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Determinants of Profitability: An Analysis of Large Australian Firms

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Abstract

This paper identifies the determinants of firm profitability and quantifies their relative importance. Using a panel of large Australian firms for the period 1995 to 2005, the analysis estimates a dynamic profit model that, unlike most existing research, directly includes measures of productivity and productivity persistence. Descriptive statistics illustrate that the sample is characterized by a large amount of profit heterogeneity, and that substantial differences exist between industries and across firms. Estimation results indicate that firm profitability is predominantly determined by firm-level characteristics, and that sector effects are relevant, but to a much smaller extent. The analysis also reveals that, among firm effects, productivity and productivity persistence enhance profitability.

Keywords: Firm Performance, Determinants of Profit, Dynamic Panel Bias, Total Factor Productivity.

JEL Classification: C23, D24, L25.

1 Introduction and Background

The objective of this paper is to improve the understanding of what drives firm performance. The central hypotheses are that firms are heterogeneous in their profit performance and that differences in productivity help to explain differences in profitability. The analysis connects with the abundance of theoretical and empirical research devoted to the analysis of firm profits. Using a sample of 961 large Australian firms for the period 1995 to 2005, the analysis identifies the determinants of profitability and assesses their relative importance.

Modern literature in industrial economics suggests two schools of thought explaining performance in terms of profitability: the structure-conduct-performance (SCP) and firm effect models. See Schmalensee (1989) and Mauri and Michaels (1998) for a discussion. In short, the SCP model argues that an exogenously given market structure determines firm behavior and profitability, whereas in firm effect models market structure in endogenous and the result of firm characteristics.[1]

The SCP model is embedded in neoclassical theory and based on the notion of a representative firm. Any differences between firms are either transitory or not important, implying that profitability is determined by common structural characteristics of the industry. Bain (1951) proposes the market structure as the principal explanation of firm and industry profitability arguing that the average profitability of firms in highly concentrated industries is higher than in less concentrated industries. The underlying assumption is that concentration facilitates collusion and that colluding firms raise price above competitive levels. As pointed out by Bain (1956), barriers to entry, such as economies of scale or capital requirements, prevent high profits to be eroded by the entry of new firms into the market.

In firm effect models on the other hand, the fundamental assumption is that heterogeneity in profitability is due to persistent differences across firms. Within this school of thought, Demsetz (1973) introduces the superior firm hypothesis stating that firms differ with respect to their level of productivity and that these interfirm differences are the major factor behind

[1] Firm effect models are also referred to as revisionist, heterogeneity or resource-based models. In this paper, the emphasis is on studies that highlight differences in firm characteristics and their impact on profitability. Prominent examples are Rumelt (1991), Hawawini et al. (2003) or Grossmann (2007).

profit heterogeneity. The logic behind it is that firms operating at relatively higher productivity levels have competitive advantages over less productive competitors which are reflected in their profitability.[2]

Another crucial argument in firm effect models is the persistence of differences across firms. With respect to productivity, this can be related to theoretical models, such as Jovanovic (1982) and Lambson (1991), where (despite the absence of barriers to entry) some firms are consistently more productive than others and firms with low productivity do not catch up with the leaders. Bartelsman and Doms (2000) provide evidence on this issue for a wide range of industries. Following this logic, this class of models relates profit heterogeneity not only to productivity differences but explicitly to persistent productivity differences.

From an empirical point of view, the above two schools of thought are not mutually exclusive. At its very essence, the SCP model excludes the influence of firm-level variables on profitability, whereas in firm effect models industry and firm effects can co-exist. In fact, there is consensus in the literature that both the SCP and firm effect models are plausible, implying that industry and firm effects are empirically relevant. McGahan and Porter (2002) and Slade (2004) comprehensively survey the empirical literature. However, there is ongoing debate about the relative importance of these two effects.

The relative contribution of industry and firm effects is important because the two models have contradictory implications for welfare. The SCP model interprets the existence of persistent profit differences (across industries) as evidence of market failure implying sub-optimal social welfare. In firm effect models, high firm profitability is not necessarily associated with welfare losses. The reason is that markets function competitively and prices equal marginal costs. High profitability coincides with high industry concentration but is not necessarily caused by it.

In view of the assertions above, the question of whether firm or industry effects determine profitability has far-reaching implications for the design and implementation of competition policy. In the SCP model, a situation of persistent profit differences is not consistent with

[2] Productivity, in this analysis, refers to the level of cost-efficiency in the production process and will be used interchangeably with total factor productivity (TFP), efficiency and cost-efficiency.

competition prevailing in the market, whereas in firm effect models, some firms can persistently perform better than others without a reduced degree of competition.

The following analysis addresses these issues and advances the literature by investigating firm profitability using a dynamic model that is based on a reduced form profit function and explicitly incorporates firm- and industry-level variables. The empirical part of the paper identifies the determinants of profitability and examines the relative contribution of firm and industry effects. This allows to discriminate between the SCP and firm effect models and to draw conclusions on competition policy. Unlike most of the related research, the model in this paper also includes firm-level and time-variant measures of productivity and productivity persistence.

The remainder of the paper is organized as follows. The subsequent section develops a dynamic model of firm profitability, and Section 3 provides the definition of key variables and descriptive statistics for the sample. Section 4 produces results from random and fixed effects regressions and from several methods that correct for dynamic panel bias. Evidence on the relative importance of effects is provided in Section 5, while the last section concludes.

2 Empirical Specification

In accordance with related literature (summarized in Slade (2004) for example) the following equation specifies a linear, dynamic model of firm profitability

$$\pi_{ij,t} = \alpha + \beta\pi_{ij,t-1} + \delta X_{ij,t-1} + dD_j + \epsilon_{ij,t}, \tag{1}$$

where $\pi_{ij,t}$ and $\pi_{ij,t-1}$ represent current and past firm profitability, $X_{ij,t-1}$ is a vector of lagged firm-level characteristics, D_j are sector dummy variables, $\epsilon_{ij,t}$ is an error term and α, β, δ and d are the parameters to be estimated.

The dependent variable $\pi_{ij,t}$ is the profit rate of firm i in sector j at time t. Following Geroski and Jaquemin (1998) and Mueller (1990), the model in (1) considers serial correlation in profitability where the lagged dependent variable $\pi_{ij,t-1}$ accounts for a dynamic component in profitability. The vector X contains a set of lagged firm-level characteristics, such as size and leverage ratio, and time-invariant variables, such as age and financial risk.[3] It also comprises the estimates for total factor productivity and measures of productivity persistence.

