IPA-Deakin SME Research Centre's Submission to the Productivity Commission's Inquiry into Australia's Productivity Performance

Innovation, exports and productivity among Australia's SMEs

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Abstract

We outline the link between innovation, exports and productivity in Australian SMEs by estimating a series of production functions to obtain a better understanding of how productivity differs across different types of private companies. Results show that average productivity growth of all private companies (including SMEs) increased by a mediocre 2.04 per cent across all industries in Australia between 2006 and 2018, providing support to Australian Treasury and OECD research indicating slowdown of productivity growth across OECD member countries. We observe substantial heterogeneity in productivity across different private entities by size, age and industry sectors, suggesting that productivity gains are more challenging for resource-constrained smaller and younger firms compared to larger and older firms. Similarly, we reveal that private company innovators, exporters and companies operating in export-heavy industries are significantly more efficient than companies that are non-innovators and non-exporters, with modelling showing that exporters decrease their productivity gap from the efficient frontier by at least 3 points. We conclude by highlighting the implications of these findings for evidence-based policy.

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1. Background and Introduction

Since its inception in 2013, the IPA-Deakin SME Research Centre (IDSRC) has been tracking the economic behaviours of small to medium-sized enterprises (SMEs) in Australia, highlighting and reporting in its Small Business White Papers (SBWPs) (2015, 2018, 2021) the performance of these businesses in relation to financing, innovation, skills and human capital, competition, and regulation. In 2021, the SBWP focused on highlighting Australia's private sector's persistently poor performance on innovation and R&D, which have been long considered by economists to be primary drivers of a nation's productivity and growth. The SBWP (2021) reported that on almost every measure, Australian private companies have been lagging their global peers in this critical area for years. Australian business sector expenditure on R&D, for example, has been at or below OECD averages for most of the past two decades and that Australian businesses rank among the least effective in the OECD at introducing product and process innovations. In this Productivity Commission submission report, we extend the SBWP 2021 analyses by focusing on investigating the impact that innovation (measured by the firm's introduction of a new or significantly improved good or service, operational process, organisational/managerial process, or marketing method) and exports have on Australia's small and medium sized enterprises (SMEs) productivity.

Australia's Chief Scientist, Dr Cathy Foley, called on the Federal Government in 2021 to make science and innovation the "heart" of Australian policy development[1]. In a cautionary presentation, Dr Foley warned that many local innovation opportunities were being under-utilised by Australians and capitalised on by foreign businesses. There is considerable evidence to support Dr Foley's warning. On a range of measures, Australia's performance in commercial research and innovation has been lagging relative to other countries. Business expenditure on research and development (R&D) has been consistently at or below OECD averages, and Australian businesses rank among the least effective in the OECD at introducing product and process innovations (Australian Innovation System Report, 2016). Australia has a pressing need to diversify its sources of economic growth and an

[1]https://todayspaper.smedia.com.au/afr/shared/ShowArticle.aspx?doc=AFR%2F2021%2F03%2F18&entity=Ar01303&sk=431F20EE&mode=text

obvious area in which Australia can – and should – diversify its sources of growth and security is in the areas of SME innovation and exports.

The economic measure of productivity fundamentally assesses the efficiency of the production of goods and services and, hence, it is usually defined as total outputs (e.g., goods or services) that can be produced with given amounts of input (e.g., labour, capital, resources). As productivity is a key driver of economic growth, social prosperity and living standards, it is vital that a country's economy achieves productivity growth as it is only through these efficiencies that economies can improve their per capita incomes and living standards, especially over the longer term. In fact, as stated by Nobel Laureate Paul Krugman: *Productivity isn't everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker.*[2] Moreover, productivity is about how well businesses, industries or countries combine resources to produce goods and services. This includes resources such as raw materials, labour, skills, capital equipment, land, intellectual property, managerial capability, technology, financial capital, knowledge and ideas. Simply put, growth in productivity is vital for growth in national income and living standards into the future.

Before providing a more detailed analysis of innovation and exports in relation to productivity among private companies in Australia, in particular companies that fall within the definition of SMEs,[3] it is notable to highlight the importance of SMEs and their employment capabilities in the Australian economy. While large public corporations and businesses have a significant impact on the Australian economy, SMEs play a critical role in determining the strength of the economy. SMEs are prevalent in all sectors of the Australian economy, covering a wide diversity of different types of business activities from agriculture, manufacturing to a range of different services such as accounting and other professional services. According to the counts of businesses compiled by the ABS in December 2021, there were 2,310,091 SME firms in Australia at the end of the 2020-21 financial period, making up 99.8 percent of all counts of businesses. The composition of Australian

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[2] Paul Krugman 1994, The Age of Diminishing Expectations.

[3] The Australian Bureau of Statistics (ABS) defines size of a business entity by number of employees. Accordingly, micro-businesses employ up to 4 persons, small businesses between 5 to 20 employees, and medium size businesses between 21 and 199 employees.

businesses is characterised by a high number of non-employing businesses – 1,441,105 – comprising around 62 per cent of all businesses. SMEs account for the largest proportion of businesses in Australia and for more than 95 per cent of all businesses in the OECD (OECD, 2022).

