researchers to use empirical frameworks which move away from the idea of a representative firm with a fixed percentage of industry output towards richer models which incorporate entry and exit and contraction and expansion of continuing firms. Rather than productivity increasing through the representative firm improving its efficiency, these frameworks admit a much wider range of possible sources of aggregate productivity growth such as exit of less productive firms and re-allocation of output from less productive to more productive firms.

This paper makes two contributions to this growing literature. We apply to Australian firm-level panel data, for the first time, a production function estimation technique which accounts for much of the complexity of the microeconomic reality. The estimation technique allows for firm entry and exit and, in particular, we model firms' decisions to exit production in conjunction with their observed characteristics and unobserved productivity performance. Substantial firm heterogeneity and dynamics cast doubt on the accuracy of productivity estimates obtained from an aggregate production function based upon a representative firm. Our approach produces improved production function estimates at the industry level.

Our second contribution is to use these estimates to provide a richer characterization of industry-level aggregate productivity changes. We do this by highlighting a problem with the conventional measure of aggregate (industry) productivity change in firm-level productivity studies, namely, that it captures a mixture of productivity and market share changes, instead of solely the former. We compute an indicator of industry productivity change that not only corrects for the aggregation problem with the conventional measure, but is also consistent with the growth-accounting definition of aggregate productivity growth. By looking at our proposed measure in conjunction with the standard measure we gain a deeper understanding of industry-level productivity growth in Australia.

In section two, we give a brief overview of the history of production function estimation using firm-level data. We provide a detailed review of the theoretical background and empirical methodology which we use, as this may not be familiar to our readers. We also briefly mention some of the extensions to our methodology. Section three describes and summarizes the data. Section four evaluates the estimation results. In section five, we present our method of constructing and aggregating firm-level MFP indices and our results regarding industry MFP trends based on these new estimates. The last section discusses the relationship between our results, recent productivity trends in Australia, and possible implications for policy.

2 Production Function Estimation

Historically, the standard approach to estimating production functions using firm level data was through ordinary least squares estimation of a Cobb-Douglas[1] production function using either a cross-section of firms or a set of pooled cross-sectional data

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + u_{it} \tag{1}$$

where the variables are measured in logs and y, k, and l are output, capital, and labour. Such estimates suffer from omitted variable bias (often called simultaneity bias in the production literature) when u_{it} contains productivity differences across firms (such as managerial quality or firm 'culture') which are correlated with capital and labour inputs. Such bias has been identified since at least Marschak and Andrews (1944).

This unobserved firm productivity can be both contemporaneously and serially correlated with inputs. Contemporaneous correlation occurs if more productive firms hire more workers and invest in capital in response to higher

[1] Alternately some flexible function like a translog may be used.

current and expected profitability. The problem is likely to be more acute for inputs such as labour that can be adjusted rapidly to current productivity realizations. If a firm's productivity is correlated over time, then input choices will be based on a serially correlated productivity term. OLS estimates will be biased upwards in a single input case, but the direction of the inconsistency is indeterminate in a multivariate setting. For example, in certain cases where labour and capital are positively correlated, but labour is more strongly correlated with the productivity term than capital, then the labour coefficient will tend to be overestimated, and the capital coefficient underestimated.

The standard solution is to treat unobserved productivity as constant over time and varying across firms. With a panel of firm-level data this allows for fixed-effects estimation of

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \alpha_i + v_{it} \tag{2}$$

where α_i represents firm-specific productivity differences. Empirically, researchers using fixed effects continued to find unreasonably low capital coefficients and unreasonably high labour coefficients. Theoretically, the rigid assumption of fixed firm-specific effects is flawed. It rules out changing productivity during periods of policy and structural changes and furthermore, it rules out firms taking any action to change their own productivity performance. But casual observation strongly suggests that firms spend great money and effort to invest in managerial quality, firm culture, etc. This point has been made strongly by Muendler (2004a,b). All of this suggests that productivity varies across firms and across time, invalidating the fixed-effects assumption.

Another estimation problem involves the fact that most industries are characterized by substantial amounts of firm entry and exit.[2] This is not random, but rather the result of conscious decision that expected profits are too low to justify continuation of business. If a firm's future returns are positively related to the size of its capital stock at any given current productivity level, then firms with greater capital stock are more likely to survive lower productivity realizations. The expectation of (unobserved) productivity conditional on the selected sample of surviving firms is thus decreasing in capital, violating our standard regression assumptions and leading to a negative selection bias in the capital

[2] Bartelsman et al. (2004) document turnover rates of 10 to 25 per cent across a range of developed and developing countries.

coefficient. This problem is exacerbated in 'balanced' panel analysis which is the traditional way to avoid dealing with entry and exit.

The selection problem created by firm entry and exit has been recognized in the empirical literature at least sine Wedervang (1965). Olley and Pakes (1996) developed an innovative methodology to address both simultaneity and selection problems, which is increasingly being applied in production function estimation. We will adopt this approach, which is underpinned by a dynamic and realistic model of firm behaviour that incorporates time-varying and firm-specific productivity differences and allows for endogenous firm exits.

2.1 Theoretical model

The centrepiece of the Olley and Pakes (1996) methodology (henceforth, OP method) is the expression of the unobserved productivity term in terms of observable firm data (specifically, investment demand), as derived from a behavioural framework which allows for correlation between firm productivity and input choices. Furthermore, changes in productivity over time can be proxied by changes in observable variables. This eliminates the need to assume that unobservable, firm-specific productivity realizations are time-invariant.[3]

Theoretically, firms decide at each point in time, t, whether to continue or cease business on the basis of current productivity realizations (observable only to the firm, not to the econometrician), the sell-off value of its capital, current profits and expected future profits. Labour is fully flexible and productivity is assumed to evolve as a first-order Markov process, providing information to the firm which it uses to form expectations of future profits. All firms within an industry are assumed to face common factor prices and market structure. Capital depreciates at rate δ and can be replaced by investment.

Ericson and Pakes (1995) use the value function generated by this set-up to solve the firm's optimization problem and to generate an exit rule

$$\begin{aligned} \chi_{it} &= 1 \text{ continue operation, if } \omega_{it} \geq \omega_t^* \left(k_{it}, age_{it}\right) \\ &= 0 \text{ cease operation} \end{aligned} \tag{3}$$

and an investment function

$$i_{it} = I_t \left(\omega_{it}, k_{it}, age_{it}\right) \tag{4}$$

[3]The OP method draws upon theoretical work on firm behaviour from Ericson and Pakes (1995) and Hopenhayn and Rogerson (1993).

based upon the firm's productivity, ω_{it}, capital stock, k_{it} and age.

2.2 Estimation methodology

Estimation using this theoretical framework proceeds in three stages.

Step 1 We specify a Cobb-Douglas production function[4] for each industry, with firms distinguished by Hicks-neutral efficiency differences

$$y_{it} = \beta_0 + \beta_a age_{it} + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \tag{5}$$

where y_{it} is output (value added), k_{it} is capital stock, l_{it} is labour and age_{it} is firm age. All variables are in log form except age. η is a mean zero variable which accounts for unanticipated productivity shocks and is assumed to be unrelated to the choice of inputs. Firm subscripts are omitted in subsequent equations for ease of presentation.

Labour is assumed to be the only variable input. Its demand is affected by the current value of ω_t. Capital and age are fixed factors dependent only on the distribution of ω_t conditional on information at time t-1 and past values of ω. From (4), the optimal investment level at each period is a function of the state variables (ω, k, and age). Provided that $i_t > 0$, Pakes (1994) shows that equation (4) can be inverted to express the unobservable productivity shock ω as a function of the observable state variables and investment

$$\omega_t = h_t\left(i_t, k_t, age_t\right). \tag{6}$$

Substituting (6) into (5), we have

$$y_t = \beta_l l_t + \lambda_t\left(i_t, k_t, age_t\right) + \eta_t \tag{7}$$

where

$$\lambda_t\left(i_t, k_t, age_t\right) = \beta_0 + \beta_a age_t + \beta_k k_t + h_t\left(i_t, k_t, age_t\right) \tag{8}$$

Notice that the coefficients on capital and age in (5) can not be identified since both of these variables affect output <u>and</u> the investment decision.[5] It is through the latter that capital and age are correlated with productivity. The

[4] Using a flexible form such as the translog has no impact on the results presented below.

[5] Note that the coefficient on capital, β_k in equation (8) will not be the marginal change in output for a one-unit increase in capital. There is also an effect on output of changing capital through h_t.

coefficient on labour can be identified in equation (7), a partially linear model which can be estimated using semi-parametric regression techniques. As in Olley and Pakes (1996), we use a series estimator for the unknown function λ_t. Our estimation objective, in this step, is to obtain a consistent estimate of β_l. Andrews (1991) has shown that a partially linear model using series approximation of the nonlinear portion yields consistent and asymptotically normal estimates of the coefficients in the linear part of the model. This allows us to estimate β_l without requiring identification of β_k and β_{age}.

