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Abstract

We investigate the relationship between productivity, size and age of large Australian firms employing more than 100 employees or holding assets in excess of $100 million. In addition, we also investigate the extent of productivity persistence among these firms by looking at transition matrices of productivity distribution and productivity-rank mobility. The empirical study is based on the *IBISWorld* database used to estimate *translog* cost function to measure (a residual based) productivity. We find evidence, though somewhat weak, that larger and older firms are on average less productive. Furthermore, we find stronger evidence for a high degree of inertia in terms of productivity ranking within an industry.

Keyword(s): productivity, large firms, Australia, translog cost function, transition matrix.

JEL Code(s): L25

1. Introduction

In this paper, we look at two issues of interest in the theoretical as well as empirical research in industry organization, namely the relationship between productivity and firm size and age, and firm level productivity persistence. In particular, we first ask the question of whether or not larger and older firms are systematically more productive than their younger and smaller counterparts. Then, we ask the question of whether or not there is a tendency for firms to converge in productivity level, either towards the best- or worst-performing firms, or towards the mean.

Given that the notion of a representative firm has been challenged in recent literature,[1] the answers to those questions are not clear. For example, older and less productive firms may die and exit from the market, while new and more productive firms enter. If the new firms are also more productive than the surviving older firms, then we see age and productivity to have a positive correlation. In addition, recent studies also usually find a significant heterogeneity in productivity performance across existing firms. Some firms are found to be substantially more productive than their peers and the productivity differentials tend to persist over time.[2] However, if there is relatively costless production knowledge diffusion through spillovers and imitation, for examples, one may expect to find that in the long run firms would converge to an industry average productivity level.

For the case of Australia, the Productivity Commission (1999) finds a great diversity in productivity performance among the various sectors of the Australian economy.[3] Within the manufacturing sector, for example, the study finds that firm productivity growth is highly variable. Overall, the findings suggests that firms productivity performance is not likely to be explained by a single factor and, a long with other similar studies with different country data

[1] That is it is typical to find an industry in a constant state of flux, with entries and exits occurring simultaneously.
[2] See, for examples, Bartelsman and Dhrymes (1998), Bartelsman and Doms (2000) and Brynjolfsson and Hitt (2000).
[3] See also Bland and Will (2001).

cited earlier, they lend support to a set of predictions derived from recent theoretical work on industry dynamics.[4] For examples, competitive firms with widely different productivity levels may coexist and simultaneous entries and exits are common place.

We attempt to answer the previous two questions empirically by investigating how the productivity of firms evolves over a specific period of time using data and research methodology which are distinct from those used in the two earlier works cited above. More specifically, in addition to examining the way productivity levels and growth co-vary with firm size and age, we also examine the change in productivity distribution by looking at productivity transition matrices and productivity mobility of Australian large firms.

Our empirical analysis is based on a sample of large Australian firms employing more than 100 employees or controlling assets valued in excess of AU$100 million. Although relatively few in number, large Australian firms account for a significant proportion of the country's output and employment (Dawkins et al., 1999). In fact, according to a 2000–01 Australian Bureau of Statistics (ABS) survey, while there are only slightly more than 3,200 operating businesses that can be classified as large, altogether these firms employed more than 2.4 million persons—accounting for 38 per cent of all business employment. Furthermore, their total net worth is valued at more than 75 per cent of the total net worth of all employing and trading businesses. Finally, in terms of gross output, they account for nearly 50 per cent of total industrial gross output in the survey year. Thus, arguably, the performance of these firms is critical to the economy the country.

The rest of this paper is organized as follows. Section 2 outlines the empirical framework that underpins our empirical model. Section 3 specifies the empirical model and its estimation strategy and describes the data used for estimation. Section 4 provides and discusses the estimation results. Section 5 concludes.

[4] Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995).

2. Empirical framework

We start by assuming that the production technology of any firm *i* in any period *t* can be represented by a firm-specific production function F_{it}:

$$Y_{it} = F_{it}(X_{it}),\ \ i = 1,\ldots,n\,,\ t = 1,\ldots,T \tag{1}$$

where Y_{it} denotes the firm's output and $X_{it} = \left[x_{it}^1,\ldots,x_{it}^J\right]$ is a vector of *J* factor inputs used by the firm to produce its output. Furthermore, to allow for the econometric estimation of firm productivity, we parameterise F_{it} as

$$F_{it}(X_{it}) = A_{it}F(X_{it}) \tag{2}$$

where $A_{it} > 0$ denotes a relative efficiency factor that varies by firm and time and $F(\bullet)$ is a common production technology. Thus, we assume the firm-specific efficiency (A_{it}) as the driving factor of heterogeneity in the firm-specific production function given in (1).

