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A Richer Understanding of Australia's Productivity Performance in the 1990s: Improved Estimates Based Upon Firm-Level Panel Data*

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Australian industry is characterised by differences across firms, entry of new firms and exit of unsuccessful firms. These facts highlight the inappropriateness of measuring productivity using aggregate production functions based upon representative firms. In this study, we model heterogeneous firms which change over time. We model the interrelationship between productivity shocks, input choices and decisions to cease production. Firm-level data provides production function estimates for 25 two-digit Australian industries. A new aggregation method for industry-level data allows us to separate productivity changes from output composition changes. Our study sheds new light on the Australian productivity performance.

I 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 datasets, the availability of which is a fairly recent phenomenon (see review in Bartelsman & 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

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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 characterisation 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 II, 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 III describes and summarises the data. Section IV evaluates the estimation results. In Section V, 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.

II Production Function Estimation

Historically, the standard approach to estimating production functions using firm level data was through OLS 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, respectively. 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 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 realisations. 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 (FE) 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

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

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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 characterised by substantial amounts of firm entry and exit.[2] This is not random, but rather the result of a 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 if we compare two firms that both suffer negative productivity realisations the one with greater capital stock is more likely to survive. 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 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 recognised in the empirical literature at least since 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.

(i) 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 realisations 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 realisations (observable only to the firm, not to the econometrician), the sell-off value of its capital, current profits and expected future profits. Firm-specific state variables determining current profits are assumed in this model to be a firm's age, capital stock and index of productivity. 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.

The model is consistent with several different competitive structures, including perfect competition.[4] Firms do not directly observe current productivity realisations nor investment decisions of competitors and, therefore, cannot make their own investment decisions on this basis. Intra-industry competition is the result of all firms engaging in this game with imperfectly observable actions. Competition from outside the industry is considered to be exogenous and there is a fixed cost of entry which can only be partially recouped if a firm fails. 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 optimisation problem and to generate an exit rule and an investment function which, in their model, depend upon productivity realisations and the state of the industry. We operationalise the exit rule

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

and the investment function

$$i_{it} = I_t(\omega_{it}, k_{it}, \text{age}_{it}) \tag{4}$$

following Olley and Pakes (1996) based upon the firm's productivity, ω_{it}, capital stock, k_{it} and age. As described above, ω^* is decreasing in capital. Investment is increasing in productivity realisations, but no assumption is made about the direction of the effect of capital stock and age on investment. Age is included to capture industry age structure. Older firms may have greater knowledge and experience in the industry but it may also be possible that firms which are 'too

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

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

[4] See footnote 7, page 56, of Ericson and Pakes (1995).

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old' are unable to adapt to fast-changing industries. Both age and capital are included in the empirical specification in a flexible manner which allows for non-monotonicities, as described below.

(ii) Estimation Methodology

Estimation using this theoretical framework proceeds in three stages.

Step 1 We specify a Cobb-Douglas production function[5] for each industry, with firms distinguished by Hicks-neutral efficiency differences

$$y_{it} = \beta_0 + \beta_a \text{age}_{it} + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \quad (5)$$

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 Equation (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

$$\omega_t = h_t(i_t, k_t, \text{age}_t). \quad (6)$$

Substituting Equation (6) into Equation (5), we have

$$y_t = \beta_l l_t + \lambda_t(i_t, k_t, \text{age}_t) + \eta_t \quad (7)$$

where

$$\lambda_t(i_t, k_t, \text{age}_t) = \beta_0 + \beta_a \text{age}_t + \beta_k k_t + h_t(i_t, k_t, \text{age}_t). \quad (8)$$