Step 2 We estimate survival probabilities to correct for selection. These probabilities, together with the estimated $\widehat{\beta}_l$ and $\widehat{\lambda}_t$ from step 1 will enable the identification of β_a and β_k.

Consider the value of output one period forward, for firms which continue production, under the assumption that productivity evolves as a first-order Markov process

$$y_{t+1} = \beta_0 + \beta_a age_{t+1} + \beta_k k_{t+1} + \beta_l l_{t+1} + E\left[\omega_{t+1} | \omega_t, \chi_{t+1} = 1\right] + \xi_{t+1} + \eta_{t+1} \quad (9)$$

where

$$\omega_{t+1} = E\left[\omega_{t+1} | \omega_t, \chi_{t+1} = 1\right] + \xi_{t+1}. \quad (10)$$

The first term will have non-zero mean, since both firm exit decisions and productivity at time $t+1$ are related to productivity at time t. ξ_{t+1} is the mean-zero innovation in productivity.[6] Recall that firms, but not the econometrician, observe their own productivity realization and then make their decision to continue operation or shut down. From equation (3), a firm makes this decision based upon whether its productivity at t+1 is above some threshold value ω_t^*.

Information on ω_t^* can be obtained by evaluating the probability that a firm continues to produce in time t+1

$$\begin{aligned} Pr\left(\chi_{t+1} = 1\right) &= Pr\left(\omega_{t+1} \geq \omega_{t+1}^*\left(k_{t+1}, age_{t+1}\right) | \omega_t\right) \\ &= \varphi\left(\omega_{t+1}^*\left(k_{t+1}, age_{t+1}\right), \omega_t\right) \\ &= \varphi\left(i_t, k_t, age_t\right) \equiv P_t \end{aligned} \quad (11)$$

The third line follows from the investment rule and the accumulation equations for capital and age. Survival probabilities can be estimated using a probit

[6] ξ is the stochastic component of the first-order Markov process determining productivity.

model. We allow for flexibility in the index function by using a fourth-order polynomial in investment, age, and capital. This can be viewed as a non-parametric estimator of the index function.

Step 3 In order to estimate (9) we need to control for the selection effect which is a function of the exit decision and last period's productivity realization $E\left[\omega_{t+1}|\omega_t, \chi_{t+1}=1\right] \equiv g\left(\chi_{t+1}, \omega_t\right)$. We can combine the results of the first two steps to do this. From (11), we use our probit estimates, $\widehat{P}_t$, to estimate the probability that $\chi_{t+1}=1$. From estimation of (7) and using (8), express $\omega_t \equiv \widehat{h}_t = \widehat{\lambda}_t - \beta_a age_t - \beta_k k_t$.[7] Combining these into (9) we have

$$y_{t+1} = \beta_0 + \beta_a age_{t+1} + \beta_k k_{t+1} + \beta_l l_{t+1} + g\left(\widehat{P}_t, \widehat{h}_t\right) + \epsilon_{t+1} \qquad (12)$$

where the unknown g is approximated by a fourth-order polynomial in $\left(\widehat{P}_t, \widehat{h}_t\right)$. The composite error term, $\epsilon_{t+1} \equiv \xi_{t+1} + \eta_{t+1}$, is uncorrelated with k_{t+1}, allowing for consistent estimation of the coefficient on capital. We estimate this by maximum likelihood since the model is non-linear in the parameters β_k and β_a.

We add year dummies to the basic specification to control for macro-economic effects common to all firms. We also introduce dummies to account for observations with zero investment. Theoretically, the model requires that investment be strictly positive (see equation (6)) to invert the investment function. In their empirical implementation, Olley and Pakes (1996) drop all observations with zero investment. Other authors have noted that in practice zero investment is often observed and that the methodology seems to work even when the theory is violated. (See, for example, Pavcnik (2002).) In our application, dropping firm/year combinations with zero investment would lead us to drop over half of the observations. Therefore our approach will be to retain all the observations with zero investment but to introduced dummy variables (dummy variables for zero investment interacted with state inputs) to account for these observations, as in Blalock and Gertler (2004). As a robustness check, we did estimate the model dropping all of the observations with zero investment and the resulting coefficient estimates are similar to those reported below. Standard errors are, of course, larger.

We report boostrapped standard errors (using 200 replications) for the age and capital coefficient estimates. The series estimator used for $g(\cdot)$ in equation

[7] Note that $\widehat{h}_t$ contains estimated $\widehat{\lambda}$ and unknown β_a and β_k.

(12) has no known limiting properties, although Olley and Pakes (1996), who provide asymptotic results for the kernel estimator of $g(\cdot)$, suggest that the series estimator should have the same properties as the kernel estimator, since the parameter estimates yielded by the two were not significantly different. Following Levinsohn and Petrin (1999) we implemented specification tests to compare this procedure to OLS and fixed effects, both of which are nested in this model.

2.3 Extensions to the Methodology

While one group of papers use the OP methodology with little or no change (for example, Pavcnik (2002) and Blalock and Gertler (2004)) several recent papers extend and enrich the basic OP methodology in response to either its practical or theoretical limitations. We briefly mention these to demonstrate the widespread popularity and applicability of this framework. Levinsohn and Petrin (1999) use intermediate inputs, instead of investment, as the productivity proxy. Criscuolo and Martin (2004) allow for imperfect competition and show that profits, not investment, is an appropriate predictor for the unobserved productivity term.

Muendler (2004a) and Muendler (2004b) substantially enrich the behavioural model underlying the OP algorithm. He approximates the productivity term with a multivariate set of 'expectation proxies'–physical investments, sector-level competition variables and their interactions. Muendler's framework incorporates features such as imperfect competition, managerial investments in capital and efficiency-relevant assets and the evolution of MFP in dependence on managerial effort. Combining endogenous productivity choice with convex adjustment costs, productivity, in his framework, monotonically increases in investment unconditionally. This removes the need to drop non-positive investment from the sample, unlike in OP. In our application, this provides justification for our decision to keep observations with zero investment.

Ackerberg et al. (2005) highlight the restrictiveness of assuming that labour is perfectly flexible. They suggest an alternative, consistent with the assumptions of the OP methodology, that labour is not flexible but is chosen before the productivity realization. Wooldridge (2005) proposes a more efficient, one-step, generalized method of moments estimation approach.

The standard OP technique remains the main tool in the literature, as none of these extensions or alternatives has yet to emerge as superior in all cases. We would stress that the estimation technique is consistent with a range of realistic underlying assumptions about firm behaviour including those of the original OP model and many of the extensions.

3 Data

We use data from the Business Longitudinal Survey (BLS) of the Australian Bureau of Statistics (ABS), Australia's only longitudinal data that tracks firm entry and exit. Four waves of data were collected from 1994-95 to 1997-98. The sample was drawn from the ABS Business Register, stratified on industry and employment size. The first wave sample of 9000 firms was post-stratified into two categories in the second year of the survey. The first category was firms which were identified as innovators, exporters, or those with high employment or sales growth. All firms in this first category, about 3400, continued to be surveyed. Of the remaining 5600 which formed the second category, about 2200 were selected for continuation in the survey. A random sample of new firms was selected and added to the the 1995-96 (wave two) survey. In subsequent years, all firms surveyed in the previous year were tracked and re-interviewed, exits were recorded, and a sample of new births from each year was included.

We use the main unit record file (MURF) which comprises both large and small firms and is more representative of the business population than the publicly available confidentialised unit record file (CURF).[8] The CURF excludes firms with more than 200 employees or very large sales. The results reported here are with respect to the BLS MURF, and any subsequent mention of the BLS should be taken to refer to the MURF sample.

The BLS covers only non-agricultural market sectors, and excludes industries with heavy government involvement, such as health and education and communications services. We analyze 25 2-digit industries.[9] We exclude industries such as mining for lack of observations and financial services due to the difficulty of measuring output, as identified by Rogers (1998).

Our "full sample" (unbalanced panel) is constructed using firms which appear in all four waves, by retaining firms that eventually exit until the year

[8] The CURF is described in detail in Australian Bureau of Statistics (2000).

[9] Although we know the 4-digit industry of each firm, communication from the ABS convinced us that there is too much noise in the data at the 4-digit level for reliable estimation.

prior to their exit, and by introducing new entrants as they appear. One issue especially important to us is the classification of 'truly' new entering and exiting firms. Will and Wilson (2001) document anomalies in the data on births and deaths, and derived criteria for identifying 'true' births and deaths. We have investigated this issue further, and decided to modify their 'true' birth rule but adopt their rule for removing 'illegitimate' deaths.[10] In short, true births are identified as firms coded as entrants that are aged less than 4 years, with total employment of less than 30 OR not more than median industry sales at survey entry. True deaths are defined as firms that exit the survey and record no change or a fall in employment, and a rise in capital stock of no more than 5 per cent, in the year prior to exit.

Entry and exit rates by industry are presented in Table 1. We provide these as information about our sample, not as estimates of aggregate (national-level) entry and exit rates for these industries.[11] A comparison to unpublished, Australian Tax Office (ATO) business income tax data reveals higher entry rates than we find in the BLS. However, these include companies that have undergone restructuring, form new subsidiaries, or break up into several new firms, and identify themselves as 'commencing business'. Entry is certainly overstated in the ATO data, however it may be understated in the BLS. ATO exit rates are moderately lower than those registered in the BLS.