The interpretation of (2) is straightforward. Without lost of generality, suppose we normalize A_{it} such that $A_{i0} = 1$. Suppose also that the existing production knowledge available to all firms in the initial period ($t = 0$) allows firm *i* to produce at the most Y_{i0} of output for a given vector inputs X_{i0}. Then, in period t>0, given the same amount of inputs, the firm can produce a maximum output of $A_{it}Y_{i0}$. In this case, firm *i* is more efficient in period *t* compared to in period 0 if and only if $A_{it} > 1$. In other words, one may then use an unbiased and consistent coefficient estimate of A_{it} to measure the efficiency level of any firm at any period and its associated change overtime.[5]

Unfortunately, an econometric estimation of the production function in equation (2) has been known to suffer from several potential drawbacks. In particular, it is quite likely for the right hand side variables such as labour and capital inputs to be dependent on the unobserved

[5] In this paper, we use the terms 'productivity' and 'efficiency' interchangeably.

level of A_{it}, leading to a simultaneity bias. Because of this, instead of using (2) as a basis for obtaining an unbiased estimate of A_{it}, we exploit the duality relationship and specify an estimating equation based on a cost function described below.[6]

To do this, we assume firms as cost minimizers and price takers at the input and output markets. These assumptions lead to a cost function $C_{it}(\bullet)$ such that $W_t X_{it} = C_{it}(Y_{it}, W_t)$ where $W_t = [w_{1t}, \ldots w_{Jt}]$ denotes a vector of factor prices corresponding to the factor inputs X_{it}. Notice that the price taking assumption implies that each firm faces a common vector of factor prices W_t. As in equation (2), we parameterise $C_{it}(\bullet)$ such that

$$C_{it}(X_{it}) = (1/A_{it})C(Y_{it}, W_t) \tag{3}$$

where A_{it} is as before and $C(\bullet)$ is a common and time-independent cost function. Thus, suppose, as before, the period 0 output level for a firm *i* is y_i, A_{it} is normalised as $A_{i0} = 1$, and an associated vector of factor prices is given as *W*. Then, if $A_{it} > 1$, the cost of producing the same output level y_i in period t>0 is lower than the cost in period 0 by a factor of $1/A_{it}$. Therefore, a natural measure of productivity change for any firm *i* going from periods *s* to *t*, $t > s \geq 0$ is simply the ratio $\beta_i^{s,t} = A_{it}/A_{is}$. For example, if $\beta_i^{s,t} > 1$ then firm *i*'s efficiency has improved between the two periods.

In this paper, we look at how the levels and distribution of A_{it} evolve over time. For this purpose, the notions of active and passive learning are particularly relevant.[7] Under both learning models, each firm is assumed to be endowed with an unknown value of a profitability parameter, which determines the distribution of its profits. The firm only knows that this parameter is a random draw from some known distribution. Under passive learning,

[6] See Olley and Pakes (1996), for example, for another way of solving the simultaneity bias without resorting to the dual.
[7] See, for examples, Jovanovic (1982), Pakes and Ericson (1989), and Ericson and Pakes (1995).

the profitability parameter is time invariant. Thus, past profit realisations contain information on the value of the parameter which determines the distribution of possible future profit streams, and this fact is used by the firm's management to form a profitability distribution over future profits. If the firm stays in business, this updating continues and decisions are made on the basis of the sequence of updated posteriors. The empirical implication is thus, as age increases, the profitability distribution of the surviving firms improves, and hence by implication their productivity. This is a result of self-selection. As time passes firms with lower profitability parameter are more likely to have a poor draw and exit the industry.

Under active learning, firms are assumed to know the current value of the parameter that determines the distribution of its profits, but that the value of the parameter changes over time in response to the stochastic outcomes of the firm's own investments, and those of other firms in the industry. Unlike passive learning, in the active learning model the parameter determining the firm's profitability distribution evolves over time. Later year realizations are governed by a potentially different parameter value than those from earlier years, and as time passes, the dependence between the later and earlier values, and therefore of size, dies out.

We further note that both passive and active learning models are consistent with the convergence hypothesis, which states that firm productivity growth converges to some long--run rate steady state (Bernard and Jones 1996). If technology is global, then we expect firms to converge towards some fixed industry parameter in the long run, given by the industry fixed effect. However, if firms have permanent differences in their productivity levels due to, say, differences in management capability, then each of them converges toward its own individual steady state. These individual steady states are not necessarily the same across firms.

3. Model specification and data

Productivity measure

For econometric estimation, we transform (3) so that

$$\ln C_{it}(Y_{it}, W) = -\ln A_{it} + \ln C(Y_{it}, W_t) \tag{4}$$

and specify a translog cost function

$$\begin{aligned} \ln C(Y_{it}, W_t) &= \beta_0 + \beta_y \ln Y_{it} + \sum_j \beta_j \ln w_j + \tfrac{1}{2}\beta_{yy} (\ln Y_{it})^2 \\ &+ \sum_j \beta_{yj} \ln Y_{it} \ln w_j + \tfrac{1}{2}\sum_j \sum_k \beta_{jk} \ln w_j \ln w_k \end{aligned} \tag{5}$$

where, by symmetry and the homogeneity property of the cost function, $\beta_{jk} = \beta_{kj}$ and $\sum_j \beta_j = 1$, $\sum_j \beta_{yj} = 0$, and $\sum_k \beta_{jk} = 0$ for all *j* and *k*.