The international research literature reports that varying patterns and causes of productivity slowdown at the firm level have been observed among OECD member countries, including Australia, since the beginning of the 2008-09 global financial crisis (Owalla et al., 2022; Cowling & Tanewski, 2019; Criscuolo, 2018; OECD, 2018). Some studies demonstrate significant and persistent productivity differences across all private firms in different industries (Syverson 2011), with OECD firm-level data for the period 2001 to 2012 showing differences of 14 per cent between firms in the top and bottom deciles of productivity levels (Owalla et al., 2022). These productivity differences especially can be observed between technological and non-technological frontier firms (Andrew et al., 2016) and between large and small firms, particularly in the manufacturing sectors (OECD, 2018). Furthermore, Cowling and Tanewski (2019) identify that the Australian SME sector is faced with decreasing returns to scale indicating that not all firm growth will lead to productivity gains. Moreover, the capital contribution to value added among the largest 25 per cent of private firms in Australia is four times that of the smallest 25 per cent of firms, including significant industry sector variations in productivity (Cowling & Tanewski, 2019). Following on this literature, which recommends capturing productivity growth heterogeneity among different firm size groups (Owalla et al., 2022; Cowling & Tanewski, 2019), this submission report essentially focuses on the areas of firm-level innovation and exports in relation to firm-level productivity among different private company size, age and sector groups to address the primary objectives of the Productivity Commission inquiry, namely, to identify some of the unique key drivers of productivity growth in Australia that can assist government policy and to prioritise reform.

It is also important to take into consideration that SMEs operate under different constraints compared to large firms, indicating that productivity among SMEs will vary according to the firm's size, age and industry. For example, not only are economies of scale different between small and large firms, but small firms tend to be owner-managed and decision-making is usually confined to one key decision-maker, who is constrained by her/his bounded rationality, understanding, experience, education-level, skills and the quality of the information content being utlised to make an informed decision (Owalla et al., 2022; Gherhes et al., 2016; Onkelinx et al., 2016). Hence, to obtain a better understanding of heterogeneity in productivity among SMEs in Australia, we extend Cowling and Tanewski's (2019) research by first focusing on productivity differences at the firm-level across different size, age, and industry sector groups to identify how the responsiveness of output with respect to labour and capital varies across these distinctive firm categories We then examine firm-level productivity variations in private companies that innovate (do not innovate) and export (do not export) to understand how value added is created, what combinations of labour and capital are combined to create value added, and the role of human capital and collaboration in productivity growth when firms innovate and export.

Our focus on innovation and exports draws upon the economic theory of the production function which examines the effects of financial capital, human capital and innovation on productivity and economic growth. All three factors, both individually and collectively, have been found to significantly and positively affect productivity growth. Moreover, endogenous growth theory (e.g., Romer, 1986; Aghion et al., 1998) recognises both innovation and exports as important drivers of productivity and key long-term antecedents of competitiveness and economic growth. So, while there is wide agreement that innovation and exports lead to productivity growth, this submission takes into account the resource constraints experienced by SMEs and hence it considers firm-heterogeneity factors such as size and age when analysing several potential internal firm capabilities that are associated with innovation and exports.

2. Data and Research Methods

Our data comes from the ABS's Business Longitudinal Analysis Data Environment (BLADE), which contains firm-level longitudinal data from tax filings, business registrations, and various ABS surveys. These data are anonymised by the ABS and firm-level observations are available between the financial years 2001-02 and 2018-19. Financial data comes primarily from the ATO's Business Income Tax (BIT) and where BIT data are missing, we supplement these with data obtained from the ATO's Business Activity Statement (BAS) and from the ABS's EAS (Economic Activity Survey). Data on R&D comes from the ABS's survey of Business

Expenditure on R&D (BERD) and is supplemented by additional BIT data and data obtained from the ABS's Business Characteristics Survey (BCS). Data on intellectual property filings comes from IP Australia's Intellectual Property Longitudinal Research Dataset (IPLORD).

In this report we examine the effect of innovation and exports by taking into consideration several potential internal firm capabilities such as technical and business skills on SME productivity and efficiency. We estimate the efficiency of private companies by utilising a Cobb-Douglas production stochastic frontier model to create a measure of relative efficiency of each private company within its respective industry for each year between 2006 and 2018. We estimate an efficient frontier for all private companies across 19 industries over the 13-year period by assessing the amount and mix of resources used by the company to generate output, measured by total income, within the company's industry. The inputs for each company are measured by the capital expenditure, labour, R&D expenditure and several human skill indicators. We expect companies that operate on the frontier are the most efficient and, hence, assign these companies a score of one. In contrast, companies assigned lower scores (less than one) are deemed inefficient relative to companies operating on the frontier. Hence, the further the score is towards unity, the lower its efficiency.

2.1. Measure of Productivity

Productivity growth in Australia is measured by the ABS and others using one or two interrelated measures. The first is *labour productivity*, which is defined as output per unit of labour input (typically measured in terms of hours worked). The second is *multifactor productivity* (MFP), which is a residual measure after taking out the contribution made by the increased use of capital inputs per unit of labour input in production (termed 'capital deepening'). MFP is generally interpreted as a measure of the efficiency with which labour and capital inputs combined are used in productivity. Most analysis typically assesses changes in productivity growth rates over time rather than focusing on the underlying level of productivity.