Consider the following error term structure $\epsilon_{ij,t} = e_{ij,t} + \nu_i$ with $e_{ij,t} \sim i.i.d.N(0, \sigma_e^2)$ and $\nu_i \sim i.i.d.N(0, \sigma_\nu^2)$ and independence of errors: $E(e_{ij,t}, e_{kj,s}) = 0$ if $t \neq s$ or $i \neq k$ and $E(\nu_i, \nu_k) = 0$ if $i \neq k$. The term $e_{ij,t}$ is an idiosyncratic error that accounts for the proportion of firm profit that correlates neither across time nor across firms. The term ν_i controls for unobserved heterogeneity in firm profitability. It captures permanent firm rents and comprises a collection of factors that are unique to firm i and relevant with respect to profitability. The model in (1) is estimated using random and fixed effects models.

Nickell (1981) points out that estimating (1) with fixed effects yields inconsistent parameter estimates. This can be shown by taking the first lag of (1) which gives

$$\pi_{ij,t-1} = \alpha + \beta\pi_{ij,t-2} + \delta X_{ij,t-2} + dD_j + \epsilon_{ij,t-1}, \tag{2}$$

with the disturbances $\epsilon_{ij,t-1} = e_{ij,t-1} + \nu_i$. Inserting (2) back into (1) shows that the firm-specific effect ν_i appears in the regressor $\pi_{ij,t-1}$ and in the error term $\epsilon_{ij,t}$, implying that the composite error $\epsilon_{ij,t}$ is not independent from the regressor, $E(\pi_{ij,t-1}; \epsilon_{ij,t}) \neq 0$. This violates a necessary assumption for consistency of least-squares estimation.

Kiviet (1995) proposes a method to correct for dynamic panel bias, Bun and Kiviet (2003) provide an extension to unbalanced panels. Let ψ contain the fixed effect coefficients in (1), $\hat{\psi}_{fe} = [\hat{\beta}, \hat{\delta}]$. Then, the bias-corrected estimator, $\hat{\psi}_{bc}$, is obtained from subtracting the estimate for the bias from the original fixed effects estimator

$$\hat{\psi}_{bc} = \hat{\psi}_{fe} - \widehat{bias}. \tag{3}$$

In particular, the bias approximation is a function of the consistent parameter estimate $\hat{\psi}_m$ and its variance $\hat{\sigma}^2_{e,m}$, $\widehat{bias} = f(\hat{\psi}_m, \hat{\sigma}^2_{e,m})$. Kiviet (1995) and Bruno (2005) document the algorithm for the bias correction algebraically.[4] Ideally, one would use the true parameter

[3] Firm age is, of course, not time-independent but treated as such in a panel dataset with yearly observations.

[4] Linearity in the dynamic model in (1) is a prerequisite for first-differencing and, hence, correcting for dynamic panel bias.

value and its variance to define $\widehat{bias}$ but they are, of course, not observed. Instead the literature suggests several methods to derive a preliminary consistent estimator.

The present analysis considers three preliminary estimators, which all rely on a first-difference model, to initiate the bias correction: the instrument variable (IV) estimator introduced by Anderson and Hsiao (1982), the difference GMM estimators in Arellano and Bond (1991) and the system GMM estimators derived in Blundell and Bond (1998).

Bun and Carree (2005) provide evidence that a bias-corrected fixed effects estimator can be more appropriate than the alternatives. Judson and Owen (1999) compare the performance of various dynamic panel data estimators and find that the corrected fixed effects estimator can outperform IV and GMM estimators. Kiviet (1995) argues that a bias-corrected fixed effects estimator is much more efficient than IV or GMM estimators. Further, Harris et al. (2009) conduct a set of Monte Carlo simulations on popular dynamic panel data estimators and advocate the use of the latter two estimators.

Correcting for dynamic panel bias produces consistent fixed effects estimates. The first-difference model eliminates the source of the bias, i.e. ν_i, but at the cost of excluding any other time-invariant regressor. In the present context, it seems reasonable to consider the impact of constant or structural firm variables on firm profitability. To address this issue, the vector of lagged explanatory variables $X_{ij,t-1}$ is augmented with additional firm attributes, such as firm age, financial risk and measures of productivity persistence, and the model in (1) is re-estimated with random effects.

Each of the methodologies outlined above has particular characteristics. Estimating (1) with fixed effects does account for unobserved heterogeneity in firm profitability but produces inconsistent coefficients. Correcting for dynamic panel bias yields consistent parameter estimates but, as uncorrected fixed effects, omits potentially relevant time-invariant explanatory variables. Augmented random effects include these, but the coefficients are affected by dynamic panel bias. In sum, results from bias-correction are statistically the most reliable, but the random effects models are needed to compare firm and sector effects.

3 Data and Descriptive Statistics

The sample used in this study comprises 961 large Australian firms for the period 1995 to 2005. The sample is moderately unbalanced because of missing observations.[5] The main source of the data is Integrated Real-Time Equity System (IRESS), a financial information system that observes the Australian Stock Exchange (ASX). The information provided by IRESS stem from balance sheet items, from profit and loss and from cash flow statements. The database is supplemented with information from the Australian Bureau of Statistics (ABS) and the Australian Securities and Investments Commission (ASIC).

The database has a number of specific features. Firms in the sample represent Australia's largest firms, implying that, in comparison to the total population of Australian firms, the average firm size in the sample is greater. However, there is no precise minimum size requirement for listed firms, for instance in terms of total sales revenue or number of employees. Further, all firms in the sample are listed on the ASX, which induces a self-selection bias because seeking and maintaining an ASX-listing is the firm's own decision.

Lastly, a generalization of the results is limited because the observed time period can be insufficiently long or arbitrarily chosen. To overcome this problem, Mueller (1977) proposes using projected long-term profit rates which proxy for equilibrium profit rates. Applications of his idea can be found in, for instance, Grabowski and Mueller (1978) and Yurtoglu (2004). Due to the relatively small number of periods observed, this proposal cannot be implemented in this study.

Firm profitability is measured with an adjusted accounting profit rate, computed as the ratio of the profit level to the value of total assets. The profit level is defined as the difference between sales revenue and total costs, where total costs include labor and material costs and are adjusted for opportunity cost of capital. More specifically, the profit level measure is obtained by deducting the product of the 10-year money market interest rate and the book value of fixed assets from the profit-loss statement item EBITDA.

[5] Observations in the highest and lowest percentiles in terms of profitability are discarded. The Ahrens and Pincus (1981) index indicates a moderate degree of unbalancedness, $API = 0.6200$.