The estimation of (4)-(5) can be further enhanced by making use of Shephard's lemma, which states that $\frac{\partial C}{\partial w_j} = x_j$. Thus, for our translog cost function given in (5), we can derive the firm-specific cost share of a factor input *k* in total cost ($s_k \equiv w_k x_x \big/ \sum_j w_j x_j$) as

$$s_{ik} = \beta_k + \sum_j \beta_{jk} \ln w_j + \beta_{yk} \ln Y_i \tag{6}$$

The total cost, the cost shares, and the cross-equation restrictions (equations (4)-(6)) can then be jointly estimated using Seemingly Unrelated Regression (SUR) after we introduce random error terms to the cost function and certain assumptions on their probability distribution.[8] In particular, to take into account the panel nature of the firm data we use, we specify the following linear additive error terms:

$$\varepsilon_{it} = \nu_i + \mu_{it} \tag{7}$$

[8] Since the input cost shares must sum to one, one of the input cost share equation is excluded from the system. The estimation results are invariant to which cost share equation is excluded.

where $v_i \sim i.i.d.(0,\sigma_{v_i}^2)$ is a time-invariant, firm-specific component, $\mu_{it} \sim i.i.d.(0,\sigma_{\mu}^2)$ is a random white noise component, and v_i and μ_{it} are independent.

The presence of the heteroscedastic error terms trough v_i leaves the standard SUR estimates inefficient, so in the estimation we use transformed variable to ensure homoscedasticity. This transformation requires the estimates of the variances of each error components, $\sigma_{v_i}^2$ and σ_{μ}^2 which we obtain using the procedure outlined in Bhattacharyya *et. al.* (1997) as follows:

(1). Perform a within-transformation of the cost function (equation (5)) and estimate the within-transformed cost function, with factor cost share equations and the symmetry and homogeneity restrictions imposed, using iterative SUR. The mean square error of the estimated residuals of the cost function gives an unbiased and consistent estimate of σ_{μ}^2.

(2). Re-estimate the same system of equations using iterative SUR again, but this time without performing the within transformation. Using the estimated residuals, denoted as e_{it}, compute an estimate for the variance of ε_{it}, $\hat{\sigma}_{\varepsilon_t}^2 = \sum_{t=1}^{T_i} e_{it}^2 / T_i$.

(3). Since $\sigma_{\varepsilon_i}^2 = \sigma_{v_i}^2 + \sigma_{\mu}^2$ from (7) and the independence assumption, then $\hat{\sigma}_{v_i}^2 = \hat{\sigma}_{\varepsilon_i}^2 - \hat{\sigma}_{\mu}^2$.

(4). Compute the transformation parameter: $$\theta_i = 1 - \frac{\hat{\sigma}_{\mu}^2}{\sqrt{\hat{\sigma}_{\mu}^2 + T_i \hat{\sigma}_{v_i}^2}}$$

(5). Lastly, transform the cost function by subtracting from each variable a fraction θ_i of its group mean and re-estimate (4)-(6) using the transformed variables and iterative SUR. For example, for any variable z which appears in equation (5), the transformation is given by $\tilde{z}_{it} = z_{it} - \theta_i \sum_{t=1}^{T_i} z_{it} / T_i$.

We then use the residuals of the last regression estimates to obtain estimates of A_{it} and to characterise firm-level productivity. Specifically, from (4), we have

$$-\ln \hat{A}_{it} = \ln C_{it}(Y_{it}, W) - \ln \hat{C}(Y_{it}, W_t)$$

This productivity measure is used in the second stage for characterising the relationship between productivity on the one hand and age and size on the other and the dynamics of firm productivity over the sample period. For the first purpose, we consider two possible scenarios. First, if we assume firm production technology as determined by a combination of random shocks to productivity level and a deterministic growth, then a simple linear specification of A_{it} is given by

$$-\ln \hat{A}_{it} = g(Age, Size; \gamma) + \beta t + \xi_{it} \qquad (8)$$

where $g(Age, Size\gamma)$ represents the effects of age and size with γ as the parameter vector, *t* is time and ξ_{it} is a white noise error term. Thus, in this scenario, controlling for age and size, A_{it} consists of two parts: a deterministic growth component (βt) and a random shock component ε_{it} *(i.i.d.* distribution that is time invariant). The deterministic component ensures that the average level of productivity in the entire distribution rises over time, whereas the variance of the productivity distribution of firms relative to the mean remains constant. Note that the relative position of a firm in the productivity distribution is determined solely by the random shock component. Thus firms with above average productivity in one period are likely to have below average productivity the next period. In other words, the rank of a firm in the productivity distribution will therefore have low cross-time persistence.

Second, if any unobserved firm heterogeneity can be attributed to a time-invariant, firm-specific fixed effects, (8) can be replaced by

$$-\ln \hat{A}_{it} = g(Age, Size; \gamma) + \beta t + \lambda_i + \xi_{it} \qquad (9)$$

where λ_i represents a fixed productivity constant for firm *i* and the other terms are as defined before. In this case, after controlling for firm age and size, firms display permanent differences in their productivity levels. Even though there is a random component ε_{it}, each firm's position remains broadly stable within the productivity distribution, for example, within the same quintile.

We use firm-level panel data to estimate the system of equations (4)-(9) in two stages. In the first stage, a translog cost function in the form of (5) and the associated share equations are estimated. Then, it is followed by the estimation of the (8) and (9), separately. Finally, we construct transition matrices based on the distribution of productivity across firms and years and analyse their changes over the sample period.

Data

The main source of the panel data used for the estimation is IBISWorld, a commercial business information provider in Australia. We supplement the data with estimates of firm age derived from company registration data provided by the Australian Securities and Investment Commission, an independent Australian government body charged with the regulation of corporations. Since the IBISWorld financial database contains only large firm data, we restrict our study to large firms employing more than 100 employees or controlling total assets valued at more than AU$100 million.