Looking at Table 1, there has been modest entry and exit over a three year period, with rates varying across industries. The entry rate ranged from 4.1 per cent (machinery and equipment) to 22.7 per cent (food retailing), while the exit rate was between 6.9 per cent (metal product) and 22.8 per cent (sport and recreation). While both manufacturing and service sectors experience turnover, more services industries experience greater flux, in particular retail trade and accommodation, cafes and restaurants. These general patterns correspond to the international experience (see Bartelsman et al. (2004)).

Variable definitions and their construction from the BLS are described in

[10] Readers interested in obtaining a more detailed write-up on the correction for true births and deaths can email the corresponding author.

[11] We provide unweighted statistics in all tables. Given that we have re-classified some entries and exits relative to the BLS, we are uncomfortable using the weights provided by the ABS. As indicated in the first paragraph of this section, the BLS is a highly non-representative sample. Parham (2002b), amongst others, highlight the difficulty of trying to replicate national aggregates using the BLS, even when taking account of the weights. The purpose of this paper is to focus on firm-level estimates and firm-level dynamics, not on reproducing national aggregates. We return to this issue in the discussion of our results in section 5.3.

appendix Table A1. Appendix Table A2 presents firm characteristics by entrants, continuing firms and exiting firms for each industry. Both mean and median values are given, as the means are heavily influenced by a number of large values. Unsurprisingly, continuing firms have higher average value added, employment, business age, capital stock and investment. Exiting firms tend to be smaller, although the exits of some large firms raises the average value added and capital stock of exiting firms in a few industries. The lower average business age of exiting firms is consistent with findings that younger firms have a lower survival rate.

4 Regression results

We estimate production functions for 25 industries at the 2-digit ANZSIC code level by ordinary least squares (OLS), fixed effects, (FE), and the OP methodology described in section 2.2 above. We further compare OLS and FE on the balanced and unbalanced panels. Detailed results by industry are reported in Table 2. Table 3 summarizes the changes in the labour and capital coefficients that we are particularly interested in examining. These are, namely, the changes in coefficient estimates moving from OLS estimation on the balanced panel to OLS on the full sample to OP.

4.1 OLS: balanced and unbalanced panels

If restoring observations to a balanced panel to form an unbalanced panel alleviates the simultaneity and selection problems, we would expect the labour coefficient to fall and the capital coefficient to rise. Slightly half of the industries register the expected change in direction for both coefficients, consistent with the presence of selection and omitted variable biases as discussed in section 2 above. The proportion of industries yielding either a higher capital coefficient or a lower labour coefficient in the unbalanced panel is around 56 per cent. Where the labour coefficient is lower, the decrease is usually less than 10 per cent. Where the capital coefficient is higher, the increase is usually between 2 and 38 per cent. These changes are smaller than those reported by Olley and Pakes (1996). This is not surprising, however, as in their case moving from a balanced to an unbalanced panel increased their sample size by 189 per cent! Our sample size increases by only about one-sixth this amount.

4.2 Comparing OLS to OP method

Since OLS regression, even on a full sample, does not control for firm-specific differences in productivity, we would expect the OLS labour coefficient to remain biased upwards because of the correlation between observable input choices and unobservable productivity. Under the assumptions of section 2.1 above, our estimates using the OP methodology should correct for this bias. Our results for the labour coefficient are consistent with this hypothesis, as 72 per cent of the industries have lower labour coefficients in the OP estimates than in the OLS estimates. The drop in point estimates ranges from 0.5 to 13 per cent.

The direction of change of the capital coefficient from OLS on the full sample to OP is negative for 60 per cent of the industries, with decreases between 1 and 80 per cent. This implies a positive bias in the OLS capital coefficient. For the 40 per cent of industries where the coefficient increased, the change was between 2 and 40 per cent.

The tendency of positive bias in the OLS capital coefficient contrasts with the results of Olley and Pakes (1996) and several others. However, they are not perplexing within the current framework. There are multiple biases of varying magnitudes working in different directions in this setting. Selection for survival will generate a negative bias in the coefficient on capital in the OLS estimates, but contemporaneous or serial correlation between capital usage and productivity can cause a positive bias in the OLS capital coefficient. While simultaneity between capital and productivity is not inconsistent with the OP model, OP had emphasized the effect of selection. This is not surprising given that, in their application, use of the balanced panel involved such large reductions in sample size–throwing away two-thirds of the sample would certainly focus the mind on selection! Muendler (2004a) has explicitly illustrated that an upward bias in the OLS capital coefficient can arise from a positive relationship between capital and MFP. Thus, it is unclear a priori which source of bias will dominate.

Our findings indicate a strong correlation between capital and productivity and, subsequently, that simultaneity bias dominates selection bias in most cases. This is perhaps not surprising given the fairly modest exit rates (an average of 12 per cent cumulative over three years) in the sample, which is from a period of steady expansion in the Australian economy.

4.3 Other observations on results

Our sample includes industries in both the manufacturing and services sectors. We do not find systematic differences in output elasticities across industries on the basis of whether an industry is goods or services-based. One interesting note is that manufacturing industries have a greater propensity to register a higher capital coefficient estimate in OP compared with OLS. In the OP estimates, 44 per cent of all manufacturing industries show an increase in the OLS capital coefficient contrasted with only 35 per cent for the service industries. Previous studies have only used manufacturing industries and generally yielded higher capital coefficients when correcting for selection. It is possible that manufacturing industries, with their higher levels of capital stock, are more likely to experience negative selection problem than services industries.

If we compare fixed effects (FE) on the full sample to fixed effects on the balanced panel, estimation using the full sample lowers the labour coefficient (by between 0.4 and 33 per cent) and increases the capital coefficient (by between 1 and 81 per cent) in around 60 per cent of the industries. Relative to OLS and OP, both FE labour and capital coefficients, even on the full sample, are much lower. On average, they are about half the value of the OLS and OP coefficients. This is consistent with many studies which find that FE estimates usually disagree markedly with other estimators. Our study is further evidence that the assumption of a time-invariant, firm fixed effect is a poor one.

We include firm age as a control with no strong prior belief about its effect. Older firms might have lower profitability or they might have higher profitability because of accumulated knowledge. For 92 per cent of the industries, age is insignificant. Dropping the age variable and re-estimating does not affect any of the substantive results.

OLS imposes an assumption that residuals from a firm over time are uncorrelated whereas FE imposes perfect correlation in the firm fixed effects over time. Using a Wald test, we strongly reject both of these restrictions when tested against the OP model. The residuals are correlated, but in a time-varying manner, consistent with the assumptions underlying the OP methodology.

4.4 Comparison with other studies

As other studies do, we find that using OP reduces the coefficient on labour which is suggestive of simultaneity (omitted variable) bias in the OLS estimates. We find that capital is generally over-estimated in the OLS regressions consistent with simultaneity bias being more important than selection bias from firm exit. This is not surprising given our sample from a period of general expansion in the Australian economy with only modest exit rates.

Olley and Pakes (1996), Pavcnik (2002), and Levinsohn and Petrin (1999) all find smaller labour coefficients when correcting for simultaneity. They find larger capital coefficients for manufacturing industries, however they generally have larger proportional increases in sample size when correcting for sample selection than in our study. Levinsohn and Petrin (2003) observe large drops in coefficient values when using fixed effects and we concur with their conclusion that this highlights the inappropriateness, for this economic problem, of the assumptions underlying the fixed effects model.

5 Multi-factor productivity results

5.1 Construction and Aggregation

We construct firm-level multi-factor productivity (MFP) as the exponential of the residual from the production function regression, or in other words, the residual output after accounting for the contribution of the combined inputs (as in Olley and Pakes (1996) and Levinsohn and Petrin (1999)).

$$P_{it} = exp\left(y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it}\right) \tag{13}$$

Aggregate productivity at a point in time, P_t, in any sector can be represented as a weighted share of firm-level MFP at that time period, P_{it}. Firms' shares of industry output are usually used as weights in MFP analysis, while employment shares are typically used in weighting labour productivity. Thus,

$$P_t = \sum_{i=1}^{n} \theta_{it} P_{it} \tag{14}$$

where θ_{it} is firm i's share of industry value added at time t. Aggregate productivity growth between periods 0 and 1 is conventionally computed as

$$\Delta P_{0,1}^{A} = \sum_{i=1}^{n} \theta_{i1} P_{i1} - \sum_{i=1}^{n} \theta_{i0} P_{i0} \tag{15}$$

Fox (2004) pointed out that the formulation above suffers from a fundamental aggregation problem in that it fails to satisfy the basic property of monotonicity. Even if all firms increase productivity, aggregate productivity can fall. The reason is that the output shares are not held constant in going between periods 0 and 1, and hence quantity changes are confounded with share movements. If this measure is interpreted as 'pure' productivity change, which most studies do, analysis is potentially misleading.