Accounting profit levels and rates are a common measure of firm profitability, and frequently used, for example, in Rumelt (1991) and Hawawini et al. (2003). Schmalensee (1989) and Mueller (1990) discuss the strengths and weaknesses associated with accounting profit rates. A major drawback of the accounting profit measure is, as pointed out in Grabowski and Mueller (1978), the treatment of R&D investments, advertisement outlays and cost of human capital as current expenses (instead of capitalized stock) which potentially understates assets and overstates rates of return. Other potential sources of distortions are differences in depreciation practices and the management of output price inflation.

The adjusted accounting profit rate used in this study is, despite criticisms, a useful quantity to approximate for firm performance and serves as an instrument in the empirical analysis, However, it does not necessarily quantify economic profit. Table A-1 in the Appendix A-1 presents a correlation matrix for alternative accounting profit measures and Tobin's q and indicates a significantly positive correlation.

Table 1 presents profitability by sector. On average over sectors and years, firms earned an accounting profit of 0.5 per cent. The finding that listed firms are, on average, just profitable might be surprising, especially with respect to the prosperous development of the Australian economy during the observed period. However, this seemingly counter-intuitive result can be explained by looking at each sector individually and at the magnitude of the variance.

First of all, it becomes evident that the finding of almost zero profit is not pervasive across all sectors. This leads to the conclusion that substantial differences exists between the sectors. For example, firms in Discretionary, Industrials and Consumer Staples earn, on average, positive profits, while other sectors, such as Energy and Health, show negative sector mean profitability. Table A-2 in Appendix A-1 illustrates that alternative accounting and market value-based profitability measures indicate similar patterns.

A potential explanation for the surprisingly low profitability is that the numbers in Table 1 state the unweighted mean profitability of all firms in a sector. Computing size-weighted sector average profitability instead, reveals that all sectors, except Financials, report positive values. In the case of Financials, negative profits can be due to overstated capital costs relative to sales revenue.

Table 1: Firm Profitability by Sector.

Sector	Number of firms	Number of obs.	Profit Rate Mean	Profit Rate S.D.
Discretionary	130	668	0.098	0.189
Energy	77	304	-0.071	0.335
Financials	99	339	0.014	0.254
Health	100	359	-0.133	0.366
Information Technology	94	369	-0.040	0.326
Industrials	143	749	0.086	0.176
Materials	239	860	-0.050	0.277
Staples	39	218	0.058	0.146
Telecommunication	25	102	-0.004	0.332
Utilities	15	59	-0.011	0.155
All Sectors	961	4,027	0.005	0.271

Note: S.D. - standard deviation. Unweighted averages for 1995-2005. Profit is defined as EBITDA deducted by capital costs. See text for details.

Another observation from Table 1 is the large magnitude of the standard deviation which illustrates a wide dispersion of firm profitability, implying that some firms make a loss in some years. Taken together, the evidence suggests that there is a substantial heterogeneity in firm performance. Average profitability differs widely between sectors and across firms. With respect to theoretical literature on profitability, this finding can be interpreted as a preliminary indicator for the existence of firm and sector effects on profitability.

A principle objective of this paper is to explore the relationship between productivity and profitability at the firm level. This relates to the superior firm hypothesis articulated in Demsetz (1973) and stating that productivity is the major factor driving profitability, and also that more productive firms are more profitable than their rivals. The variable market share is typically used to test for Demsetz' view of explaining profits. The underlying assumption is that high market shares are the result of the growth of efficient firms, and that the market share effect can be interpreted as an efficiency or productivity effect.[6]

There are reasons, however, to question the validity and adequacy of using market share as a proxy for the effect of productivity on profitability. For example, in a highly developed and dynamic economy, the definition of markets can be insufficiently accurate. Market share

[6] Applications can be found in, for example, Ravenscraft (1983) and Bothwell et al. (1984).

is a complex variable in itself and is potentially influenced by a number of observed and unobserved factors. Further, if a firm's position in the market is mainly driven by rent-seeking behavior, such as predatory pricing, market share would pick up effects that are not related to efficiency at all.[7]

Advancing the existing literature in the area, the dynamic profit model in (1) directly includes firm-level measures for productivity and productivity persistence.[8] The measure of total factor productivity is, in this study, obtained from estimating a translog cost function, in which productivity refers to the level of cost-efficiency in the production process. Diewert (1992) and Coelli et al. (2005) provide comprehensive overviews of concepts of productivity measurements.

The following equation defines cost-efficiency as the log-difference between predicted and empirical costs

$$\ln \hat{A}_{ijt} = \ln \hat{C}(Y_{ijt}, W_{jt}) - \ln C_{ijt}(Y_{ijt}, W_{jt}), \tag{4}$$

with $\ln \hat{C}$ as predicted costs and $\ln C_{ijt}$ as empirically observed costs of firm i in sector j at time t. W_{jt} and Y_{ijt} are sector-wide input prices and individual firm output, respectively. Larger values of $\ln \hat{A}_{ijt}$ imply higher efficiency levels and identify higher productivity firms. Productivity, as specified in (4), is firm-specific and time-varying, accounts for all inputs used in the production process and assumes allocative and technical efficiency at any point in time. It is an estimate that contains standard errors.

Following the general argument in firm effect models that inter-firm differences persist and do not disappear instantly, the profit model in (1) includes not only measures of productivity but also indicators of productivity persistence. Therefore, the specification (1) employs a dummy variable for productivity persistence and an interaction term of productivity level and productivity persistence. The reason for this is to capture the level and persistence effect on profitability. The persistence dummy indicates whether a firm shows a persistent pattern in

[7]See, for instance, Shepherd (1972) and Kurtz and Rhoades (1992). Recently, a number of studies, such as Lim and Lovell (2009), have emerged that explicitly use productivity measures to explain firm profitability. Nevertheless, a common criticism of these studies is the failure of exploiting the economic theory on profits.

[8]The hypothesis in (1) is that past productivity is a principal determinant of current profits. However, feedback effects of current profits on productivity are not accounted for, which potentially causes an endogeneity problem.

its productivity evolution over time, though this is irrespective of the level. The purpose of the interaction term is to account for the influence of persistent high productivity levels.