The starting point in terms of generating an efficiency measure is the Cobb-Douglas stochastic frontier model. The specification of the model is represented as:

$$Y_{it} = \exp(X_{it}\beta + \varepsilon_{it} - U_{it})$$

Where subscripts denote the *i*th firm in the *t*th year respectively. X is a vector of inputs, β is the set of parameters to be estimated, ε is assumed to be independent and identically distributed random error which have normal distribution with mean zero and unknown variance. U is the non-negative unobservable random variable associated with the technical efficiency of production.

The functional form of the Cobb Douglas stochastic frontier production is thus converted for estimation as:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 H_{it} + \beta_4 \ln R_{it} + \varepsilon_{it} + U_{it}$$

Where Y, the dependent variable is represented as total income. The inputs for each firm are capital expenditure (K), labour (L), a measure of human capital skills (H) and R &D expenditure (R). We estimate the efficiency of private companies by utilising the above functional form to generate a measure of relative efficiency of each private company within its respective industry for each year between 2006 and 2018. We estimate an efficient frontier for all private companies across 19 industries over the 13-year period by assessing the above inputs used by the company to generate the output.

We use two composite measures to represent the firm's human capabilities: technical skills and business skills. The composite measure representing technical skills – TECH - comprises skills in the following areas: engineering; scientific and research; information technology professionals; information technology support technicians; transport, plant and machinery operation. The composite measure representing business skills – BUSS – comprises skills in trades; marketing; project management; business management; and financial. Accordingly, the variable 'technical skills' is an indicator variable which takes the value of 1 if a firm comprises at least one of the skills as described above, 0 otherwise. The same applies to the indicator variable 'business skills'. While we generated technical efficiency scores based on separate stochastic frontier models, that is, one model includes technical human skills and the other model includes business skills along with the other inputs as outlined earlier, there were no significant differences in the technical efficiency scores generated by these two models.

Definitions and explanations of explanatory and control variables are provided in the relevant results sections below.

3. Results

3.1. Productivity (Technical Efficiency) of Australian Private Companies

Analyses of the data in the ABS BLADE environment shows that the unweighted average productivity/ technical efficiency growth of all private companies (including SMEs) increased by a mediocre 2.04 per cent across all industries in Australia between 2006 and 2018. Figure 1 shows that the highest average efficiency score of 36.25 was observed in 2018, which had a growth rate of 8.06 per cent over the previous year, with the lowest average efficiency score of 28.5 observed in 2006, providing additional evidence of a slowdown in productivity growth in Australia's private company sector (Andrews et al., 2022; OECD, 2018; Cowling & Tanewski, 2019).