After eliminating records with missing observations from the sample, we have a total of 6,989 observations over a 12 year period. Table 1 presents the distribution of firms across ten broad industries in five selected years: 1992, 1995, 1998, 2001, and 2003. We note that manufacturing is well represented in the sample; making up for 40.4 per cent of all firms, and the second largest industry is wholesale trade, with 20.5 per cent. As one would expect, the smallest industry group in terms of number is electricity, gas and water supply, which accounts for only 0.6 per cent of all firms.

Table 1: Number of firms by industries and selected years

Industry	All years	%	1992	1995	1998	2001	2003
Accommodation, cafes & restaurants	87	1.2	5	6	10	8	6
Agriculture, forestry & fishing	73	1.0	3	4	6	9	8
Construction	291	4.2	13	20	25	36	23
Electricity, gas & water supply	40	0.6	2	3	4	4	4
Finance & insurance	505	7.2	31	38	53	45	23
Manufacturing	2,823	40.4	180	237	258	292	152
Mining	473	6.8	22	37	48	50	25
Property & business services	720	10.3	36	51	67	80	54
Retail trade	543	7.8	27	41	48	57	48
Wholesale trade	1,434	20.5	77	125	134	148	81
All industries	6,989	100.0	396	562	653	729	424

Table 2 presents the dollar values of total costs by industries, and average cost shares of capital, labour, and materials, and the corresponding standard deviations. Note that the averaging is across all firms in the respective industry and across all years. It is obvious that there is large heterogeneity in production costs both within and across industries. The pattern of costs across industries is as expected. Electricity, gas and water supply has the highest total cost, followed by mining, and finance and insurance. The industry with the lowest total cost is accommodation, cafes and restaurants. The most capital intensive industry is electricity, gas and water supply, followed by mining. The most labour intensive industry is property and business services, followed by the construction industry. [9]

[9] See the appendix for more details about the data in general and the definition of the cost and other variables.

Table 2: Total costs and factor shares by industries

Industry	Total cost ($'000) Mean	s.d.	Capital share Mean	s.d.	Labour share Mean	s.d.	Material share Mean	s.d.
Accomm., cafes & rest.	523.7	503.2	0.665	0.253	0.089	0.067	0.246	0.186
Agri., forestry & fishing	796.0	697.8	0.788	0.122	0.029	0.016	0.184	0.106
Construction	834.1	1,481.5	0.438	0.206	0.095	0.035	0.467	0.172
Elect., gas & water supp.	28,917.2	28,435.0	0.925	0.068	0.008	0.008	0.067	0.061
Finance & insurance	7,364.8	19,386.2	0.749	0.241	0.080	0.077	0.172	0.164
Manufacturing	2,117.8	5,108.3	0.662	0.169	0.061	0.031	0.277	0.138
Mining	11,806.2	33,114.5	0.888	0.091	0.018	0.015	0.094	0.076
Prop. & business serv.	1,942.0	5,968.1	0.543	0.261	0.155	0.089	0.302	0.172
Retail trade	2,235.7	6,943.7	0.475	0.211	0.062	0.025	0.463	0.186
Wholesale trade	721.5	1,504.3	0.397	0.202	0.050	0.017	0.553	0.185
All industries	2,920.9	11,674.6	0.596	0.242	0.068	0.054	0.336	0.211

Note: s.d. is standard deviation

4. Results

Determinants of productivity

The empirical estimation consists of two stages. In the first stage, we estimate a system of three equations consisting of the cost function and two factor share equations, labour and capital cost shares. Table 3 lists the variables used in the estimation and all variables are expressed in natural logarithms. All variables listed in that table, with the exception of the age and employment variables, are used in the first stage estimation.

Following the procedure outlined in the preceding section, we obtain an estimated *translog* cost function, whose coefficients are presented in Table 4. We note that most of the parameter estimates are statistically significant. As explained earlier, we use the residuals from the consistently estimated cost function to obtain firm level productivity estimates.

Table 3: List of variables

	Dependent variable
$\ln C$	Total cost of operation (in dollars)
$\ln s_1$	Labour cost share (labour cost / total cost)
$\ln s_2$	Capital cost share (capital cost / total cost)
$\ln s_3$	Materials cost share (materials cost / total cost)
	Independent variable
$\ln y$	sales revenue (in dollars)
$\ln w_1$	Wage cost per employee
$\ln w_2$	Capital cost per dollar of sales revenue
$\ln w_3$	Material cost per dollar of sales revenue
$\ln Age$	Age of firms (in years)
$\ln Empl$	Employment, number of employees (fulltime equivalent)

We use the productivity estimates in the estimation of the determinants of current productivity. In this estimation, we make use of the following variables: firm age, the square of firm age, previous period sales revenue and employment, and the interaction between the last two variables. These variables are supposed to capture a form of learning effects. If there is any learning-by-doing, then larger and older firms may have better learning-by-doing opportunities and hence be more productive.

We estimate three different models of productivity determinants depending on the specification of the unobservables as shown in equation (8) and (9). Model A is a straightforward OLS estimation, model B is a fixed effects model, and model C is a random effects model. Table 5 presents the estimated coefficients and relevant statistics for each model.