The problem with the conventional formulation in measuring MFP change and share change is also substantiated in Petrin and Levinsohn (2005), although from a different perspective. While Fox identifies this as an aggregation issue, Petrin and Levinsohn emphasize its lack of a theoretical basis. Specifically, it does not approximate the growth accounting measure of MFP change.

The use of an average period share for the aggregate productivity change indicator will resolve both the aggregation problem and inconsistency with the growth accounting measure of aggregate productivity growth. This requires applying a Bennet (1920) indicator, as suggested in Fox (2004)

$$\begin{aligned} \Delta P^B_{0,1} &= \sum_{i=1}^{n} \left(\frac{1}{2}\right) (\theta_{i1} + \theta_{i0}) (P_{i1} - P_{i0}) \\ &= \sum_{i=1}^{n} \left(\frac{1}{2}\right) (\theta_{i1} + \theta_{i0}) \Delta P_{i1} \end{aligned} \tag{16}$$

To demonstrate the interpretation problem associated with the use of $\Delta P^A_{0,1}$ from equation (15), Fox (2004) further defined an aggregate share-change indicator in a similar vein to the aggregate Bennet productivity-change indicator in equation (16)

$$\Delta S^B_{0,1} = \sum_{i=1}^{n} \left(\frac{1}{2}\right) (P_{i1} + P_{i0}) \Delta\theta_{i1} \tag{17}$$

and noted that

$$\Delta P^A_{0,1} = \Delta P^B_{0,1} + \Delta S^B_{0,1} \tag{18}$$

From equation (18) it is clear that interpreting $\Delta P^A_{0,1}$ as a pure productivity change is flawed in that it erroneously conflates productivity and share changes.

5.2 Analysis of trends in multi-factor productivity

This section examines how aggregate MFP has changed over the four years covered by the BLS data across industries. To verify the impact of aggregation method on the results, we first compile aggregate MFP based upon the conventional method of equation (15), weighting each year's firm-level MFP by firms' output shares in that year. We call this "MFP-A" in what follows. The majority of previous studies have used this aggregation. We compare this with industry MFP aggregated using the Bennet indicator in equation (16), that is, weighting each year's firm-level MFP by the arithmetic mean of firms' output shares between two periods. We subsequently refer to this as "MFP-B".

Recall from equation (18) that $\Delta P_{0,1}^{A}$ will reflect the sum of productivity and share changes. Note that the share-change indicator of equation (17) is not without productivity connotations, since share changes are weighted by the productivity level of each firm averaged over the base and end periods. If firms that are more productive on average gain greater market shares, then we expect the share change term to be more strongly positive. In that case, $\Delta P_{0,1}^{A}$ will be greater than $\Delta P_{0,1}^{B}$, which measures productivity change only. Interpreted in this light, researchers should be interested in both measures. MFP-B provides "pure productivity" changes and MFP-A provides insight into the combination of market share reallocation and productivity changes.

Table 4 shows industry average productivity changes using our two methods between 1994-95 and 1997-98. Two patterns can be discerned

1. In 17 industries, changes in MFP-A and MFP-B move in the same direction. MFP growth rates are both positive for example, in Food, beverage and tobacco and Business services. Meanwhile, industries such as Textile, clothing, footwear and leather and Basic material wholesaling exhibit negative productivity changes irrespective of how the aggregation is done.

2. In eight industries, the direction of change in MFP-A is positive while MFP-B records a decline (for example, Machinery and equipment, and Accommodation, cafes and restaurants).

In the case of pattern (1), the use of either MFP change measure gives the same qualitative finding: that there is robust evidence of MFP growth or decline in the industries concerned. Pattern (2) highlights the importance of exercising caution in interpreting aggregate productivity changes. Previous studies have interpreted MFP-A changes as pure productivity changes and concluded that productivity is increasing for the average firm in these industries. This is misleading in the case of a positive change in MFP-A combined with a negative one for MFP-B. MFP-A is simultaneously changing the definition of average as it changes productivity. Pattern (2) indicates that output reallocation has resulted in the average productivity-weighted firm gaining market shares between periods 1 and 0 such that the positive share change outweighs the negative 'pure' MFP change.

In general, there is a difference in the magnitudes of aggregate MFP change using the alternative aggregation methods even if the changes move in the same direction. Often, the rise in MFP-A is greater and the decline in MFP-A is smaller than the change in MFP-B. This tendency, combined with the 2nd pattern noted above, indicates that the share change portion of the change in MFP-A is almost always positive. In other words, the allocation of activities and resources is changing in favor of firms with higher average productivity level.

There is a further point to note from Table 4. Looking at MFP-B figures, industries experiencing annual positive MFP growth between 1994-95 and 1997-98 are predominantly in the services sector. They constitute 69 per cent of the services sector. Only two manufacturing industries record MFP-B increases. These are Food, beverage and tobacco and Other manufacturing. On the other hand, an additional four manufacturing industries show positive growth in MFP-A. This suggests that shifts in market share towards more productive firms seems to be particularly strong in manufacturing industries.

In a world of homogenous firms with no output and resource reallocation MFP-A and MFP-B would be equal. The fact that they are so different from one another highlights the importance of exercising care in interpreting MFP-A measures. If the focus is on 'pure productivity' changes, then MFP-B provides a better measure. These large differences are also a function of firm heterogeneity which takes us back to the importance of our estimation approach which specifically accounts for firm-level differences.

5.3 Comparison with other productivity studies

The overall picture of the Australian economy which emerges from looking at MFP growth on the basis of our firm-level estimates is consistent with that found by other researchers, namely, that manufacturing industries are the poor performers and that the service industries have dramatically improved productivity over this period. Our results support the conclusion that the service industries have been the major contributor to Australian productivity growth in the 1990s.

Looking more closely, there are some important differences between our findings and those of others. The Productivity Commission (PC) has compiled MFP estimates at the divisional industry level and for eight manufacturing sub-industries at the 2 or 3-digit ANZSIC level, based on unpublished data provided by the ABS.[12] These estimates for the manufacturing sector as a whole (see appendix Table A3) show positive MFP growth between 1994-95 and 1997-98. This is in quite striking contrast to our estimates (MFP-B) based upon firm-level data where we find that 7 of 9 manufacturing industries record negative productivity changes.[13] Our results do agree with those of the PC about the rapid productivity growth in the food, beverage and tobacco industry.[14]

PC finds, as we do, that MFP growth in services is generally higher than in manufacturing. PC estimates of MFP changes among services industries are all positive, except for accommodation, cafes and restaurants and cultural and recreational services. We find productivity declines in the former, but increases in cultural and recreational services. While PC reports that the wholesale trade sector has the highest annual MFP growth, wholesale trade sub-sectors in our study display predominantly negative MFP changes. Only the personal and household good wholesaling subdivision records positive MFP growth.

Productivity in the construction and retail trade sectors in our study move primarily in the same, positive direction as the divisional level MFP growth calculated by the PC. All retail subdivisions show MFP gains in our study. PC does not include the property and business services sector in their study, areas where we find large productivity increases.[15]

[12]The ABS releases productivity estimates only at the 1-digit level. The eight manufacturing sub-industries of the PC do not correspond exactly with the eight 2-digit ANZSIC subdivisions which we use, because PC researchers retained some categories from the earlier ASIC (Australian Standard Industry Classification) classification, such as activities with a high level of government support. For more detail, see Appendix A of Gretton and Fisher (1997).

[13]Users of the PC data appear to interpret these numbers as 'pure' productivity changes so we compare them to our MFP-B figures. Alternatively, one could compare them to MFP-A.

[14]This industry has grown rapidly over the last two decades to become the largest subdivision (in terms of value added) within the manufacturing sector. Much of this growth is due to success in exports, including wine exports, as domestic demand is not increasing much faster than population growth–see Revesz et al. (2004). MFP gains in this industry may be linked to its export orientation.

[15]Parham (2004) posits that any productivity acceleration in the property and business

Revesz et al. (2004) examine productivity performance in 2 and 3 digit manufacturing industries from the mid-1980s to the end of the 1990s. Within the metal product industry, Revesz et al. (2004) (and Productivity Commission (2003)) showed that basic metal product groups (iron and steel and non-ferrous metals) recorded large MFP gains in the 1980s, but growth moderated in the 1990s, especially for the iron and steel group, as output contracted because of a fall in steel exports. Iron and steel manufacturing experienced a MFP decline between 1995-96 and 2000-01, according to Revesz et al. (2004). This matches the productivity decreases which we find for the metal product industry, where a disproportionately large share of the value added in our sample was from the iron and steel sub-group.

In the case of the petroleum, coal, chemical and associated product and machinery and equipment industries, Revesz et al. (2004) highlighted substantial output and MFP acceleration in several 3-digit 'star' groups, such as pharmaceuticals, motor vehicles, medical and scientific equipment and electronic equipment manufacturing. We find that the strong performance among these groups does not translate into MFP gains for the broader 2-digit industries to which they belong. A likely reason is that the mix of firms in these 2-digit industries are such that any MFP gains made by firms in the 'star' 3-digit industry groups are more than offset by MFP reductions of firms in other groups, such as other transport equipment, and production and machinery equipment machinery, both of which contracted in the 1990s.