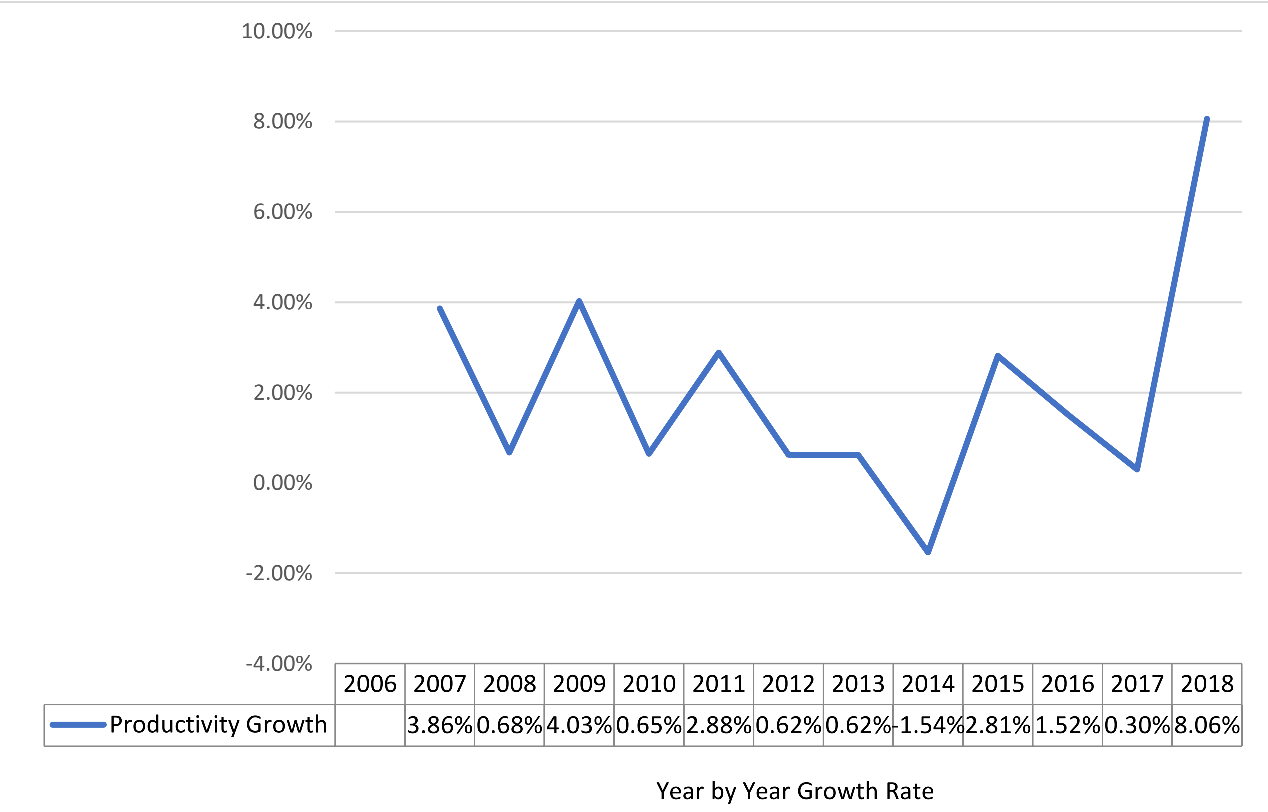

Figure 1. Annual unweighted-average productivity (technical efficiency) growth of SMEs in Australia: 2006-2018

Figure 2 displays the unweighted-average technical efficiency of Australia's private companies by industry. As we estimate a stochastic frontier model, companies that operate on the frontier are the most efficient and are assigned a score of one, whereas companies assigned lower scores (less than one) are deemed inefficient relative to companies operating on the frontier. The most efficient industries during the 2006-2018 period, that is those with the lowest productivity gap from the frontier, were Public Administration and Safety with an average score of 0.425, followed by Education and Training (0.402), Manufacturing (0.399) and Mining (0.391), whereas sectors such as Agriculture, Forestry and Fishing (0.176), Finance and Insurance Services (0.246), Rental, Hiring and Real Estate Services (0.286), Retail Trade (0.295) and Administrative and Support Services (0.304) show the lowest efficiency averages. The results described above are contrary to what Cowling and Tanewski (2019) reported[4].

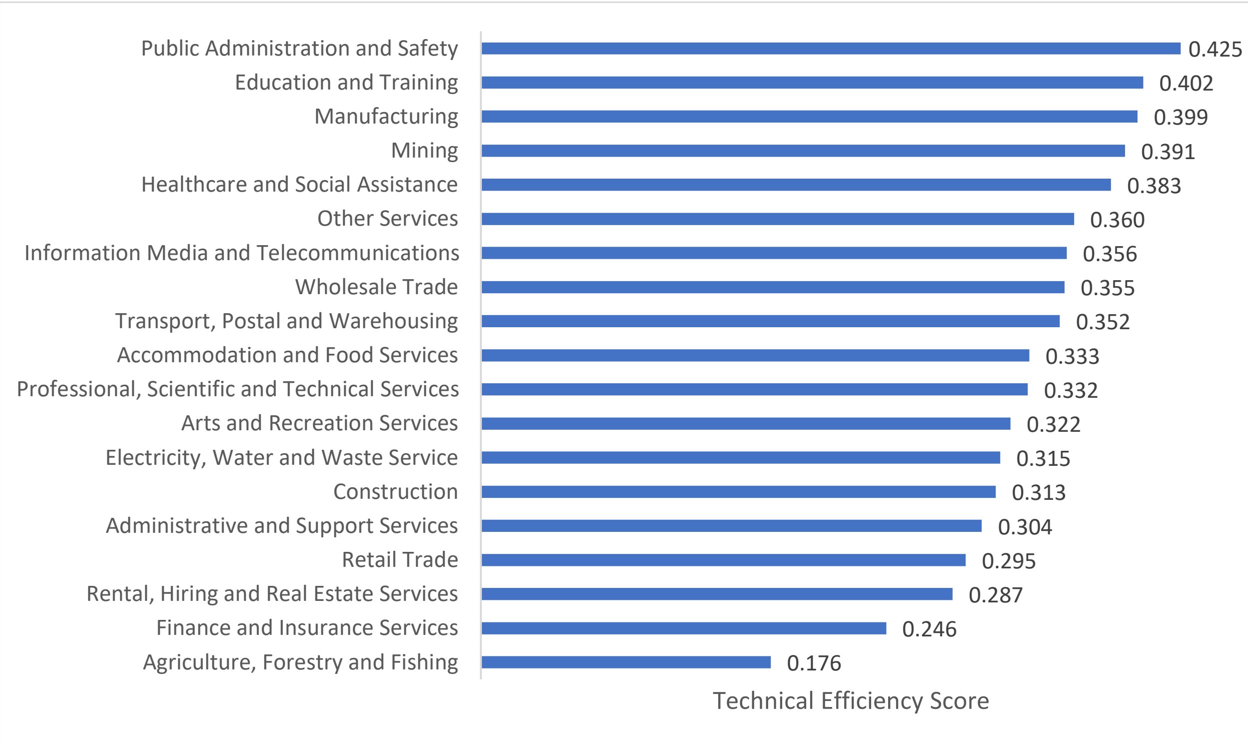

Figure 2. Unweighted-average productivity (technical efficiency) of SMEs in Australia by Industry: 2006-2018

[4]The results outlined in this report are based on longitudinal firm-level data estimates using a stochastic frontier model that includes capital expenditure, labour, a measure of human capital skills and R &D expenditure as inputs for each firm within its respective industry between 2006 and 2018, whereas Cowling and Tanewski (2019) use cross-sectional aggregated data grouped by 380 classes of firm for the 2014–15 financial year.