From Table 5, we see that age is not statistically significant in all models. In addition, the square of age is only significant in the fixed effects model at a 10% significance level. Thus, once other control variables are introduced, it seems that age is an unimportant determinant of firm productivity. On the other hand, the two variables representing firm size, namely lagged sales revenue and lagged employment, are both negative and statistically significant in

Table 4: ITSUR Parameter estimates of cost function

Dependent variable	Parameter estimate	Standard error	t statistics
$\ln w_1$	0.0236	0.0037	6.4
$\ln w_2$	0.6374	0.0032	200.2
$\ln w_3$	0.3389	0.0047	71.5
$\ln y$	1.1360	0.0031	367.1
$(\ln w_1)^2$	0.0117	0.0005	22.0
$\ln w_1 \ln w_2$	0.0176	0.0003	53.4
$\ln w_1 \ln w_3$	0.0059	0.0006	10.1
$(\ln w_2)^2$	0.1291	0.0005	240.0
$\ln w_2 \ln w_3$	0.1116	0.0005	202.9
$(\ln w_3)^2$	0.1056	0.0009	123.6
$(\ln y)^2$	0.0111	0.0004	30.6
$\ln y \ln w_1$	0.0007	0.0003	2.1
$\ln y \ln w_2$	0.0050	0.0003	16.2
$\ln y \ln w_3$	0.0094	0.0018	5.2
Constant	0.2583	0.0114	22.6
No. obs.	6,989		

both the OLS and random effects models. This suggests some productivity advantage of the larger firms. The relationship between productivity and size, however, is not linear. The interaction term between sales revenue and employment is also statistically significant.

To see whether if the data can guide us with regards to which model is more appropriate, random effects or fixed effects, we conduct a standard F-test with a null hypothesis of no fixed effects and a Breusch-Pagan Lagrange Multiplier test with a null hypothesis of no random effects. The fixed-effect test statistics is 2.28 with degrees of freedom of 877 and 4,517, so we reject the null at a 1% level. For the random effects test, the $\chi 2$ test statistic is 442.7 and given the degree of freedom we also reject the null. Hence, it is not clear whether or not one model is more appropriate than the other.

Table 5: Productivity equation estimates

	Model A: OLS		Model B: Fixed effects		Model C: Random effects	
Dependent variable	Parameter estimate	Std. error	Parameter estimate	Std. error	Parameter estimate	Std. error
Age	0.0696	0.0435	0.0074	0.1044	0.0666	0.0523
Age^2	-0.0064	0.0042	0.0275 †	0.0144	-0.0055	0.0051
$Sales_{t-1}$	-0.0712 **	0.0177	-0.0186	0.0414	-0.0622 **	0.0215
$Empl_{t-1}$	-0.0758 **	0.0199	-0.0475	0.0539	-0.0719 **	0.0250
$Sales_{t-1} \times Empl_{t-1}$	0.0075 **	0.0014	0.0046	0.0041	0.0069 **	0.0018
$Age_{t-1} \times Empl_{t-1}$	0.0052	0.0047	0.0017	0.0111	0.0055	0.0057
$Age_{t-1} \times Sales_{t-1}$	-0.0057	0.0045	-0.0112	0.0102	-0.0061	0.0055
Constant	-0.5538 **	0.1525	-1.0242 **	0.3764	-0.6252 **	0.1868
No. observations	5,400		5,400		5,400	
Adjusted-R2	0.041		0.003		0.042	

Note: Statistical significance symbols: ** at 1%, *at 5%, †at 10%. All variables are in log values.

Productivity Transition

It has been argued that transition matrices can be more informative for examining the evolution of the distribution and any possible convergence of firm productivity than regression analysis.[10] We construct one-year apart TFP transition tables containing the number and percentage of firms in the k^{th} productivity quintile at $t+1$, given their quintile position at time t. We compute the productivity quintiles for each industry with sufficient number of firms for meaningful results. These industries include manufacturing, wholesale trade, property and business services, finance and insurance, retail trade, and mining. We use industry specific quintile since we think relative comparison of firm productivity is more meaningful if underlying production technology used by the firm is more homogenous.

Tables 6 (a) – (d) present one-year productivity quintile transitions for some selected time intervals: 1992–1993, 1995–1996, 1998–1999, and 2001–2002. From these tables, we can see

[10] See Bartelsman and Dhrymes (1998) and Girma and Kneller (2002).

that most firms fall within the diagonal cells or the immediate neighbours. For example, 75 per cent of firms in the first quintile in 1992 remained in the same quintile in 1993. Only 13 per cent of them moved up one rank to the second quintile. At the other extreme, 63 per cent of firms in the fifth quintile remained in the same quintile in 1993, while another 30 percent moved down one rank to the fourth quintile. A similar pattern is observed for the other time intervals, namely firm productivity rankings within each industry do not change much from one year to the next. In other words, there is a fair degree of persistence in productivity rankings. More productive firms are likely to be more productive in the next period, while less productive ones are likely to remain so.

Table 6: One-year apart transition tables, selected years.