Both terms are constructed using continuous firm-specific measures of productivity persistence. For example, the mean relative deviation from the within-firm average productivity is given as

$$\theta_{1i} = \Sigma_t \left| \frac{\hat{a}_{ijt} - \bar{\hat{a}}_i}{\bar{\hat{a}}_i} \right| / T_i, \tag{5}$$

where $\hat{a}_{ijt} = \ln \hat{A}_{ijt}$, $\bar{\hat{a}}_i = \Sigma_t \hat{a}_{ijt}/T_i$ and T_i is the number of periods firm i is observed. Another measure is the intertemporal autocorrelation (IAC). It captures the within-firm covariance between past and current productivity, $Cov(\hat{a}_{ij,t}; \hat{a}_{ij,t-1})$, and is defined as

$$\theta_{2i} = \frac{\lambda_i \cdot \sigma_\omega^2}{1 - \lambda_i^2}, \tag{6}$$

with λ_i as the slope coefficient in the AR(1) specification $\hat{a}_{ij,t} = c_i + \lambda_i \cdot \hat{a}_{ij,t-1} + \omega_{ij,t}$ and σ_ω^2 as the variance. Larger values indicate more persistent patterns of productivity.

Using θ_{1i} and θ_{2i}, the sample is divided into firms that show a persistent pattern of productivity evolution and firms with a moderate or low degree of persistence. The persistence dummy d_i takes the value unity if firm i's value of, respectively, θ_{1i} or θ_{2i} exceeds the sum of the sample average by one standard deviation. Otherwise, $d_i = 0$.

The interaction term is constructed as the product of the productivity level estimate and the persistence dummy variable, $\Psi_{ij,t} = d_i \cdot \hat{a}_{ij,t}$. In the case of productivity persistence, it takes the value of $\hat{a}_{ij,t}$ and is zero otherwise. Say, for example, there is a highly productive firm with $\hat{A}_{ij,t} = 1.5$. If the firm maintains this level over the observed periods, the productivity dummy detects persistence, $d_i = 1$ and $\Psi_{ij,t} = 1.5$. If, in contrast, the continuous variables θ_{1i} or θ_{2i} indicate fluctuation in productivity, then $d_i = 0$ and, hence, $\Psi_{ij,t} = 0 \cdot 1.5 = 0$.

Lastly, the profit model in (1) includes several control variables, such as firm size, leverage ratio and financial risk. Ravenscraft (1983) and, in particular, Schmalensee (1989) present summaries of factors potentially influencing firm profitability. To account for the influence of sector-level characteristics, the profit model in (1) includes sector dummy variables. Ideally, the regression would employ frequently measured continuous variables that proxy for, for instance, market concentration, barriers to entry or economies of scale. However, this is not feasible in this study because the IRESS database classifies firms into sectors and sub-sectors according to the GICS, where detailed information on sector characteristics is not available.

4 Results from Dynamic Panel Estimations

In what follows, a sequence of results is presented along the same order as outlined above. The discussion commences with findings from random and fixed effects regressions, followed by results from panel bias-corrected estimates. Then, the profit model is re-estimated to include explanatory variables that had to be omitted in the process of bias correction. Lastly, using parameter estimates from various models, the relative importance of specific firm and sector characteristics is assessed.

To begin with, regression results from three complementary estimations of the dynamic profit model in (1) are presented. Models I and II use random effects, where the latter includes sector dummy variables. Model III is a fixed effects regression that accounts for unobserved heterogeneity in firm profitability but, by definition, excludes sector dummies. Table 2 produces results for Models I to III. At a first glance, it becomes evident that a similar pattern emerges in all three models.

The significantly positive coefficient for lagged profit implies that firm profitability is serially correlated. A potential explanation is that high earnings in the past provide an opportunity to earn high profits in the future. Firms can benefit from profits in earlier periods if, for instance, retained earnings are re-invested into research and development, and successful product and process innovation increase future profits, as stressed by, for instance, Mairesse (1999) or Gugler (2004).

The finding and magnitude of lag-dependency of firm profitability is in line with the existing literature. Using long-term data, Cable and Mueller (2008) uncover AR(1) coefficients of 0.57 to 0.92. Jensen and Webster (2009), for example, report coefficients for lagged profit levels of 0.431 and 0.463 for Australian data. Waring (1986) finds parameter estimates of, on average, 0.36 to 0.55 and Geroski and Jaquemin (1998) of 0.410 to 0.488.

Table 2: Determinants of Firm Profitability.

	Random effects		Fixed effects
Variable	Model I	Model II	Model III
Lagged profit rate	0.385***	0.375***	0.130***
	(0.014)	*(0.015)*	*(0.018)*
Lagged productivity	0.181***	0.196***	0.142***
	(0.027)	*(0.028)*	*(0.038)*
Lagged no. of employees	0.033***	0.033***	0.018***
	(0.003)	*(0.003)*	*(0.005)*
Lagged leverage ratio	0.084***	0.061***	0.038*
	(0.019)	*(0.019)*	*(0.023)*
Constant	-0.193***	-0.189***	-0.102***
	(0.015)	*(0.045)*	*(0.024)*
Time trend	yes	yes	yes
Sector dummy	no	yes	no
R^2 (overall)	0.507	0.510	0.464
Correlation of residuals	0.132	0.131	0.241
No. of observations	4,027	4,027	4,027
No. of firms	961	961	961

Note: Statistical significance: *** at 1%, ** at 5%, * at 10%. The regressions are implemented using the command -xtreg- in Stata 9.2.

The larger the coefficient for lagged profit rate the more successful a firm has been in maintaining its competitive position. Comparing Models I to III, it becomes evident that the degree of lag-dependency decreases substantially in the fixed effects model. It could be that the fixed effect captures unobserved factors that lower the extent to which past profits determine current values.

Of particular interest is the impact of past productivity on current profitability. The coefficient for lagged productivity is significantly positive implying that more productive firms are more profitable. One interpretation of the results in Table 2 is that relatively more productive firms have a competitive advantage over less productive rivals which is reflected in higher profitability. This finding provides direct support for the superior firm hypothesis, presented in Demsetz (1973).

Productivity is, in this study, measured as the degree of cost-efficiency in the production process. There are a number of reasons why some firms operate more cost-efficiently than others. Potential factors are lower average costs of production, better quality of products and services or higher output quantities produced with fewer inputs. Higher productivity levels, can also be the result of strategic management or due to employing state-of-the-art technologies or a highly skilled workforce.

There is another way of interpreting the positive link between productivity and profitability. It could be that the level of productivity is the result of firms' innovative activity. The rationale behind it is that investments into research and development (R&D) raise the probabilities of introducing product, process or organizational innovation which, if successful, lead to increases in productivity and, according to Table 2, profitability. Applications of these ideas can be found in, for instance, Crépon et al. (1998), who formulate a structural model of the innovation process in order to quantify these relationships at the firm level. Chudnosvky et al. (2006) survey the related empirical literature.