Turning to the unweighted-average technical efficiency of private companies by size of business entity, it appears that large (0.352) and medium-size companies (0.350) are more efficient than small (0.316) and micro (0.300) businesses, while old (0.326) and mature companies are more efficient (0.322) compared to young (0.309) and start-up (0.284) companies, indicating that productivity gains are more challenging for resource-constrained smaller and younger firms compared to larger and older firms.

3.2. Productivity (Technical Efficiency) by Innovation and Exports

The ABS's definition of innovation is utilised in this report, which is the introduction of a new or significantly improved good or service, operational process, organisational/managerial process, or marketing method. Accordingly, innovation is a composite measure comprising four items gauging whether the firm introduced any new or significantly improved: (i) goods or services; (ii) new operational processes; (iii) new marketing methods, and (iv) new organisational/managerial processes. The variable takes the value of 1 if the firm has introduced innovation in at least one of the areas, 0 otherwise. Meanwhile, exports is an indicator variable that identifies whether a private company exports good/services or not. The value 1 indicates whether the company reports a positive dollar amount in export sales, and 0 otherwise.

Bivariate analyses of the unweighted-average technical efficiencies of private companies that innovate (0.357) compared to non-innovators (0.320, t-value = 20.25, p = .0000), exporters (0.384) versus non-exporters (0.297, t-value = 120.00, p = .0000), and companies operating in export heavy industries (0.381) versus non-export heavy industries (0.301, t-value = 99.98, p = .0000), indicate that innovators, exporters and companies operating in export-heavy industries have significantly smaller productivity gaps from the frontier than companies that are non-innovators and non-exporters (see Figure 3).

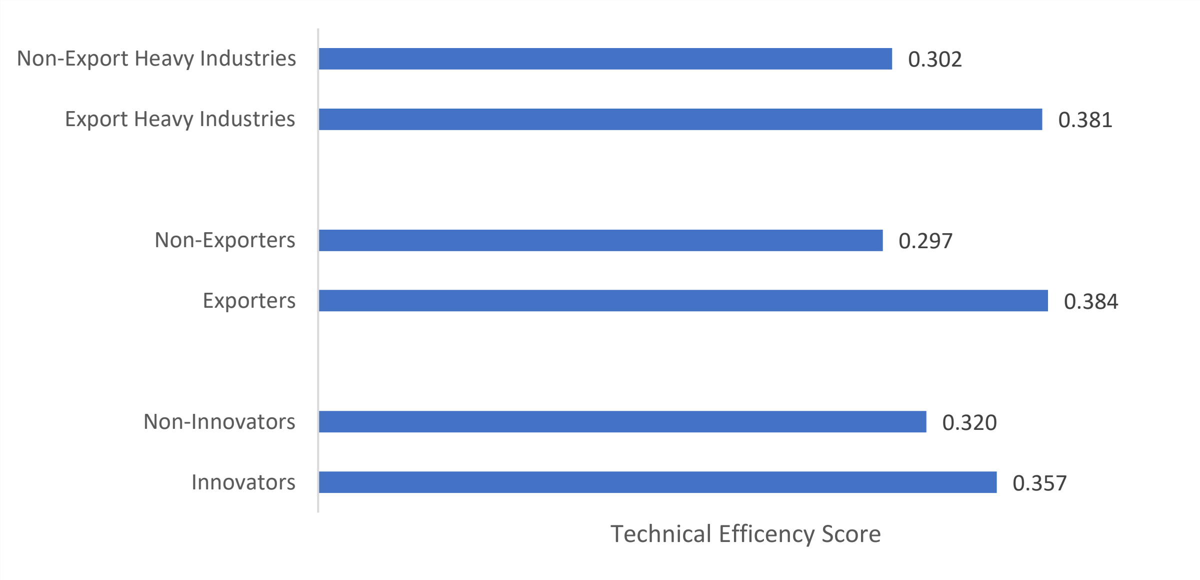

Figure 3. Unweighted-average productivity (technical efficiency) of SMEs in Australia by Innovation and Exports: 2006-2018

3.3. Regression Models of Technical Efficiency

Based on the sampling of the technical efficiency scores by innovation and exports reported in the previous section above, we observe private companies that innovate and export have on average significantly higher efficiency scores compared to those that do not innovate and export. To further substantiate these results, we extend our modelling by using the following estimation framework:

$$\ln TE_{it} = \beta_0 + \beta_1 Innovation_{it} + \beta_2 Export_{it} + \beta_3 Innovation.Export_{it} + \beta_4 \ln Foreign\ \ Own_{it} + \beta_5 Competition_{it} + \beta_6 Size_{it} + \beta_7 Age_{it} + \varepsilon_{it}$$

Where the dependent variable is technical efficiency score. The key explanatory variables are innovation and exports (included in our model to complement innovation for its considerably large impact on the technical efficiency scores). Control variables documented to be related to firm-level performance are foreign ownership and competition.