		1993				
Year		1	2	3	4	5
1	1	45	8	4	2	1
9		75%	13%	7%	3%	2%
9	2	9	34	6	2	1
2		17%	65%	12%	4%	2%
	3	3	13	26	12	3
		5%	23%	46%	21%	5%
	4	2	8	21	21	6
		3%	14%	36%	36%	10%
	5	0	0	4	17	36
		0%	0%	7%	30%	63%

(a) 1992–1993

		1996				
Year		1	2	3	4	5
1	1	67	21	4	1	1
9		71%	22%	4%	1%	1%
9	2	20	51	18	2	2
5		22%	55%	19%	2%	2%
	3	6	19	49	23	3
		6%	19%	49%	23%	3%
	4	1	2	19	53	16
		1%	2%	21%	58%	18%
	5	1	2	3	10	67
		1%	2%	4%	12%	81%

(b) 1995–1996

		1999				
Year		1	2	3	4	5
1	1	88	19	3	0	2
9		79%	17%	3%	0%	2%
9	2	20	57	24	6	0
8		19%	53%	22%	6%	0%
	3	2	19	54	21	5
		2%	19%	53%	21%	5%
	4	4	7	20	58	18
		4%	7%	19%	54%	17%
	5	2	3	3	21	71
		2%	3%	3%	21%	71%

(c) 1998–1999

		2002				
Year		1	2	3	4	5
2	1	92	14	6	2	3
0		79%	12%	5%	2%	3%
0	2	15	67	24	11	0
1		13%	57%	21%	9%	0%
	3	1	27	57	27	6
		1%	23%	48%	23%	5%
	4	2	5	27	67	21
		2%	4%	22%	55%	17%
	5	2	7	8	17	84
		2%	6%	7%	14%	71%

(d) 2001–2002

Note: In each cell, the top figure is the number of firms and the bottom figure is the corresponding row percentages.

Tables 7 (a)–(c) present three-year transition tables for the 1992–1995, 1995–1998 and 2000–2003 intervals, respectively. As one would expect, with a longer interval, the percentage of firms remaining in the same productivity quintiles is less than in the one-year interval discussed above. However, we note that the diagonal and neighbouring cells are still the dominant location, indicating that firms tend to remain in the same productivity position even three years later. This result suggests that the persistence in productivity rankings holds not only in the short term, but also when longer time intervals are considered.

Table 7: Three-year transition tables, selected years.

		1995				
Year		1	2	3	4	5
1992	1	41	17	4	4	1
		61%	25%	6%	6%	1%
	2	17	25	17	2	0
		28%	41%	28%	3%	0%
	3	6	13	30	16	1
		9%	20%	45%	24%	2%
	4	0	7	20	27	12
		0%	11%	30%	41%	18%
	5	2	1	4	13	38
		3%	2%	7%	22%	66%

(a) 1992–1995

		1998				
Year		1	2	3	4	5
1995	1	56	23	7	4	1
		62%	25%	8%	4%	1%
	2	26	31	13	18	7
		27%	33%	14%	19%	7%
	3	12	19	28	19	9
		14%	22%	32%	22%	10%
	4	2	14	33	29	15
		2%	15%	35%	31%	16%
	5	1	7	11	22	46
		1%	8%	13%	25%	53%

(b) 1995–1998

		2003				
Year		1	2	3	4	5
2000	1	33	4	5	1	5
		69%	8%	10%	2%	10%
	2	14	28	10	1	1
		26%	52%	19%	2%	2%
	3	3	20	21	12	10
		5%	30%	32%	18%	15%
	4	4	5	22	28	9
		6%	7%	32%	41%	13%
	5	2	5	5	21	34
		3%	7%	7%	31%	51%

(c) 1998–2003

Note: In each cell, the top figure is the number of firms and the bottom figure is the corresponding row percentages.

Those transition tables show strong persistence in firm productivity rankings. Firms tend not to move about randomly in their productivity rankings. A firm in the k^{th} productivity quintile is far more likely to remain in the same quintile or in the $k^{th}-1$ ($k^{th}+1$) quintiles. Such a strong persistence in productivity rankings does not lend support to the convergence hypothesis; instead, it reaffirms the earlier empirical findings that there is a large degree of heterogeneity among firms in productivity performance.

Although transition tables provide important information about the degree of mobility in an industry, there are several limitations: (i) the tables provide information on two points in time only and, for a long interval, they miss out on potential changes that may have occurred in the intervening years. (ii) The tables do not give any information about the 'distance' that firms move. It is not possible to infer if a firm moves up from its previous year ranking by one quintile or three quintile ranks.

"Usual" quintile rank

To gauge the distance of productivity movement of firms, we propose the notion of a "usual" quintile rank. It is defined as the quintile in which a firm has occupied for more than half of the time in the sample in which it has observations. That is, if a firm is observed in all years of the twelve-year sample period, its "usual" quintile rank is the quintile that the firm occupies for at least seven out of the twelve years. Notice that this definition allows for the fact that the panel is unbalanced. Furthermore, since productivity movement can only be observed if there are enough observations, we restrict ourselves to firms that have at least four observations in the sample. This restriction yields 710 firms in the sample and 455 of them (64 per cent) have "usual" quintile ranks.

Table 8 shows the distribution of the usual quintile ranks and the number of occurrences of these quintile ranks.[11] Interestingly, among firms with the "usual" quintile rank, there are more firms occupying the lowest and highest quintile ranks, and more importantly, these firms occupy their respective "usual" quintile ranks longer on average. There are, respectively, 23 and 17 firms occupying the first and fifth quintile ranks for 10 and more years, as compared to 7, 1, and 2 firms occupying the second, third and fourth quintile rank for the same length.