The positive and significant parameter estimate for firm size illustrates that, among the group of large Australian firms, bigger firms are more profitable than smaller firms. The size of a firm significantly enhances its performance. There is literature that supports a positive size effect, for instance Hall and Weiss (1967), whereas other studies, such as Vernon and Nourse (1973), fail to replicates this result. A possible reason for the finding in Table 2 is that large firms exploit scale economies and benefit from economies of scope. An alternative interpretation is that large firms can access capital at lower costs than small firms.

Consistent with previous work, such as Baker (1973) or Bothwell et al. (1984), the results indicate that higher leveraged firms (with relatively high liabilities) are more profitable. Evidently, the more extensively firms use debts as the source of financing the higher its profits. An explanation can be that more profitable firms have had easier access to debt financing and do not need to rely exclusively on equity capital. Alternatively, it could be argued that higher leveraged firms bear greater risks of bankruptcy and need to compensate stakeholders with higher profits.

Model II differs from Model I by including sector dummy variables. A Wald test rejects the null hypothesis that all sector dummy variables are jointly equal to zero, implying the presence of sector effects on firm profitability. The χ^2-test statistic is 39.02, the p-value at nine degrees of freedom is approximately zero. Using 24 sub-sector dummy variables instead does not alter the direction of results. This finding can be interpreted as support for the SCP model where market concentration facilitates collusion which enables firms to raise their price above competitive levels.

The use of dummy variables has several implications for the interpretation of results. The true components of the sector effects can only be speculated about because the dummy variables account for a collection of factors but do not distinguish between them. Consequently, it is impossible to say whether the sector effects are related to market concentration, barriers to entry or other sector characteristics. Further, dummy variables are time-invariant, implying that industry dynamics are not accounted for and that the bias-corrected model, presented in Table 3, cannot test for sector effects because first-differencing eliminates explanatory variables that are constant in time.

As argued above, the fixed effects estimates in Model III are affected by dynamic panel bias. However, there is a benefit to be had from presenting inconsistent fixed effects and random effects. The evidence in Table 2 suggests the presence of sector effects (Model II) and within-firm fixed effects (Model III). With respect to economic theory these results have important implications. They can be interpreted as support for the SCP model and firm effect models alike. Neither finding could have been established by looking at the bias-corrected estimation results in Table 3 alone.

Estimation results presented in the Table 2 contain dynamic panel bias, as highlighted by Nickell (1981). Table 3 produces results from biased-corrected estimators.[9] In the same vein as Models I to III, the evidence in Table 3 suggests that lagged firm profitability and lagged productivity have a statistically significant and positive impact on current profits. Firm profitability is moderately serially correlated, and more productive firms are more profitable.

[9] In comparison to Table 2, the number of observations is reduced because the bias correction estimates a first-difference model that requires at least three consecutive non-missing observations for each firm.

The table also reveals a positive effect of firm size and a positive, but not significant, impact of leverage.

Table 3: Results from Bias-Corrected Estimates.

Variable	Model IV	Model V	Model VI
Lagged profit rate	0.284***	0.271***	0.308***
	(0.022)	*(0.021)*	*(0.021)*
Lagged productivity	0.120***	0.123***	0.114**
	(0.047)	*(0.045)*	*(0.058)*
Lagged no. of employees	0.015**	0.015***	0.013**
	(0.006)	*(0.006)*	*(0.008)*
Lagged leverage ratio	0.039	0.039	0.043
	(0.029)	*(0.028)*	*(0.022)*
Time trend	no	no	no
Sector dummy	no	no	no
No. of observations	2,874	2,874	2,874
No. of firms	782	782	782

Note: Statistical significance: *** at 1%, ** at 5%, * at 10%. Bootstrap standard errors from 1,000 repetitions in parentheses. All models are implemented through the -xtlsdvc- module in Stata 9.2. Equivalently, Models V and VI can be estimated using the user-written command -xtabond2- producing identical estimation results.

These results complement findings obtained from the random and fixed effects regressions in Table 2. In general, Models I to VI unveil a very similar pattern. The direction of results is not sensitive to correcting or not correcting for dynamic panel bias. Parameter estimates are, except for lagged profit rate, within close proximity. In Table 3, the consistent coefficients for lagged profits are larger than in Model III but smaller then in Models I and II.

As pointed out by Bun and Kiviet (2001), the results in Table 3 are not sensitive to the choice of the initial estimator used in the bias correction. Kiviet (1995) argues that correcting for dynamic panel bias yields consistent but inefficient estimates. In comparison to Model III, the standard errors in Models IV, V and VI have increased, indeed, but are of reasonable magnitude. Reporting R^2 has no statistical meaning in the context of bias-corrected estimation.

The reason for this is that the residual sum of squares is not constrained to be smaller than the total sum of squares, and R^2 is negative if the model sum of squares is below zero.[10]

The fixed effects Model III and the bias-corrected Models IV to VI omit firm and sector characteristics that are time-invariant but potentially important in determining profitability. To address this issue, the profit model in (1) is re-estimated with random effects and including variables that disappear in fixed effects models. Only results for the relative mean deviation (θ_{1i}) as the productivity persistence measure are shown. Using the intertemporal autocorrelation (θ_{2i}) instead yields almost identical results.[11]

Table 4 reports results from augmented random effects regressions. The evidence from Model VII signals the same structure of relationships as in the models before. The coefficients for lagged profit are significantly positive and almost identical to those in Model II. The augmented model in Table 4 confirms the already established finding of a moderate degree of lag-dependency in profitability.

Model VII reveals that lagged productivity enhances firm profitability. The coefficient is significantly positive but slightly smaller than in Model II. As in all previous models, the evidence from the augmented model suggests that more productive firms are more profitable. The productivity persistence dummy variable is negative but statistically insignificant. This can be due to the nature of the dummy variable which detects persistence but does not distinguish between persistence of high and low levels of productivity.

The purpose of the interaction term between lagged productivity and productivity persistence is to separate persistently low-productivity firms from persistently high-productivity firms. It proxies for persistence of high productivity levels. In the augmented Model VII, the coefficients are positive and statistically significant. This implies that firms are more profitable the higher the level of productivity and the more persistent the high productivity over time. Both factors together enhance firm profitability.

[10] This is also valid for Model VII in the Table 4 below.

[11] In both scenarios, the persistence dummy takes the value unity when θ_{1i} or θ_{2i} exceed the 75th percentile, respectively. The results presented are robust to alternative persistence thresholds, such as the sum of sample mean and one standard deviation.

Table 4: Results from Dynamic Panel Regressions.