Some of these differences in aggregate MFP growth findings may come from technique–the PC, for example, uses the growth accounting technique, where MFP is computed as the ratio of output (value added) to a Törnqvist index of combined labour and capital inputs, relying on the assumptions of constant returns to scale and perfect competition in factor markets. The BLS is a fairly small sample, accounting for only about 5 per cent of total industry value added. For some industries, it may not be sufficiently representative to estimate industry-level productivity change. However, as noted above, the overall productivity trends appear to be robust to these issues.

services industries could be linked to a rise in information and communication technology (ICT) related research and development activities and increased use of ICT.

6 Summary and conclusions

This paper approaches the analysis of Australia's productivity performance from the perspective that aggregate productivity is a result of substantial heterogeneity amongst firms and entry and exit at the firm level. This reality calls into question the appropriateness of measuring productivity with an aggregate production function based upon a representative firm. We apply, for the first time to Australian data, the technique developed by Olley and Pakes (1996), based upon more realistic assumptions about firm behavior, to arrive at more accurate production function estimates. Our results support the view that the OP method improves productivity estimates. Lower coefficients on labor support the hypothesis that standard estimates suffer from simultaneity between firms' labour input choices and productivity. We also find evidence of simultaneity bias between firms' capital usage and productivity. Statistical tests reject standard OLS and fixed effects techniques in favor of the method we employ.

Using these improved production function estimates, we apply a Bennet (1920) type indicator, following a suggestion by Fox (2004), to accurately separate the portion of aggregate productivity change that can be labeled as "pure" productivity change from that resulting from re-allocation of output to more productive firms. Our results show that both effects are important in explaining Australia's productivity growth in the 1990s. The re-allocation effect was almost always positive whereas "pure" productivity change is mixed across industries. Our results highlight the importance of carefully interpreting productivity changes correctly with respect to the chosen method of aggregation. Although we use a sample that is not representative of the Australian economy, we do find, as others before us, that service industries led the way in Australia's productivity revival in the 1990s.

Australia experienced a productivity surge in the 1990s, which underpinned its strong output growth. Parham (2002a) has documented the diversity of performance across industries. Our study complements this by showing that this heterogeneity across industries is mimicked by heterogeneity in firm performance within industries. Australia's productivity growth in the 2000s has come off its record highs in the 1990s. Again, this masks unequal performances among industries. Manufacturing has performed well, while industries such as electricity, gas and water, and communication services have experienced average

MFP declines; see Parham and Wong (2006). Unfortunately there is no Business Longitudinal Survey for the first decade of the new millennium. Our study highlights the need for firm-level longitudinal data to explore in more detail changing productivity performance.

Both entry and exit were fairly common in the 1990s, even during a robust expansion. (See also Bickerdyke et al. (2000)). These trends have also continued beyond 2000–new firms have continued to arrive even as incumbents exit. Between 2002-03 and 2003-04, average entry rate was 11.2 and exit rate was 4.2 per cent for all industries, see Australian Bureau of Statistics (2005).

Recognizing that aggregate productivity increase is the net outcome of firm diversity and constant flux from firm entry and exit, policies aimed at enhancing aggregate productivity and economic growth will have to take into account the process through which growth is generated at the level of individual firms. For instance, policies that raise the costs of entry or discourage exit may keep inefficient firms in the market and lower average productivity.

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Table 1: Industry entry and exit rates
Business Longitudinal Survey

INDUSTRY	ANZSIC	Entry rate	Exit rate
Manufacturing	C		
Food, Beverage, and Tobacco	21	9.7	14.5
Textile, Clothing, Footwear and Leather	22	10.4	10.1
Wood and Paper Product	23	16.1	12.1
Printing, Publishing and Recorded Media	24	8.8	10.6
Petroleum, Coal, Chemical and Associated Product	25	7.8	8.0
Non-metallic Mineral Product Manufacturing	26	18.0	10.3
Metal Product	27	7.5	6.9
Machinery and Equipment	28	4.1	9.3
Other	29	12.6	12.4
Construction	E		
General Construction	41	20.2	12.5
Construction Trade Services	42	15.3	9.6
Wholesale Trade	F		
Basic Material Wholesaling	45	7.3	7.1
Machinery and Motor Vehicle Wholesaling	46	8.9	8.8
Personal and Household Good Wholesaling	47	15.3	8.9
Retail Trade	G		
Food Retailing	51	22.7	19.1
Personal and Household Good Retailing	52	14.8	18.1
Motor Vehicle Retailing and Services	53	7.3	8.1
Accommodation, Cafes and Restaurants	H/57	17.2	19.6
Transport and Storage	I		
Road Transport	61	10.5	10.4
Services to Transport	66	15.7	11.9
Cultural and Recreational Services	P		
Motion Picture, Radio, and Television Services	91	6.7	11.5
Sport and Recreation	93	17.9	22.8
Personal and Other Services	P		
Personal Services	95	19.5	14.3

Source: Business longitudinal survey, Australian Bureau of Statistics
Entries in table are percentages
Entry rates are calculated as the number of entrants between 1995/96 and 1997/98 divided by the total number of incumbent and new firms in 1997/98.
Exit rates are calculated as the number of firms exiting the sample between 1995/96 and 1997/98 divided by the total number of incumbent firms in 1994/95.

Table 2: Production function estimation results by industry

ANZSIC/Industry	Balanced panel		Full sample		
	(1)	(2)	(3)	(4)	(5)
	OLS	FE	OLS	FE	OP
Manufacturing					
21 Food, Beverage and Tobacco					
Labour	0.755	0.466	0.768	0.590	0.749
	(0.026)**	(0.055)**	(0.027)**	(0.059)**	(0.028)**
Capital	0.334	0.130	0.329	0.225	0.257
	(0.021)**	(0.031)**	(0.021)**	(0.033)**	(0.054)**
Age	0.001	0.005	0.003	0.006	-0.041
	(0.002)	(0.160)	(0.002)+	(0.018)	(0.034)
N	668	668	802	781	565
22 Textile, Clothing, Footwear and Leather					
Labour	0.774	0.284	0.721	0.340	0.676
	(0.028)**	(0.076)**	(0.028)**	(0.076)**	(0.030)**
Capital	0.287	0.183	0.318	0.194	0.339
	(0.023)**	(0.036)**	(0.022)**	(0.033)**	(0.093)**
Age	0.005	0.044	0.007	0.042	0.017
	(0.002)*	(0.019)*	(0.002)**	(0.020)*	(0.020)
N	488	488	584	569	413
23 Wood and Paper Product					
Labour	0.792	0.662	0.91	0.592	0.87
	(0.047)**	(0.087)**	(0.042)**	(0.084)**	(0.050)**
Capital	0.299	0.052	0.218	0.094	0.201
	(0.034)**	(0.037)	(0.030)**	(0.037)*	(0.098)*
Age	0.001	-0.009	0.002	-0.024	0.004
	(0.003)	(0.021)	(0.003)	(0.022)	(0.030)
N	332	332	439	427	305
24 Printing, Publishing and Recorded Media					
Labour	0.8	0.329	0.809	0.264	0.732
	(0.039)**	(0.079)**	(0.036)**	(0.068)**	(0.040)**
Capital	0.259	0.141	0.245	0.153	0.293
	(0.028)**	(0.033)**	(0.025)**	(0.031)**	(0.066)**
Age	0.006	0.032	0.008	0.035	0.037
	(0.002)*	(0.020)	(0.002)**	(0.018)+	(0.019)+
N	464	464	571	559	404
25 Petroleum, Coal, Chemical and Associated Product					
Labour	0.801	0.626	0.841	0.535	0.799
	(0.029)**	(0.073)**	(0.028)**	(0.068)**	(0.030)**
Capital	0.323	0.078	0.281	0.059	0.119
	(0.020)**	(0.029)**	(0.019)**	(0.028)*	(0.051)*
Age	-0.002	0.024	-0.001	0.03	0.007
	(0.002)	(0.017)	(0.002)	(0.017)+	(0.012)
N	776	776	888	867	638
26 Non-Metallic Mineral Product Manufacturing					
Labour	0.913	0.418	0.916	0.362	0.959
	(0.052)**	(0.086)**	(0.050)**	(0.097)**	(0.052)**
Capital	0.226	0.052	0.231	0.069	0.191
	(0.035)**	(0.043)	(0.033)**	(0.050)	(0.047)**
Age	0.002	0.011	0.003	0.03	-0.008
	(0.004)	(0.022)	(0.004)	(0.025)	(0.012)
N	312	312	403	388	277