Foreign-owned firms can provide useful access to resources, such as financing and human capital required for productivity, as well as possessing more superior knowledge and experience about foreign markets than their domestic counterparts (Hiep & Ohta, 2009). In addition, foreign presence can increase efficiencies for local firms through spill-over effects or by generating positive externalities, which can be generated within the same industry or across different industries (Orlic et al., 2018; Takii, 2011). While spill-over effects can be transmitted through imitation, R&D, training, etc., Liu (2018) maintains that foreign players can aid in the ability to absorb technology and skills. Accordingly, we include the percentage of foreign ownership as a control variable in the regression model as follows: 0 for 0% ownership; 1 for > 0% - < 10%; 2 for ≥10% - < 50%, and 3 for > 50% ownerships.

Degree of competition is seen as an important external driver of performance. Increased competition for resources encourages firms to differentiate (Henderson & Mitchell 1997) and seek opportunities abroad to secure critical resources to ensure business survival and development (Westhead et al., 2001). The argument in support of a positive relationship between competition and productivity performance rests on the idea of slacking in an environment of monopoly power. Existence of more firms in the industry leads to a sharpening of effort because the unobserved productivity shocks are likely to be correlated across firms operating in the same industry (Nickell, 1996). Green and Mayes (1991) and Caves and Bailey (1992) have done comprehensive studies to relate technical efficiency with competition. Empirical findings suggest that competition leads to firms' employment of more effective decision-making structure. The variable competition included in the regression is derived as an ordinal variable ranging from 0 to 3 as follows: 0 represents no competition; 1 is minimal competition (in BLADE it is 1 or 2); 2 is moderate competition (3 or 4), and 3 is strong competition (5 or more).

We also include size (as defined by the ABS) and age (as defined by the OECD) as control variables in our estimation framework. The same classifications were used in the analysis of the technical efficiency scores outlined in the Data and Research Methods section of this report. Firms are classified into four dummy variables for size: micro businesses (MICRO) 1-4 employees; small businesses (SMALL) 5-19 employees; medium business (MEDIUM) 20-199 employees; and, large business (LARGE) 200+ employees. Age is categorised by four dummy variables as follows: start-up (STARTUP) between 0 to 2 years; young firm (YOUNG) 3 to 5 years; mature firm (MATURE) 6 to 9 years, and; old firm (OLD) 10 years or more.

We employ a matching procedure to sample observations to address certain baseline characteristic differences that might be inherent in the population. As potential endogeneity can also arise due to self-selection of firms into innovation (Becker & Egger, 2013), we use an entropy balancing technique to account for these potential endogeneity issues. Entropy balancing (Hainmueller, 2012) addresses the shortcomings of low levels of covariate balance in practice. The indirect search process used in most matching procedures often fails to jointly balance out all the covariates and, in some cases, even counteracts bias reduction when balance on some covariates decreases as a result of the pre-processing (Iacus et al., 2012). As such, entropy balancing uses a pre-processing scheme where covariate balance is directly built into the weight function that is used to adjust the control units. Accordingly, we match companies obtained from the BLADE datasets by using entropy balancing to maximise the available sample of companies while ensuring mean balancing between innovative and non-innovative companies. We match the companies based on exports, competition, degree of foreign ownerships, firm size and age.

After matching our sample of private companies that innovate with those that do not innovate by using an entropy balancing technique, regression estimates are reported in Table 1. The results show that innovation has a positive and significant effect on the technical efficiency private companies and this is robust after the inclusion of different measures of technical and business human skills into the Cobb Douglas stochastic frontier production model. Exports also show strong robust positive effects at the 1 per cent level of significance across all the estimations. Regardless of the stochastic frontier model used (i.e., inclusion of business skills in equations 1 and 2 or technical skills in equations 3 and 4 in Table 1), regression estimates show companies that export are associated with on average increases of 0.0314, 0.0342, 0.0316 and 0.0342 in efficiency scores, respectively, suggesting that these entities decrease the productivity gap from the efficient frontier by at least 3 points. Similarly, innovation is associated with on average increases of 0.00582, 0.00269, 0.00637 and 0.00341 in efficiency scores, respectively, although the magnitude of the effect of innovation on technical efficiency is not as strong as that of exports. The interaction term between innovation and exports shows significant and positive effects on technical efficiency, suggesting that private companies that innovate and export demonstrate lower productivity gaps from the efficient frontier. Results in Table 1 also disclose that Australian private companies with foreign ownership and that companies operating in competitive industries are positively associated with technical efficiencies, although the magnitude of the effect of foreign ownership on technical efficiency is stronger than that of competition.