Variable	Model VII	Model VIII	Model IX
Lagged profit rate	0.360***	0.442***	0.325***
	(0.015)	*(0.020)*	*(0.019)*
Lagged productivity	0.104**	0.059	-0.103
	(0.047)	*(0.026)*	*(0.073)*
Lagged productivity -	0.122**	0.127**	0.217***
persistence interacted	*(0.053)*	*(0.031)*	*(0.077)*
Productivity	-0.014	-0.016***	-0.012
persistence dummy	*(0.013)*	*(0.006)*	*(0.013)*
Lagged no. of employees	0.030***	0.023***	0.008
	(0.003)	*(0.002)*	*(0.005)*
Lagged leverage ratio	0.066***	0.079***	0.072***
	(0.020)	*(0.013)*	*(0.024)*
Age	-0.001	-0.001	0.000
	(0.001)	*(0.000)*	*(0.000)*
Financial risk	-0.223***	-0.174***	-0.092*
	(0.000)	*(0.000)*	*(0.048)*
Constant	-0.157***	-0.127***	-0.146***
	(0.045)	*(0.020)*	*(0.044)*
Initially observed profit rate	–	–	0.197***
			(0.024)
Mean lagged productivity	–	–	0.268***
			(0.094)
Mean lagged productivity -	–	–	-0.101
persistence interacted			*(0.111)*
Mean lagged no. of employees	–	–	0.024***
			(0.006)
Mean lagged leverage ratio	–	–	-0.047
			(0.040)
Mean age	–	–	-0.001
			(0.001)
R^2 (overall)	0.511	–	–
Correlation of residuals	0.132	–	–
Log-likelihood	–	–	1,195.649
No. of observations	3,926	3,926	3,926
No. of firms	939	939	939

Note: Statistical significance: *** at 1%, ** at 5%, * at 10%. The regressions are implemented through the -xtreg- (Models VII and VIII) and -xtabond2- (Model IX) commands in Stata 9.2. Including firm age in the set of regressors means excluding the time trend. All models contain sector dummy variables. In comparison to Table 2, the number of observations is reduced by 101 because of the missing values of additional explanatory variables.

Interestingly, the coefficients for lagged productivity (0.104) and for the productivity and persistence interaction term (0.122) in Model VII are within similar magnitude of the parameter estimate for lagged productivity (0.196) in Model II. A potential interpretation is that high productivity and persistence of high productivity together that have a significant impact on profitability. Later, Table 5 reveals that, indeed, the relative contribution of productivity and its persistence (Model VII) is almost as important as the impact of productivity itself (Model II).

Table 4 provides evidence on the impact of several firm characteristics on firm profitability. The age of the firm has no statistical significant effect. Firm age can be a proxy for the effect of intangible capital on firm profitability. A potential explanation for the absence of an age effect is that the benefits from intangible capital are already incorporated in high levels of cost-efficiency. Since productivity is, in this application, defined in terms of cost-efficiency, it is possible that the effect of age is accounted for in the coefficient for lagged productivity. The direction of results is not affected by considering a non-linear impact of firm age.

It also becomes evident that firm profitability depends on financial risk measured as the variance of weekly stock market returns over the entire period. However, the finding of a negative coefficient for financial risk is not consistent with the predictions of the capital asset pricing model.[12] A potential explanation is that high return variability induces costs to the firm, for example in the form of increased costs to access capital, that ultimately reduce profits. Hurdle (1974) points out that the positive coefficient for the variable leverage already accounts for the risk of bankruptcy. Lastly, the profit-risk relationship can be distorted if risk is, as in the case of this study, measured as the variance in stock market returns, and share prices contain a large speculative component.

Table 4 demonstrates positive size and leverage effects supporting the results established in previous scenarios that, among the group of large firms, bigger and more leveraged firms are more profitable than small firms and those with relatively less debt. A Wald test safely

[12]See Sharpe (1964), Lintner (1965) and Black (1972) for the CAPM. Brennan (2008) and Huberman and Wang (2008), among others, provide overviews of empirical studies that test the CAPM. The results presented here are robust to a number of alternative financial risk measures, discussed in, for example, Bromiley et al. (2001).

rejects the null hypothesis that all sector dummy variables are jointly equal to zero. The χ^2-test statistic is, respectively, 42.60 and 41.89, and the p-values at nine degrees of freedom are approximately zero implying the presence of sector-specific effects. The result is robust to replacing the ten sector dummies in the regression with 24 sub-sector dummy variables.

In terms of robustness tests, there are ways to estimate the augmented dynamic profit model, include sector dummies and time-invariant variables and correct for dynamic panel bias. For example, the unofficial user-written Stata command -xtabond2-, developed by Roodman (2006), estimates the model through system GMM with orthogonal forward deviation. Estimation output, presented as Model VIII in Table 4, demonstrates that, in comparison to Models I to VII, the direction of results does not change much.

Another possibility is to estimate the dynamic profit model in (1) using the correlated random effects approach suggested in Mundlak (1978) and Chamberlain (1984). The method accounts for sector effects (in addition to individual effects) by considering distributional assumptions on the unobserved heterogeneity. The model is estimated using random effects and, hence, deters dynamic panel bias. Appendix A-3 presents the model specification and Model IX in Table 4 the estimation results. It becomes evident that the findings are, generally, in concordance with the previously presented models.

5 Relative Importance of Effects

Based on the Models I to IX, the purpose of what follows is to quantify the relative importance of specific firm and, where available, sector effects. Assessing the relative contribution of effects is important because there are far-reaching implications for welfare. Findings of large sector effects, for example, would indicate that firm profitability is primarily related to sector-level characteristics, implying that all firms (irrespective of their productivity) in a sector are highly profitable. Consequences on the design and implementation of competition policy arise if this is related to market failures, such as collusion or barriers to entry. In contrast, dominant firm effects would indicate that firm profitability is predominantly determined by fundamental differences across firms which, in turn, would lend support to firm effect models where markets are assumed to function competitively.

Using the results obtained in earlier regressions, Table 5 illustrates the relative importance of firm and sector effects for selected models. Following Jensen and Webster (2009), marginal effects are computed as the variation of the dependent variable due to the transition in one of the explanatory variables from one standard deviation below its mean to one standard deviation above its mean, leaving all other variables equal. For sector dummy variables the change is from zero to one.

Table 5: Relative Importance of Firm and Sector Effects.