27 Metal Product					
Labour	0.888	0.512	0.934	0.514	0.900
	(0.025)**	(0.049)**	(0.025)**	(0.048)**	(0.028)**
Capital	0.238	0.108	0.210	0.125	0.238
	(0.018)**	(0.023)**	(0.018)**	(0.025)**	(0.048)**
Age	-0.001	-0.007	-0.002	-0.006	-0.004
	(0.002)	(0.013)	(0.002)	(0.014)	(0.016)
N	812	812	926	908	661
28 Machinery and Equipment					
Labour	0.875	0.498	0.866	0.436	0.862
	(0.019)**	(0.058)**	(0.021)**	(0.054)**	(0.023)**
Capital	0.220	0.125	0.224	0.134	0.201
	(0.015)**	(0.021)**	(0.016)**	(0.021)**	(0.032)**
Age	0.001	0.003	0.003	0.009	-0.005
	(0.001)	(0.014)	(0.002)+	(0.015)	(0.020)
N	1488	1488	1703	1679	1224
29 Other					
Labour	0.904	0.835	0.926	0.717	0.838
	(0.030)**	(0.070)**	(0.028)**	(0.069)**	(0.033)**
Capital	0.181	0.091	0.167	0.109	0.222
	(0.022)**	(0.032)**	(0.020)**	(0.030)**	(0.051)**
Age	0.009	-0.008	0.011	-0.006	0.005
	(0.002)**	(0.021)	(0.003)**	(0.022)	(0.018)
N	560	560	662	646	466
Construction					
41 General Construction					
Labour	0.877	0.437	0.872	0.406	0.876
	(0.051)**	(0.156)**	(0.039)**	(0.127)**	(0.042)**
Capital	0.209	0.135	0.207	0.180	0.284
	(0.040)**	(0.061)*	(0.031)**	(0.053)**	(0.040)**
Age	0.004	0.065	0.004	0.045	-0.007
	(0.005)	(0.056)	(0.005)	(0.051)	(0.016)
N	268	268	369	350	246
42 Construction Trade Services					
Labour	0.879	0.448	0.906	0.421	0.875
	(0.026)**	(0.076)**	(0.027)**	(0.077)**	(0.033)**
Capital	0.246	0.088	0.226	0.089	0.216
	(0.020)**	(0.033)**	(0.019)**	(0.030)**	(0.047)**
Age	-0.001	-0.008	-0.004	-0.029	-0.017
	(0.003)	(0.025)	(0.003)	(0.026)	(0.020)
N	496	496	651	637	452
Wholesale Trade					
45 Basic Material Wholesaling					
Labour	0.862	0.733	0.845	0.647	0.793
	(0.035)**	(0.089)**	(0.037)**	(0.088)**	(0.042)**
Capital	0.177	0.039	0.234	0.017	0.232
	(0.027)**	(0.023)+	(0.027)**	(0.026)	(0.090)*
Age	0.008	-0.006	0.011	-0.025	0.016
	(0.002)**	(0.016)	(0.003)**	(0.019)	(0.024)
N	572	572	656	642	470
46 Machinery and Motor Vehicle Wholesaling					
Labour	0.995	0.604	0.997	0.55	0.972
	(0.025)**	(0.073)**	(0.024)**	(0.067)**	(0.028)**
Capital	0.124	0.041	0.149	0.039	0.177
	(0.020)**	(0.027)	(0.019)**	(0.024)	(0.046)**
Age	0.001	0.009	0.002	0.024	0.007
	(0.002)	(0.017)	(0.002)	(0.017)	(0.027)
N	1008	1008	1232	1217	876

47 Personal and Household Good Wholesaling					
Labour	0.878	0.599	0.841	0.500	0.780
	(0.028)**	(0.060)**	(0.029)**	(0.060)**	(0.033)**
Capital	0.196	0.113	0.237	0.099	0.255
	(0.021)**	(0.022)**	(0.021)**	(0.021)**	(0.068)*
Age	-0.003	-0.008	0.000	0.003	0.008
	(0.002)	(0.015)	(0.002)	(0.015)	(0.012)
N	692	692	851	830	595
Retail Trade					
51 Food Retailing					
Labour	0.621	0.135	0.651	0.138	0.626
	(0.029)**	(0.081)+	(0.026)**	(0.069)*	(0.029)**
Capital	0.396	0.274	0.369	0.271	0.375
	(0.025)**	(0.032)**	(0.023)**	(0.030)**	(0.055)**
Age	0.017	0.019	0.015	0.027	0.010
	(0.003)**	(0.024)	(0.003)**	(0.023)	(0.016)
N	400	400	545	513	368
52 Personal and Household Good Retailing					
Labour	0.747	0.263	0.737	0.260	0.782
	(0.024)**	(0.077)**	(0.025)**	(0.083)**	(0.031)**
Capital	0.288	0.167	0.315	0.188	0.232
	(0.021)**	(0.025)**	(0.021)**	(0.028)**	(0.062)**
Age	0.001	0.015	0.007	0.040	-0.005
	(0.002)	(0.023)	(0.003)**	(0.025)	(0.014)
N	568	568	716	685	494
53 Motor Vehicle Retailing and Services					
Labour	0.979	0.367	0.979	0.393	0.944
	(0.022)**	(0.068)**	(0.022)**	(0.066)**	(0.026)**
Capital	0.164	0.043	0.168	0.049	0.115
	(0.017)**	(0.021)*	(0.017)**	(0.020)*	(0.035)**
Age	0.001	-0.029	0.002	-0.018	-0.033
	(0.002)	(0.017)+	(0.002)	(0.017)	(0.028)
N	560	560	636	626	456
57 Accommodation, cafes and restaurants					
Labour	0.902	0.574	0.900	0.431	0.866
	(0.025)**	(0.066)**	(0.022)**	(0.065)**	(0.026)**
Capital	0.253	0.105	0.248	0.097	0.230
	(0.020)**	(0.023)**	(0.018)**	(0.024)**	(0.053)**
Age	0.002	0.016	0.001	0.025	-0.038
	(0.002)	(0.019)	(0.002)	(0.020)	(0.030)
N	536	536	748	714	506
Transport & Storage					
61 Road transport					
Labour	0.765	0.251	0.788	0.264	0.807
	(0.037)**	(0.071)**	(0.032)**	(0.065)**	(0.038)**
Capital	0.302	0.135	0.286	0.128	0.322
	(0.026)**	(0.025)**	(0.023)**	(0.023)**	(0.059)**
Age	0.002	0.012	0.000	0.022	-0.009
	(0.003)	(0.017)	(0.003)	(0.018)	(0.031)
N	368	368	462	451	326

66 Services to transport					
Labour	1.057	0.591	0.961	0.458	1.064
	(0.047)**	(0.145)**	(0.053)**	(0.125)**	(0.065)**
Capital	0.109	0.152	0.234	0.117	0.18
	(0.042)*	(0.052)**	(0.042)**	(0.050)*	(0.092)*
Age	0.002	-0.002	0.002	0.034	0.022
	(0.005)	(0.038)	(0.007)	(0.039)	(0.059)
N	116	116	182	179	123
Property & business services					
77 Property services					
Labour	0.862	0.446	0.842	0.430	0.842
	(0.035)**	(0.090)**	(0.029)**	(0.074)**	(0.032)**
Capital	0.278	0.132	0.32	0.154	0.199
	(0.023)**	(0.046)**	(0.020)**	(0.038)**	(0.076)**
Age	-0.005	0.027	-0.002	0.020	-0.030
	(0.004)	(0.038)	(0.004)	(0.034)	(0.026)
N	408	408	645	615	426
78 Business services					
Labour	0.870	0.427	0.865	0.441	0.823
	(0.017)**	(0.036)**	(0.016)**	(0.034)**	(0.017)**
Capital	0.209	0.069	0.213	0.083	0.171
	(0.013)**	(0.015)**	(0.011)**	(0.015)**	(0.033)**
Age	0.005	0.001	0.005	-0.001	-0.009
	(0.002)*	(0.016)	(0.002)*	(0.016)	(0.024)
N	1452	1452	1830	1774	1267
Cultural & recreational services					
91 Motion Picture, Radio and Television Services					
Labour	0.493	0.262	0.478	0.261	0.486
	(0.061)**	(0.106)*	(0.060)**	(0.100)*	(0.070)**
Capital	0.488	0.176	0.506	0.193	0.454
	(0.040)**	(0.073)*	(0.037)**	(0.060)**	(0.170)**
Age	0.000	-0.006	0.006	0.009	0.011
	(0.007)	(0.057)	(0.007)	(0.054)	(0.105)
N	152	152	202	192	136
93 Sport and Recreation					
Labour	0.914	0.504	0.884	0.336	0.877
	(0.087)**	(0.198)*	(0.054)**	(0.129)*	(0.067)**
Capital	0.224	0.156	0.257	0.150	0.265
	(0.057)**	(0.078)+	(0.038)**	(0.046)*	(0.167)
Age	-0.027	-0.141	-0.026	-0.141	-0.038
	(0.012)*	(0.073)+	(0.006)**	(0.045)**	(0.049)
N	72	72	167	155	98
Personal & other services					
95 Personal services					
Labour	0.839	0.369	0.708	0.387	0.668
	(0.031)**	(0.083)**	(0.035)**	(0.060)**	(0.045)**
Capital	0.277	0.180	0.377	0.169	0.267
	(0.026)**	(0.039)**	(0.028)**	(0.037)**	(0.076)**
Age	-0.003	0.012	0.007	0.034	0.063
	(0.003)	(0.025)	(0.003)*	(0.027)	(0.026)*
N	332	332	453	438	313