Table 1: Effect of innovation and exports on Australian private companies' technical efficiency

	Eff_buss		Eff_tech	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Innovation	0.00582*	0.00269*	0.00637*	0.00341*
	[1.745]	[1.771]	[1.905]	[1.910]
Export	0.0314***	0.0342***	0.0316***	0.0342***
	[7.892]	[5.338]	[7.933]	[5.331]
Innovation x Export		0.00483*		0.00456*
		[1.877]		[1.901]
Competition	0.00328*	0.00320*	0.00368**	0.00361**
	[1.909]	[1.863]	[2.141]	[2.097]
Foreign_own	0.0758***	0.0759***	0.0768***	0.0769***
	[20.02]	[20]	[20.21]	[20.19]
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj.R^2	0.26	0.27	0.25	0.27
Num.obs.	366,152	366,152	366,507	366,507

The numbers in parentheses are absolute *t*-statistics. This table reports the results of OLS regressions estimating the effect of innovation on technical efficiency post entropy matching. The dependent variables are *eff_buss* and *eff_tech* which are the technical efficiency scores based on business skills and technical skills respectively along with the other inputs, generated from the stochastic frontier model. The primary explanatory variable is *innovation*, a binary indicator variable equal to one for companies that innovate, and equal to zero otherwise. Constants, age and size dummies are included in all regressions, but their coefficients are not reported for brevity. ***,** and * signify statistical significance at the 1%, 5% and 10% levels. Standard errors are clustered by company.

3.4. R&D Expenditure Activities

As mentioned earlier in the introduction that Australian business sector expenditure on R&D has been at or below OECD averages for most of the past two decades, we briefly focus on examining research and development (R&D) expenditure activities identified in BLADE during the period 2006 to 2018 to provide additional understanding of the link between innovation and technical efficiency in private companies. Our analysis reveals that on average around six per cent of private companies annually claim tax deductions based on R&D expenditures, but since 2006 these activities have declined by 9.2 per cent over the 13-year period (see Figures 3). While there was growth in the number of companies claiming tax deductions on R&D expenditure activities between 2008 and 2011 during the R&D tax concession program, these activities declined under the R&D tax incentive program that was introduced in 2011, hence the significant decline of 119.14 per cent in R&D expenditure activities observed in 2012 during the first year of the tax incentive program.

Figure 3. Proportion of Australian SME's Annual R&D Expenditure Activities: 2006-2018

Of the 43,127 entities on average that annually reveal R&D expenditures, around 17 per cent are large private companies, 11.2 per cent are medium size, 5.9 percent are small and 1.9 per cent are micro-businesses. With respect to age of private company, 8.2 per cent are classified old, 12.8 per cent mature, 11.8 per cent young and 4.0 per cent startup. The industry sectors that report the highest proportions of companies with R&D expenditures are the Manufacturing (19.3%), Professional, Scientific and Technical Services (16.1%) and Electricity, Water and Waste Services (11.4%).

3.5. Regression Models of R&D Inputs and Outcomes

We discussed earlier in this report that SMEs operate under different constraints compared to large firms. The research literature argues (e.g., Coad et al., 2014) that to successfully exploit innovation opportunities, firms need the right combination of financial and human capital resources. But as these two resources are often in short supply among SMEs, due to constraints associated with the "liability of smallness" (Aldrich & Auster, 1986), we argue external collaborations can be important for innovation and R&D, and that these external collaborations can be translated into productivity gains.

To provide evidence to our argument that investment in external collaborations can support innovation and research, we examine the empirical association between external collaboration and both research inputs and outcomes. The analysis makes use of two measures of external collaboration provided in the ABS BLADE data. The first measure of external collaboration is *coopjres_bcs*, which reflects companies that self-report on the ABS Business Characteristics Survey engagement in external collaborative agreements to conduct R&D. These external collaborative agreements may be with either publicly-funded partners or private partners. The second measure of external collaboration is *col_uni*, which reflects companies that self-report external collaboration on R&D with publicly- and privately-funded research institutions, specifically.

Table 2 shows the distribution of these external collaboration measures by year. In Panel A, for the more general measure of external collaboration, *coopjres_bcs*, the data span the period from 2007 to 2018. Approximately 25 percent of the sample companies collaborate externally on research. Across the 10-year sample, this rate of external collaboration has been relatively stable. In Panel B, data of research institution collaboration was collected by the ABS in only three fiscal years – 2007, 2009 and 2011. Compared to the more general measure of external collaboration, relatively few companies engage in collaboration with research institutions, with yearly proportions of *col_uni* ranging between 4.2 and 6.1 per cent. The rate of external collaboration grew marginally across the sample period.

Table 2: Proportion of companies collaborating by year

Panel A: coopjres_bcs

Year	Proportion (%)	Observations
2007	19.6	271
2008	29.1	289
2009	25.4	291
2010	28.1	327
2011	25.7	358
2012	30.2	252
2014	22.5	333
2016	24.7	190
2018	24.5	147

Panel B: col_uni

Year	Proportion (%)	Observations
2007	4.2	288
2009	4.7	295
2011	6.1	361

Tables 3 reports our analysis on the association between external collaboration arrangements and R&D expenditures, an input measure of the resources companies commit to innovation. The dependent variable is the natural logarithm of R&D expenditure. We include in our regression model a range of additional variables to control for effects associated with a range of company characteristics, including the claiming of taxation subsidies (*taxoffset*) and whether these subsidies were claimed under the R&D Tax Concession scheme, or the R&D Tax Incentive scheme introduced in 2012 (*post*). We examine the association both within industry and year and within industry-year using fixed effect models.