	Marginal Effects in Model			
Variable	II	III	V	VII
Lagged profit rate	0.2014	0.0698	0.1494	0.1946
Lagged productivity level	0.0595	0.0429	0.0372	0.0314
Lagged productivity - persistence interacted	–	–	–	0.0270
Productivity - persistence dummy	–	–	–	-0.0120
Lagged no. of employees	0.1640	0.0899	0.0754	0.1452
Lagged leverage ratio	0.0281	0.0177	0.0179	0.0301
Firm age	–	–	–	-0.0131
Financial risk	–	–	–	-0.0531
Sector dummy variables	0.0275	–	–	0.0264
No. of firms	961	961	782	939
No. of observations	4,027	4,027	2,874	3,926

Note: Results are derived from earlier regressions. Model II: random effects and Model III: fixed effects from Table 2, Model V: bias-corrected estimation from Table 3, Model VII: augmented random effects from Table 4.

Table 5 reveals that lagged profits and firm size are the principal determinants of firm profitability. Other firm characteristics, such as productivity level, productivity persistence, leverage ratio and financial risk, are relevant but to a smaller extent. The random effects Models II and VII illustrate that sector effects are present, but play a relatively minor role. The conclusions drawn are robust to random and fixed effects regressions and those that correct for dynamic panel bias.[13]

Table 5 shows the average absolute contribution of the nine sector dummies included in the regression. Their marginal effects are bound in the interval [-0.0418, 0.0771] and [-0.0495, 0.0800] for Model II and VII, respectively. This implies that sector effects are at most half as important as firm size effects. Re-estimating Models II and VII and using 24 sub-sector dummy variables reveals that sector-level influences become more important but remain small in comparison to firm effects.

What do these findings imply for the debate on whether firm or sector effects determine firm profitability? First of all, Table 5 indicates that profitability is predominantly influenced by firm-level characteristics and that lagged profit rate and firm size are the most important factors. This can be interpreted as support for firm effect models and, in particular, for the argument in Peltzman (1977) where efficient firms grow and are also highly profitable. However, the relative contribution of lagged productivity and productivity persistence is relatively small. A potential explanation is that the lag-dependency in profits already accounts for that.

There is an alternative interpretation for the large firm size effect. The large contribution of firm size may, implicitly, reflect sector-specific characteristics. This is the case if large firm size is not the result of efficiency advantages but is related to systematic differences in average firm size across sectors. For example, it can be that some sectors, such as Mining, require minimum efficient scales. This, and the operationalization with sector dummies instead of continuous variables, could be an explanation for the finding of relatively small sector effects.

Taken together, the analysis finds support for both the SCP and firm effect models, although there seems to be more evidence for the firm effect models. The results are, in general, consistent with the existing literature. Mauri and Michaels (1998), for instance, discuss the complementarity of both schools of thought. In particular, the finding of a large contribution of lagged profits can be related to existing research, such as Cable and Mueller (2008).

[13]Further, estimation results from alternative approaches, such as Roodman (2006) or Mundlak (1978) and Chamberlain (1984), paint a similar picture.

In terms of applied research using Australian data, Round (1974) provides support for firm effect models. Analyzing 33 manufacturing industries in the financial year 1971-72, he finds that the dispersion of profitability within industries widens as concentration increases. Jensen and Webster (2009) estimate abnormal profits for 1,922 Australian companies over a 16-year period and find firm effects to be much larger than industry effects.

6 Conclusion

The objective of this analysis was to investigate firm profitability and to identify its determinants. Using a dataset of 961 large Australian firms, the study examined the influence of firm and sector effects and also quantified the contribution of specific firm-level variables. A particular aspect of the analysis was to assess the consequences of persistent productivity differences for firm profitability. Therefore, the model included, unlike most existing studies in the area, firm-level measures of productivity and productivity persistence.

Descriptive statistics illustrated that the sample contains a large amount of profit heterogeneity and that substantial differences in average profitability exist across sectors and firms. These findings can be interpreted as preliminary indicators of the relevance of sector- and firm-level characteristics with respect to profitability. From estimation results, it could be concluded that the lag-dependency in profits and the firm's size have the largest contribution in explaining heterogeneity in profitability. The analysis also revealed that, among firm effects, productivity and productivity persistence enhance firm profitability.

Taken together, the main findings were that firm profitability is predominantly determined by firm-level variables, and that sector effects play a relatively minor role. A possible interpretation is that heterogeneity in profitability is due to competitive advantages caused by unique characteristics of the firm. This would lend support to the predictions of firm effect models where markets function competitively and can be seen as an indicator that performance differences across firms are not necessarily linked to market failure that would justify competition policy.

Appendix

A-1 Alternative Profitability Measures

Table A-1: Correlation Matrix for Alternative Profitability Measures.

	AdROE	AdROA	ROE	ROA	EBITM	NPBTM	Tobin's q
AdOE	1						
AdROA	0.448*	1					
ROE	0.839*	0.610*	1				
ROA	0.467*	0.962*	0.679*	1			
EBITM	0.340*	0.703*	0.550*	0.759*	1		
NPBTM	0.335*	0.693*	0.569*	0.752*	0.941*	1	
Tobin's q	0.497*	0.251*	0.418*	0.274*	0.273*	0.266*	1

Number of observations: 4,027. Number of firms: 961. * - Correlation statistically significant at the 1% level. ROA: accounting return on assets = EBIT / total assets. ROE: accounting return on equity = NPBT / equity capital. AdROE: adjusted return on equity = ([EBITDA - (fixed assets · 10year interest rate)] / equity capital). AdROA: adjusted return on assets = ([EBITDA - (fixed assets · 10year interest rate)] / total assets). EBITM: EBIT margin = (EBIT / sales revenue). NPBTM: NPBT margin = (NPBT / sales revenue). Tobin's q = market value of assets / book value of assets. Note: sales revenue - total costs = EBITDA. EBITDA - (depreciation+amortization) = EBIT. EBIT - net interest = NPBT. NPBT - tax = NPAT.

Table A-2: Alternative Profit Rates by Sector.

	No. of	No. of	ROA		AdROE		ROE	
Sector	firms	obs.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Discret.	130	668	0.068	0.188	0.605	0.885	0.253	0.319
Energy	77	304	-0.067	0.252	0.339	0.989	0.046	0.294
Financials	99	339	0.018	0.214	0.336	0.705	0.149	0.316
Health	100	359	-0.130	0.295	0.234	0.986	-0.020	0.303
Info. Techn.	94	369	-0.091	0.290	0.130	0.502	-0.006	0.277
Industrials	143	749	0.049	0.171	0.693	1.056	0.209	0.323
Materials	239	860	-0.065	0.236	0.274	0.782	0.045	0.279
Staples	39	218	0.054	0.107	0.401	0.729	0.188	0.260
Telco.	25	102	-0.086	0.301	0.255	0.578	0.053	0.397
Utilities	15	59	-0.009	0.166	0.220	0.455	0.092	0.336
All Sectors	961	4,027	-0.016	0.235	0.407	0.873	0.114	0.318

S.D. - standard deviation. See Table A-1 for a definition of variables.