Standard errors in parentheses (bootstrapped standard error reported for capital and age coefficients in column 5)

+ significant at 10%; * significant at 5%; ** significant at 1%

Table 3. Impact on Labour and Capital Coefficients of Different Estimation Methodologies

INDUSTRY	ANZSIC	Variables	OLS(balanced panel) to OLS(full sample)	OLS(full sample) to OP
Food Beverages and Tobacco Manufacturing	21	L	↑	↓
		K	↓	⇓
Textile Clothing Footwear and Leather Manufacturing	22	L	⇓	⇓
		K	⇑	↑
Wood and Paper Product Manufacturing	23	L	⇑	↓
		K	⇓	↓
Printing Publishing and Recorded Media	24	L	↑	⇓
		K	↓	↑
Petroleum Coal Chemical Product Manufacturing	25	L	⇑	⇓
		K	⇓	⇓
Non-metallic Mineral Product Manufacturing	26	L	↑	↑
		K	↑	↓
Metal Product Manufacturing	27	L	⇑	⇓
		K	⇓	↑
Machinery and Equipment Manufacturing	28	L	↓	↓
		K	↑	↓
Other Manufacturing	29	L	↑	⇓
		K	↓	⇑
General Construction	41	L	↓	↑
		K	↓	↑
Construction Trade Services	42	L	⇑	↓
		K	⇓	↓
Basic Material Wholesaling	45	L	↓	⇓
		K	⇑	↓
Machinery and Motor Vehicle Wholesaling	46	L	↑	↓
		K	⇑	↑
Personal and Household Good Wholesaling	47	L	⇓	⇓
		K	↑	↑
Food Retailing	51	L	⇑	↓
		K	⇓	↑
Personal & Household Good Retailing	52	L	↓	⇑
		K	⇑	⇓
Motor Vehicle Retailing and Services	53	L	↓	⇓
		K	↑	⇓
Accommodation Cafes and Restaurants	57	L	↓	⇓
		K	↓	↓
Road transport	61	L	↑	↑
		K	↓	↑
Services to Transport	66	L	⇓	⇑
		K	⇑	↓
Property Services	77	L	↓	-
		K	⇑	⇓
Business Services	78	L	↓	⇓
		K	↑	⇓
Motion Picture Radio and Television Services	91	L	↓	↑
		K	↑	↓
Sport and Recreation	93	L	↓	↓
		K	↑	↑
Personal and Other Services	95	L	⇓	↓
		K	⇑	⇓
No. (%) of industries with ↓ in L			14 (56.0)	19 (76.0)
No. (%) of industries with ↑ in K			14 (56.0)	10 (40.0)

↑/↓ denotes a change in estimates that is within one standard error. ⇑/⇓ denotes a change in estimates that is more than one standard error. (Bootstrapped standard errors are computed for OP capital coefficient estimates.)
- indicates no change up to 3 decimal places.

Table 4: Industry-level Aggregate Changes in Multi-factor productivity 1994/95 to 1997/98

INDUSTRY	ANZSIC	MFP-A	MFP-B
Manufacturing	C		
Food, Beverage, and Tobacco	21	9.6	6.1
Textile, Clothing, Footwear and Leather	22	-2.5	-6.7
Wood and Paper Product	23	0.9	-0.6
Printing, Publishing and Recorded Media	24	-2.0	-4.5
Petroleum, Coal, Chemical and Associated Product	25	-3.1	-4.1
Non-metallic Mineral Product Manufacturing	26	2.0	-5.1
Metal Product	27	2.1	-1.7
Machinery and Equipment	28	0.5	-1.7
Other	29	1.8	1.0
Construction	E		
General Construction	41	7.0	-2.4
Construction Trade Services	42	2.7	4.4
Wholesale Trade	F		
Basic Material Wholesaling	45	-3.4	-3.7
Machinery and Motor Vehicle Wholesaling	46	0.3	-1.2
Personal and Household Good Wholesaling	47	4.5	6.6
Retail Trade	G		
Food Retailing	51	3.2	3.8
Personal and Household Good Retailing	52	1.2	0.8
Motor Vehicle Retailing and Services	53	6.2	4.8
Accommodation, Cafes and Restaurants	H/57	8.1	-3.0
Transport and Storage	I		
Road Transport	61	2.0	-0.3
Services to Transport	66	3.0	1.2
Cultural and Recreational Services	P		
Motion Picture, Radio, and Television Services	91	9.5	8.4
Sport and Recreation	93	3.0	3.7
Personal and Other Services	P		
Personal Services	95	3.1	5.0

Source: Business longitudinal survey, Australian Bureau of Statistics
Entries in table are percentage annual compound growth rates.
MFP-A is sum of individual firm MFP weighted by the share of that firm's output in each year. See equation (15).
MFP-B is the sum of individual firm MFP weighted by the arithmetic mean of share of their output in the first and last year. See equation (16).

Appendix

Table A1: Variable definitions and construction

Our abbreviation	Variable description
y_t	**value-added** sales plus change in inventories less purchases of intermediate inputs and other operating expenses.
k_t	**capital stock** book value of total non-current assets plus leasing stock. Leasing capital is obtained by dividing leasing expenses by (0.05+0.0803), where 0.05=1/20 is the average years of depreciation, and 0.0803 is the average 10 year treasury bond rate form July 1994-June 1998
l_t	**full-time equivalent persons** the number of full-time employees plus 0.426*the number of part-time employees, averaged over two years
i_t	**investment** sum of capital expenditure on plant, machinery, equipment, land, dwellings, other buildings and structures, and intangible assets
age_t	**age of firm** an age range is provided. We use the midpoint of the range.

Table A2: Characteristics of entering, continuing, and exiting firms by industry 1995/96 to 1997/98

INDUSTRY	ANZSIC	Value added ($'000)	No. of full-time equivalent employees (EE for entrants, E for others)	Capital stock ($'000)	Investment ($'000)	Age of firm (years)
Manufacturing	C					
Food, Beverage and Tobacco	21					
Entrant		379.6	16.1	770.1	512.6	2.3
		(148.5)	(7.7)	(256.9)	(0)	(3)
Continuing firm		7771.1	112.8	14475.5	2033.1	15.6
		(1371.0)	(29.0)	(2064.3)	(32.5)	(11)
Exiting firm		4207.1	84.0	7895.5	91.5	6.8
		(325.0)	(12.1)	(414.1)	(0)	(5)
Textile, Clothing, Footwear and Leather	22					
Entrant		279.4	8.9	354.1	12.2	2.6
		(86)	(3.4)	(96.7)	(0)	(3)
Continuing firm		3922.1	80.1	4133.1	354.1	16.7
		(1092)	(28.9)	(902.8)	(0)	(13)
Exiting firm		9289.0	252.5	10352.9	207.5	14.5
		(397)	(24.1)	(304.3)	(0)	(9)
Wood and Paper Product	23					
Entrant		225.5	6.6	459.3	72.4	2.8
		(158.0)	(4.9)	(127.1)	(0)	(3)
Continuing firm		22524.0	254.1	59877.8	6459.0	16.8
		(1095)	(27.0)	(1131.4)	(8)	(13)
Exiting firm		1168.1	25.7	1696.1	18.7	12.8
		(171.5)	(5)	(169.5)	(0)	(11)
Printing, Publishing and Recorded Media	24					
Entrant		148.7	5.9	248.4	96.7	2.4
		(125)	(5.2)	(177.8)	(6.0)	(3)
Continuing firm		10342.1	110.5	51498.0	1304.3	15.1
		(822.0)	(16.0)	(910.8)	(8)	(11)
Exiting firm		5952.5	98.7	7472.9	695.3	14.3
		(1382)	(36.9)	(1138.0)	(0)	(13)
Petroleum, Coal, Chemical and Associated Product	25					
Entrant		222.5	8.5	681.8	61.2	2.1
		(131.0)	(7)	(506.6)	(10)	(3)
Continuing firm		9324.8	100.9	19750.0	2317.1	16.3
		(1321.0)	(26.6)	(1705.0)	(32)	(13)
Exiting firm		11529.54	128.8	16094.9	944.3	13.5
		(2490)	(42.9)	(4000.7)	(0)	(15)
Non-Metallic Mineral Product Manufacturing	26					
Entrant		493.9	14.1	669.3	112.5	2.4
		(398)	(12.4)	(553.5)	(7)	(3)
Continuing firm		17142.9	165.4	40760.7	3481.6	16.4
		(1383)	(27.0)	(1371.0)	(40)	(15)
Exiting firm		24909.7	231.6	51318.8	690.3	7.5
		(269.0)	(6.8)	(265)	(0)	(6)
Metal Product	27					
Entrant		290.4	8.0	254.0	17.8	2.6
		(205.0)	(3.0)	(160.0)	(0)	(3)
Continuing firm		9098.3	117.6	27113.1	2184.5	16.6
		(1074.5)	(24.2)	(983.3)	(14)	(15)
Exiting firm		22771.9	280.8	46671.0	3765.5	13.2
		(489)	(21)	(920.8)	(0)	(9)
Machinery and Equipment	28					
Entrant		189.9	8.0	803.6	236.4	2.0
		(101)	(4)	(112.8)	(0)	(1)
Continuing firm		4745.0	68.8	5216.8	571.4	15.7
		(691)	(15.1)	(640.9)	(2)	(13)
Exiting firm		7625.8	106.2	9237.9	1014.3	14.4
		(1115)	(32)	(1200)	(0)	(9)
Other	29					
Entrant		176.8	7.1	237.8	21.5	2.7