Notice that the coefficients on capital and age in Equation (5) can not be identified since both of these variables affect output *and* the investment decision.[6] It is through the latter that capital and age are correlated with productivity. The coefficient on labour can be identified in Equation (7), a partially linear model which can be estimated using semiparametric 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 $\hat{\beta}_l$ and $\hat{\lambda}_t$ 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

$$y_{t+1} = \beta_0 + \beta_a \text{age}_{t+1} + \beta_k k_{t+1} + \beta_l l_{t+1} + E[\omega_{t+1} \mid \omega_t, \chi_{t+1} = 1] + \xi_{t+1} + \eta_{t+1} \quad (9)$$

where

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

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.[7] Recall that firms, but not the econometrician, observe their own productivity realisation 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 $t+1$

$$\begin{aligned} P_r(\chi_{t+1} = 1) &= P_r(\omega_{t+1} \geq \omega_{t+1}^*(k_{t+1}, \text{age}_{t+1}) \mid \omega_t) \\ &= \varphi(\omega_{t+1}^*(k_{t+1}, \text{age}_{t+1}), \omega_t) \\ &= \varphi(i_t, k_t, \text{age}_t) \equiv P_t. \end{aligned} \quad (11)$$

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

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

[6] 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.

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

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

$$y_{t+1} = \beta_0 + \beta_a \text{age}_{t+1} + \beta_k k_{t+1} + \beta_l l_{t+1} + g(\hat{P}_t, \hat{h}_t) + \varepsilon_{t+1}, \tag{12}$$

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

We add year dummies to control for macroeconomic 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 Eqn 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 e.g. 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 introduce dummy variables (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 (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. Following Levinsohn and Petrin (1999) we implemented specification tests to compare this procedure to OLS and FE, both of which are nested in this model.

(iii) Extensions to the Methodology

Finally, we note that there have been many recent extensions to this methodology. Levinsohn and Petrin (1999) use intermediate inputs, instead of investment, as the productivity proxy. Criscuolo and Martin (2004) allow for imperfect competition. Muendler (2004a) and Muendler (2004b) enrich the behavioural model. Ackerberg *et al*. (2005) highlight the restrictiveness of assuming that labour is perfectly flexible and suggest a theoretical alternative which is consistent with the empirical OP methodology. Wooldridge (2005) proposes a more efficient generalised method of moments estimation approach. We would stress, as many of these papers point out, that the estimation technique we employ is consistent with a range of realistic underlying assumptions about firm behaviour including those of the original OP model and many of the extensions.

III Data

We use data from the business longitudinal survey (BLS) of the ABS, Australia's only longitudinal data that tracks firm entry and exit. Four waves of data were collected from 1994–1995 to 1997–1998. The sample was drawn from the ABS Business Register, stratified on industry and employment size. The first wave sample of 9000 firms was poststratified into two categories in the second year of the survey. The first category was firms that 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 1995–1996 (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).[9] The CURF excludes firms with more

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

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

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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 analyse 25 two-digit industries.[10] 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 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.[11] 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.[12] 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.[13] 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 3 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 Appendix Table Al. 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.[14]

IV Regression Results

We estimate production functions for 25 industries at the two-digit ANZSIC code level by OLS, FE, and the OP methodology described in Section II(ii) above. We further compare OLS and FE on the balanced and unbalanced panels. Detailed results by industry are reported in Table 2. Table 3 summarises the changes in the

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

[11] Readers interested in obtaining a more detailed write-up on the correction for true births and deaths can contact the authors.

[12] We provide unweighted statistics in all tables. Given that we have reclassified 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, highlights 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 V(iii).

[13] Between 2002–2003 and 2003–2004, average entry rate was 11.2 and exit rate was 4.2 per cent for all industries, see Australian Bureau of Statistics (2005).

[14] Detailed firm characteristics by entrants, continuing firms and exiting firms are available from the authors.

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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

Notes: Entries in table are percentages. Entry rates are calculated as the number of entrants between 1995–1996 and 1997–1998 divided by the total number of incumbent and new firms in 1997–1998. Exit rates are calculated as the number of firms exiting the sample between 1995–1996 and 1997–1998 divided by the total number of incumbent firms in 1994–1995.
Source: ABS (2000).

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.

(i) 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 II 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.