Table 8: Usual quintile ranks: Frequency counts

	Usual quintile rank					
Occurrences	1	2	3	4	5	Total freq.
3–5	32	34	25	47	47	185
6	13	18	14	12	14	71
7	23	17	13	14	12	79
8	11	5	4	4	9	33
9	16	3	3	4	11	37
10–12	23	7	1	2	17	50
Total freq.	118	84	60	83	110	455
Avg. occurrences	7.22	6.08	5.72	5.45	6.55	–
Std. dev.	2.42	2.04	1.83	1.86	2.52	–

Borrowing the notion of mobility from the income mobility literature (see, for examples, Gardiner and Hills (1999) and Zaidi et. al. (2001)), we use the "usual" quintile ranks to identify firms that are of "low mobility".[12] We say a firm is of low mobility in productivity movement if it has not experienced any movement of more than one quintile above or below its "usual" quintile rank. Using this definition, of the 455 firms that have a "usual" quintile

[11] Recall that we have unbalance panel data. Thus, if a firm with four observations in the sample, its "usual" quintile rank is defined if it occupies the same quintile rank for at least three of the four years.

[12] This is basically a relative positional mobility measure (see the discussion in Fields, 2005). This measure is chosen because of our main interest on the extent of changes in the productivity ranking of the firms rather than, say, on the extent of the dispersion. Furthermore, the relative measure is more desirable because it is plausible, for example, for firms to be mobile in absolute productivity but immobile in relative terms. In that case, we may not observe productivity convergence even under high level of absolute mobility. On the other hand, in order for firms to converge to an industry long run level of productivity, we expect to see significant relative mobility among the firms. Also, if firm only converges to its own long-run productivity level which may be different across firms, we would see a low level of relative mobility and, plausibly, accompanied with significant absolute mobility.

rank, 334 (73 per cent) belong to the low-mobility group. Table 9 presents the distribution of these low-mobility firms by their usual quintile rank and the number of years they stay in their usual quintile ranks.

Table 9: Low-mobility firms and their usual quintile

	Usual quintile rank					
Number of years	1	2	3	4	5	Total freq.
3–5	16	28	18	36	29	127
6	9	13	10	9	5	46
7	15	15	10	12	6	58
8	6	5	2	4	6	23
9	14	3	3	4	10	34
10–12	20	6	1	2	17	46
Total freq.	80	70	44	67	73	334

To summarize, we note three points. First, 64 percent of firms have a “usual” quintile rank, that is, the quintile rank that they have been occupying for more than half of the time. Second, 73 percent of these firms do not move from their “usual” quintile rank by more than one quintile rank, that is, they have low-mobility. Third, more of these low-mobility firms belong to the lowest and highest quintiles. Taken together, the results suggest that there is limited productivity movement among firms, and this is particularly so for firms in the lowest and highest productivity rankings.

Low versus high productivity firms

We classify firms according to their productivity status using information from the entire sample period. We define a “low productivity firm at time *t*” as the one with a quintile rank at in the lowest two quintiles or a missing observation at time t. Subsequently, we define a firm a “low productivity firm” in if it is a low productivity firm at time *t* for all *t* in the sample period. A “high productivity” firm is defined similarly, except the quintile rank is the top two quintiles instead of the bottom two or missing observation. Also, any firm that does not fit either definition is collected under the heading of “other.” Furthermore, since the sample is an unbalanced panel, we restrict the analysis to firms with at least four observations in the sample, yielding a total of 710 firms.

Table 10 gives a breakdown of firms by the number of observations and productivity status. Of the total of 710 firms, 115 (16 per cent) and 102 (14 per cent) are in, respectively, the low and high productivity groups. The remaining (493 firms) do not belong to either groups. It is worth noting that distributions of low and high productivity firms are not excessively skewed towards firms with fewer observations.

Table 10: Productivity status of firms

Number of years observed	Low productivity	High productivity.	Other	Total
4	7	18	39	64
5	9	14	32	55
6	11	14	39	64
7	10	11	43	64
8	10	4	57	71
9	19	5	63	87
10	15	9	66	90
11	22	12	87	121
12	12	15	67	94
Total	115	102	493	710

By construction, low and high productivity firms are also firms with low mobility across quintile ranks. Indeed, as shown in Table 11, most of the high- and low-productivity firms also have “usual” quintile ranks, whereas this is not the case for firms in the “others” category. Notice also that the “usual” the high- and low-productivity firms are found in, respectively, the highest and lowest usual quintiles (the ratio is approximately 3 to 1 that they are found in the most extreme quintiles). In contrast, the “usual” quintile ranks of firms in the "others" category are fairly evenly distributed across the five quintiles. Thus, there seems to be some evidence for low and high-productivity firms to end up in the extreme quintile ranks and, at the same time, they are unlikely to move out of their position.

Table 11: "Usual" quintiles and Productivity status

Usual quintile	"Others"	High prod.	Low prod.	Total
1	38	0	80	118
2	54	0	30	84
3	60	0	0	60
4	59	24	0	83
5	37	73	0	110
N/A	245	5	5	255
Total	493	102	115	710

Note: N/A refers to firms without any usual quintile.