Entrant		176.8	7.1	237.8	21.5	2.7
		(82.5)	(5.4)	(112.7)	(0)	(3)
Continuing firm		2049.4	43.3	2540.3	344.8	13.6
		(526.0)	(12.1)	(477.2)	(0)	(11)
Exiting firm		612.7	19.1	606.1	1.1	10.1
		(159.0)	(6.5)	(90.7)	(0)	(9)
Construction	E					
General construction	41					
Entrant		123.3	3.4	85.0	9.9	2.3
		(68.6)	(2)	(34.3)	(0)	(3)
Continuing firm		5555.8	82.1	4749.1	373.5	13.2
		(209)	(5.2)	(233.0)	(0)	(11)
Exiting firm		11097.5	188.2	40744.8	699.4	10.6
		(730.5)	(18.4)	(157.3)		(10)
Construction Trade Services	42					
Entrant		497.6	7.7	748.2	13.9	2.7
		(87)	(2.2)	(65.3)	(0)	(3)
Continuing firm		2436.5	42.3	1738.5	73.0	14.0
		(221)	(5.2)	(165.8)	(0)	(13)
Exiting firm		305.9	6.8	245.8	1.0	10.8
		(176.5)	(3.7)	(94.7)	(0)	(9)
Wholesale Trade	F					
Basic Material Wholesaling	45					
Entrant		412.27	11.5	1221.0	178.7	2.2
		(31.0)	(4.6)	(65.7)	(0)	(3)
Continuing firm		5606.9	64.6	12883.0	503.0	18.0
		(1155.0)	(22.1)	(1062.6)	(13.5)	(15.0)
Exiting firm		10386.7	87.0	1627.4	158.2	12.2
		(1573)	(23.7)	(275.0)	(0)	(7)
Machinery and Motor Vehicle Wholesaling	46					
Entrant		361.8	7.2	589.4	40.6	2.2
		(215)	(5)	(296.5)	(3)	(3)
Continuing firm		7072.4	91.2	6832.1	523.4	16.5
		(1215)	(24.5)	(982.4)	(4)	(15)
Exiting firm		2285.1	41.0	1427.3	8.9	8.5
		(84)	(4)	(132.5)	(0)	(5)
Personal and Household Good Wholesaling	47					
Entrant		412.6	13.9	953.9	181.1	2.2
		(155.5)	(9.2)	(488.6)	(0.5)	(3)
Continuing firm		2637.9	39.2	4749.2	263.3	17.2
		(1009.0)	(19.9)	(872.7)	(10)	(15)
Exiting firm		1259.5	21.5	1298.1	170.5	9.8
		(129.0)	(4)	(277.5)	(0)	(7)
Retail Trade	G					
Food Retailing	51					
Entrant		123.8	5.5	329.8	40.9	2.3
		(73)	(4)	(209.7)	(0)	(3)
Continuing firm		4565.0	120.3	11136.2	2121.8	10.2
		(299)	(12.7)	(580.0)	(0)	(9)
Exiting firm		813.8	29.3	1761.7	144.6	7.1
		(115.0)	(5)	(168.7)	(0)	(7)
Personal and Household Good Retailing	52					
Entrant		203.1	7.7	846.6	185.9	1.9
		(115.0)	(5.1)	(207.1)	(0)	(1)
Continuing firm		4040.9	115.8	7164.0	490.3	14.9
		(437)	(9.9)	(769.7)	(0)	(13)
Exiting firm		456.1	12.3	931.1	2.6	10.7
		(89)	(3.3)	(268.6)	(0)	(9)
Motor Vehicle Retailing and Services	53					
Entrant		377.1	8.6	695.4	65.1	2.2
		(180.0)	(4.6)	(293.6)	(0)	(3)
Continuing firm		1365.9	28.2	1703.4	86.8	14.3
		(590.0)	(15.2)	(592.8)	(0)	(11)
Exiting firm		1133.4	22.4	2728.1	117.2	10.4
		(694.5)	(15.3)	(729.3)	(10)	(7)
Accommodation, cafes and restaurants	H/57					

Entrant		293.1 (179.6)	8.3 (7.1)	858.7 (521.6)	72.5 (0)	2.5 (3)
Continuing firm		2808.8 (212.5)	62.4 (6.6)	7548.9 (600.5)	1083.4 (0)	14.6 (9)
Exiting firm		7728.1 (137.5)	251.4 (4.3)	14054.3 (454.8)	11.3 (0)	7.0 (5)
Transport & Storage	I					
Road transport	61					
Entrant		122.3 (188)	7.3 (5.5)	487.2 (198.9)	206.0 (0)	2.7 (3)
Continuing firm		2899.3 (347)	44.7 (9.5)	5383.5 (479.4)	447.2 (0)	16.3 (13)
Exiting firm		389.7 (57)	12.2 (3)	759.8 (73.0)	47.4 (0)	7.2 (5)
Services to transport	66					
Entrant		284.5 (81)	6.7 (4.4)	406.7 (217.8)	46 (0)	3.3 (3)
Continuing firm		11474.5 (649.5)	129.4 (13.9)	20725.6 (555.7)	1521.7 (0)	13.3 (13)
Exiting firm		11946.9 (545.5)	198.6 (9.8)	10808.4 (66)	34.9 (0)	6.1 (5)
Property & business services	L					
Property services	77					
Entrant		407.1 (165)	6.2 (3.9)	688.0 (240.0)	21.6 (0)	2.7 (3)
Continuing firm		2074.1 (182)	20.6 (4.4)	13119.8 (374.7)	1162.6 (0)	12.4 (11)
Exiting firm		166.7 (77)	4.8 (2.4)	4181.0 (284.0)	26.7 (0)	11.7 (7)
Business Services	78					
Entrant		426.1 (213.5)	16.0 (7.6)	224.7 (76.7)	55.1 (0)	2.3 (3)
Continuing firm		4137.4 (429)	70.9 (10.4)	10997.6 (316)	430.1 (0)	12.0 (9)
Exiting firm		4272.5 (163)	60.0 (4.0)	17708.5 (62)	197.6 (0)	8.4 (7)
Cultural & Recreational Services	P					
Motion Picture, Radio and Television Services	91					
Entrant		-238.6 (6.5)	10.9 (5)	614.1 (84.0)	9 (0)	1.8 (3)
Continuing firm		14467.9 (421)	95.8 (8.7)	74424.8 (1118.3)	4912.1 (0)	12.1 (9)
Exiting firm		3293.4 (1462)	39.3 (45.8)	12107.5 (3779)	0 (0)	5.4 (1)
Sports and Recreation	93					
Entrant		128.8 (52)	13.8 (4)	3497.3 (124.4)	119.3 (0)	2.3 (3)
Continuing firm		11205.2 (170)	159.9 (17.6)	36530.3 (378.4)	2440.1 (0)	16.3 (11)
Exiting firm		4213.0 (89)	102.1 (7.0)	13055.7 (48)	355.9 (0)	4.7 (3)
Personal & other services	Q					
Personal Services	95					
Entrant		133.2 (58)	5.8 (3.9)	262.6 (83.7)	16.8 (0)	2.3 (3)
Continuing firm		2983.8 (139)	61.8 (5.0)	4159.5 (234.8)	725.5 (0)	13.9 (11)
Exiting firm		4207.5 (34)	146.3 (2)	12716.4 (59.4)	57.3 (0)	6.2 (5)

Source: Business longitudinal survey, Australian Bureau of Statistics
Mean values (median values in paranetheses)

Table A3: Industry changes in multi-factor productivity, 1994/95 - 1997/98
Productivity Commission Estimates

INDUSTRY	ANZSIC	MFP-PC
Manufacturing	C	1.4
Food, Beverage, and Tobacco	21	1.5
Textile, Clothing, Footwear and Leather	22	1.0
Printing, Publishing and Recorded Media	24	0.2
Petroleum, Coal, Chemical and Associated Product	25	1.8
Basic Metal Products	271,272,273	1.3
Structural and Sheet Metal Products	274, 275, 276	1.8
Transport Equipment	281	2.8
Rest of Manufacturing		0.8
Construction	E	3.0
Wholesale Trade	F	5.1
Retail Trade	G	2.9
Accommodation, Cafes and Restaurants	H/57	-0.8
Transport and Storage	I	2.7
Cultural and Recreational Services	P	-4.0

Table entries are compound annual growth rates in percentage terms
Compiled from Productivity Commission (2006).