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TABLE 2
Production Function Estimation Results by Industry

ANZSIC/Industry	Balanced panel (1) OLS	Balanced panel (2) FE	Full sample (3) OLS	Full sample (4) FE	Full sample (5) 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

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TABLE 2
Continued

	Balanced panel		Full sample		
ANZSIC/Industry	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OP
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

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TABLE 2
Continued

	Balanced panel		Full sample		
ANZSIC/Industry	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OP
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

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Table 2
Continued

	Balanced panel		Full sample		
ANZSIC/Industry	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OP
Transport and 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 and 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 and 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

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TABLE 2
Continued

	Balanced panel		Full sample		
ANZSIC/Industry	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OP
Personal and 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

Notes: 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%. FE, fixed effects; OLS, ordinary least squares; OP, Olley and Pakes method.

(ii) 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 II(i) 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 emphasised 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 3 years) in the sample, which is from a period of steady expansion in the Australian economy.

(iii) 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

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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, beverage 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 and associated 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 and 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	⇑	⇓

Notes: Number (%) of industries with ↓ in L 14 (56.0) 19 (76.0). Number (%) 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 three decimal places.

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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 problems than services industries.

If we compare FE on the full sample to FE 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. For 92 per cent of the industries, the age variables are insignificant. Dropping the age variables 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 FE 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.

(iv) 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 FE and we concur with their conclusion that this highlights the inappropriateness, for this economic problem, of the assumptions underlying the FE model.

V Multifactor Productivity Results

(i) Construction and Aggregation

We construct firm-level multifactor 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)):

$$P_{it} = \exp(y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}). \tag{13}$$

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) points 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 is the case in most studies, 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 emphasise 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

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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):

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

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):

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

and noted that

$$\Delta P^A_{0,1} = \Delta P^B_{0,1} + \Delta S^B_{0,1}. \quad (18)$$

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.

(ii) Analysis of Trends in Multifactor 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 $\Delta P^A_{0,1}$ 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, $\Delta P^A_{0,1}$ will be greater than $\Delta P^A_{0,1}$, 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 1994–1995 and 1997–1998. 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 8 industries, the direction of change in MFP-A is positive while MFP-B records a decline (e.g. 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: 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 share 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 second 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 favour of firms with higher average productivity.

There is a further point to note from Table 4. Looking at MFP-B figures, industries experiencing

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TABLE 4
Industry-level Aggregate Changes in Multifactor Productivity from 1994–1995 to 1997–1998

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

Notes: 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).
Source: Business longitudinal survey, ABS.

annual positive MFP growth between 1994–1995 and 1997–1998 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 shift 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.

(iii) Comparison with Other Productivity Studies

The 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 service industries have dramatically

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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 subindustries at the two-digit or three-digit ANZSIC level, based on unpublished data provided by the ABS.[15] These estimates for the manufacturing sector as a whole (see appendix Table A2) show positive MFP growth between 1994–1995 and 1997–1998. 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.[16] Our results do agree with those of the PC about the rapid productivity growth in the food, beverage and tobacco industry.[17]

The Productivity Commission 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 subsectors 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.[18]

Revesz *et al*. (2004) examine productivity performance in two-digit and three-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 1995–1996 and 2000–2001, 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 subgroup.

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 three-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 two-digit industries to which they belong. A likely reason is that the mix of firms in these two-digit industries are such that any MFP gains made by firms in the 'star' three-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.[19]

Some of these differences in aggregate MFP growth findings may come from technique: the

[15] The ABS releases productivity estimates only at the one-digit level. The 8 manufacturing subindustries of the PC do not correspond exactly with the eight two-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).

[16] 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.

[17] 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.

[18] Parham (2004) posits that any productivity acceleration in the property and business services industries could be linked to a rise in information and communication technology (ICT) related research and development activities and increased use of ICT.

[19] We are unable to check this in our data, as sample sizes at the three-digit level become so small that the resulting coefficient estimates are unreliable.

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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.

VI 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 behaviour, to arrive at more accurate production function estimates. Our results support the view that the OP method improves productivity estimates. Lower coefficients on labour support the hypothesis that standard estimates suffer from simultaneity between firms' labour input choices and productivity. We view the unreasonably small estimates for the capital coefficients in OLS and FE as evidence of simultaneity bias between firms' capital usage and productivity. Statistical tests reject standard OLS and FE techniques in favour 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 labelled 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 BLS 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.

Recognising 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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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 2 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
Industry Changes in Multifactor 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).

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