A-2 Algorithm for Correcting for Dynamic Panel Bias

The dynamic panel bias approximation can be simplified into eight steps. An extensive derivation can be found in Kiviet (1995) and Bruno (2005).

(1). Consider the dynamic panel data model from (1)

$$\pi_{ij,t} = \alpha + \beta\pi_{ij,t-1} + \delta X_{ij,t-1} + \epsilon_{i,t}, \tag{A-1}$$

with $\epsilon_{ij,t} = e_{ij,t} + \nu_i$, $e_{ij,t} \sim i.i.d.N(0,\sigma_e^2)$ and $\nu_i \sim i.i.d.N(0,\sigma_\nu^2)$.

(2). Collecting data over time t and firms i gives the matrix form of (A-1) as

$$\pi = W\psi + D\nu + e, \tag{A-2}$$

where π and e are $(NT \times 1)$ vectors of the dependent variable and disturbances, $W = [\pi_{-1}\vdots X]$ a $(NT \times k)$ matrix of stacked observation, ν a $(n \times 1)$ vector of fixed effects, $D = (I_N \bigotimes \iota_T)$ a $(NT \times N)$ matrix of firm-specific dummy variables, $\psi = [\beta, \delta]$ a $(k \times 1)$ vector of parameters and N, T, k the number of observations, periods and parameters, respectively.

(3). Extending to unbalanced panels gives

$$S\pi = SW\psi + SD\nu + e,$$

where S is a $(NT \times NT)$ block-diagonal matrix with the dynamic selection rule $s_{ij,t}$ on the diagonal. Define $r_{ij,t} = 1$ if $(\pi_{ij,t}, X_{ij,t})$ is observed and 0 otherwise. Similarly, $s_{ij,t} = 1$ if $(r_{ij,t}, r_{ij,t-1}) = (1,1)$ and 0 otherwise. The dynamic selection rule s_{ijt} ensures that the unbalanced panel contains only pairs of observations for which current and one-period lagged values are not missing.

(4). The fixed effect estimator for model (A-2) is given as

$$\hat{\psi}_{fe} = (W'M_sW)^{-1}W'M_s\pi, \tag{A-3}$$

with M_s as a symmetric and idempotent $(NT \times NT)$ matrix that eliminates fixed effects and selects suitable observations, $M_s = S(I - D(D'SD)^{-1}D')S$.

(5). The bias of the estimator in (A-3) can be expressed as

$$E[\hat{\psi}_{fe}] = E[(W'M_sW)^{-1}W'M_se]. \tag{A-4}$$

(6). Kiviet (1995), Bun and Kiviet (2003) and Bruno (2005) show how after replacing M_s and some algebraic transformation an expression for the bias approximation can be obtained that is, in essence, a function of the consistent parameter estimate $\hat{\psi}_m$ and the variance $\hat{\sigma}^2_{e,m}$,

$$\widehat{bias}_m(\hat{\psi}_{fe}) = f(\hat{\psi}_m, \hat{\sigma}^2_{e,m}). \tag{A-5}$$

Given the consistent estimator $\hat{\psi}_m$, an estimate for the variance is obtained from

$$\hat{\sigma}^2_{e,m} = \frac{e_m^{'} M_s e_m}{(N-k-T)}, \tag{A-6}$$

where $e_m = \pi - W\psi_m$.

The subscript m indicates the method chosen to initialize the bias correction. The present analysis uses Anderson and Hsiao (1982) instrument variable (IV-AH), Arellano and Bond (1991) difference GMM (dGMM) and Blundell and Bond (1998) system GMM (sGMM). The bias approximation is of the order $O(N^{-1}T^{-2})$.

(7). The true parameter value and variance are, of course, unobserved and not feasible for bias correction. Instead, IV-AH, dGMM and sGMM methods are used to obtain consistent estimators for $\hat{\psi}_m$ and $\hat{\sigma}^2_{e,m}$.

(8). Lastly, insert $\hat{\psi}_m$ and $\hat{\sigma}^2_{e,m}$ into (A-5) to correct the original estimator with the bias approximation to obtain the bias-corrected estimator.

$$\hat{\psi}_{bc} = \hat{\psi}_{fe} - \widehat{bias}(\hat{\psi}_m, \hat{\sigma^2_{e,m}}). \tag{A-7}$$

A-3 Mundlak Chamberlain Dynamic Panel Regressions

This subsection outlines the random effects maximum likelihood estimator suggested in Heckman (1981) and Wooldridge (2005). Equation (1) specifies a linear, dynamic model of firm profitability

$$\pi_{ij,t} = \alpha + \beta\pi_{ij,t-1} + \delta X_{ij,t-1} + dD_j + \epsilon_{ij,t}. \tag{A-8}$$

All variables are defined in the text. The term $\epsilon_{ij,t}$ is a compound error $\epsilon_{ij,t} = e_{ij,t} + \nu_i$, where $e_{ij,t}$ is an idiosyncratic disturbance and ν_i captures unobserved heterogeneity. There is a way to estimate this model using random effects (and omit the dynamic panel bias) while accounting for individual effects.

Mundlak (1978) and Chamberlain (1984) consider a correlation between ν_i and $X_{ij,t-1}$ by assuming the following relationship

$$\nu_i = \gamma\bar{X}_{ij} + \gamma_i, \tag{A-9}$$

where $\bar{X}_{ij}$ is the mean of all time-varying variables for each firm, and γ_i is a term for unobserved heterogeneity and independent from $\bar{X}_{ij}$ and $\epsilon_{ij,t}$.

According to Heckman (1981) and Wooldridge (2005), the following specification assumes the individual effects to be correlated with the initial conditions of the dependent variable

$$\gamma_i = \gamma_0 + \gamma_1\pi_{ij,t=0} + \varpi_i, \tag{A-10}$$

with $\varpi_i \sim N(0, \sigma^2_{\varpi})$. The parameter γ_1 captures the dependence of the individual effects γ_i on the initial condition $\pi_{ij,t=0}$.

Lastly, inserting (A-10) into (A-9) and into (A-8) yields

$$\pi_{ij,t} = \alpha^* + \beta\pi_{ij,t-1} + \delta X_{ij,t-1} + dD_j + \gamma\bar{X}_{ij} + \gamma_1\pi_{ij,t=0} + e^*_{ij,t}, \tag{A-11}$$

where $\alpha^* = \alpha + \gamma_0$ and $e^*_{ij,t} = e_{ij,t} + \varpi_i$. The model in (A-11) is estimated using maximum likelihood estimation techniques.

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