5. Conclusion

In this paper, we estimates a translog cost function to obtain a consistent estimate of firm-level productivity index. Our regression analyses of the resulting productivity index show that there is a great degree of heterogeneity among large Australian firms even within a specific industry. We also find that larger firms are, on average, more productive, but this is not the case for the older firms. In fact, we find age to be adversely correlated with firm productivity in a fixed effects model of productivity determinants.

Our analyses of the one-year and three-year transition tables find strong persistence in firm productivity rankings. This finding is collaborated by the finding of our analyses of firm productivity mobility. In particular, we find firms with low or high productivity status tend to remain in the lowest or highest productivity rankings in their respective industries. Also they are less likely to depart from their usual position. Therefore, these productivity transition and mobility analyses suggest that there is no evidence that large Australian firms tend to converge in terms of productivity performance.

Appendix: Data Sources and Variable Construction

The main source of the firm financial data is IBISWorld, a commercial information provider company which offers, by subscription, financial information of the top 2,000 companies in Australia and the general business environment within which these companies operate. The company financial information that IBISWorld provides includes total operating revenue, employment, values of fixed assets and liabilities, and information useful to derive total costs and the cost components. The information on firm age is obtained from the Australian Company Number (ACN) Registration Database provided by the Australian Securities and Investments Commission (ASIC). We use the earlier registration date of each firm as its date of birth. We also use other supplementary data sources including various issues of ABS publications such as the Producer Price Index (Catalogue Number 6427.0) and the Australian Industry (8155.0).

The sample used in the data analysis is restricted to large firms employing more than 100 employees or controlling total assets valued at more than AU$100 million. After eliminating records with missing observations from the sample, we have a total of 6,989 observations over a 12 year period from 1992 to 2003. As can be seen from Table A.1, the average number of firms per year is around 582 firms. Also, the number of firms across the 12 year period is fairly evenly distributed, with 2001 having the highest number of firms at 729, while 1992 has the lowest number of firms at 396. In addition, Table A.1 also reports the dollar values of total costs, and the shares of capital, labour, and material costs. All values are averaged across firms in the respective years.

Table A.1: Summary statistics of firms by years

Year	No. of firms	Percent	Average across firms: Total cost ($'000)	Cost shares: Capital	Labour	Material
1992	396	5.67	3,667.6	0.682	0.054	0.264
1993	436	6.24	2,493.8	0.628	0.060	0.312
1994	469	6.71	3,037.6	0.658	0.056	0.286
1995	562	8.04	3,048.1	0.649	0.057	0.294
1996	612	8.76	3,504.0	0.649	0.058	0.292
1997	605	8.66	3,254.9	0.610	0.066	0.325
1998	653	9.34	2,639.8	0.554	0.075	0.371
1999	684	9.79	2,589.6	0.578	0.071	0.351
2000	716	10.24	2,889.5	0.581	0.074	0.346
2001	729	10.43	2,388.7	0.549	0.077	0.373
2002	703	10.06	2,677.5	0.546	0.078	0.376
2003	424	6.07	3,386.4	0.526	0.081	0.393
All	6,989	100.0	2,920.9	0.596	0.068	0.336

Below, we outline the construction of variables used in the analyses based on these data.[13]

(1) Total costs

The financial information concerning costs consists of the total operating costs, i.e., the costs of selling goods and services. Unfortunately this information is only available for the period 20012003, there was no such information for earlier years. We therefore derive the total costs from the identity: total sales revenue = total accounting costs of sales + gross profit. Thus, we obtain total accounting costs as the difference between total sales revenue and gross profit. We obtain gross profit figures from the expression: Gross profit = net profit before taxes + depreciation + audit fees + net interest payments. Note that since depreciation is added back in the gross profit computation, total accounting costs do not include any capital costs. Thus, we obtain the total costs by adding capital costs to the total accounting costs.

[13] All monetary values are deflated using producer price index, which we obtain from the ABS publication, Producer Price Index, 6427.0.

(2) Capital costs

The computation of capital costs is based on a consideration of opportunity costs, in the sense of how much capital income could have been generated if the investment into the firm was not made, but alternatively placed on the capital market. The ABS provides money market data, such as long term interest rates on treasury bills. The interest rate we used is a non weighted yearly average of the monthly long-term (10 years) money market interest rate. Note that the interest rate is assumed to be neither firm- nor industry-specific.

The amount of capital a firm has is taken to be the value of total fixed assets. The amount is obtained by deducting, from the value of total assets, the items cash, current and noncurrent receivables and trade debtors, inventories, other current assets and intangibles assets. The firm's capital costs are simply the opportunity costs of the fixed assets, i.e., fixed assets × long-term interest rate. The cost share of capital is then simply the proportion of capital costs to total costs.

(3) Labour costs

Although the IBIS database contains information on number of employees, there is no information on total wage bills. As such, we need to approximate the total labour costs of firms by using industry averages. We obtain industry-specific labour cost shares from ABS data (ABS Australian Industry, 8155.0). We multiply this by the firms' total operating costs to get total labour costs.

The labour costs per employee (average wage rate) are then given as the ratio of total labour costs to the total number of fulltime equivalent employees. The cost share of labour is then simply the proportion of labour cost to total costs.

(4) Material costs

The approximate value of material costs is simply the residue after deducting labour and capital costs from total costs. The cost share of materials is simply the proportion of material costs to total cost.

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