Table 3 shows a strong positive association between *coopjres_bcs* and research expenditures. The magnitude of this effect is equivalent to a 49 percent increase in R&D expenditures (t = 4.60, p = .0000 and 4.47, p = .0000). This suggests that either companies externally collaborate on larger R&D projects or that companies are prepared to commit more resources to such projects. In either case, external collaboration arrangements appear to be a valuable vehicle for undertaking such research endeavours. In untabulated results, the economic magnitude of the association attributed to research collaborations with research institutions, *col_uni*, is similarly meaningful. However, the association falls marginally outside conventional levels of statistical significance, which we attribute to the considerably smaller sample available for study, relative to our more general measure, *coopjres_bcs*, particularly for SMEs, which may benefit most from such external collaborations in the absence of internal resources.

Table 3: Association between collaborative R&D arrangements on R&D expenditure

	amttot_berd	
	Model 1	**Model 2**
coopjres_bcs	0.40***	0.40***
	[4.60]	[4.47]
taxoffset	0.24**	0.24*
	[2.08]	[1.91]
post	0.22	-1.20***
	[1.17]	[-4.21]
taxoffset x post	-0.00	-0.00
	[-0.00]	[-0.02]
govt_subsidies	0.06***	0.07***
	[7.38]	[7.58]
$revenue_{t-1}$	0.12	0.10
	[1.30]	[1.07]
ch_sales_{t-1}	-0.10**	-0.11**
	[-2.43]	[-2.56]
roa_{t-1}	-0.48**	-0.48**
	[-2.23]	[-2.24]
$loss_{t-1}$	-0.00	-0.00
	[-0.01]	[-0.01]
$assets_{t-1}$	0.23***	0.25***
	[3.80]	[3.97]
$hcnt_{t-1}$	-0.00	0.01
	[-0.05]	[0.22]
$salary_{t-1}$	0.10	0.10
	[1.27]	[1.19]
Year FE	Yes	No
Industry FE	Yes	No
Industry-Year FE	No	Yes
Num. obs.	2,450	2,450
Adj. R^2 (full model)	0.39	0.39

This table reports the results of regressions estimating the effect of cooperative R&D arrangements on R&D expenditure. The dependent variable is *amttot_berd*, the natural logarithm of reported R&D expenditure. The primary explanatory variable is *coopjres_bcs*, a binary indicator variable equal to one for companies that report cooperative R&D arrangements, and equal to zero otherwise. Standard errors are clustered by company, and t-statistics are presented in brackets.

Tables 4 and 5 report our analysis of the association between the external collaboration measures and patent filings by companies. The dependent variable is the number of patents filed by a company in the year. We include in our Poisson regression models similar additional variables to our preceding analyses. The regressions are estimated within industry and year using fixed effects. In Model 2, we also include as an additional explanatory variable the level of R&D expenditure made by the company to control for the general level of R&D resource commitment.

Table 4 shows evidence of a strong association between patent filings and general external cooperation. The coefficient estimates for our models range from 1.59 to 1.69 (z = 2.55 and 2.82). Similarly, Table 5 shows evidence a strong association between patent filings and research institution collaboration (z = 2.29 and 5.69), albeit off a small sample. While we cannot rule out companies collaborating on projects with higher likelihood of success, or endogenous selection whereby companies more likely to conduct fruitful research are also more likely to engage in collaborative agreements, these results are consistent with external collaboration forming an important part of the research process for companies that are successful in producing tangible research outputs.

To the extent that these associations may reflect a causal relationship between conducting R&D in a collaborative process (either between companies or between companies and research institutions), collaborative research may constitute an important lever in improving labour productivity in Australia. As previously discussed, progressing in labour productivity requires propagation of businesses in technical fields, leveraging highly skilled labour to deliver scalable products and services. Should external collaboration improve research outcomes, collaborative research may both enhance the quality, and therefore competitiveness, of innovative products and services or reduce cost and knowledge frictions that prevent Australian companies from innovating in technical areas. Accordingly, government policies focussed on R&D should further support collaborative R&D, especially for companies partnering with Australia’s world class teaching and research institutions.[5] While incentive for such collaboration can be provided through the existing R&DTI tax subsidy for research activity, we strongly recommend policymakers to consider the application of research collaboration vouchers, which have been shown to both support additional research and innovation activities and encouraging value adding collaboration between business and research institutions.[6]

Table 4: Association between collaborative R&D agreements on patent filings

	p_filed	
	Model 1	**Model 2**
coopjres_bcs	1.69***	1.59***
	[2.82]	[2.55]
taxoffset	0.79	0.71
	[1.02]	[0.92]
post	-4.28**	-4.86**
	[-2.45]	[-2.32]
taxoffset x post	2.52	3.01
	[1.82]	[1.63]
govt_subsidies	0.00	-0.02
	[0.09]	[-0.47]
$revenue_{t-1}$	-0.75	-0.79
	[-1.74]	[-1.75]
ch_sales_{t-1}	0.17*	0.18
	[0.66]	[0.73]
roa_{t-1}	-1.04	-0.73
	[-0.93]	[-0.71]
$loss_{t-1}$	-0.94	-1.01
	[-1.27]	[-1.28]
$assets_{t-1}$	-0.41	-0.53
	[-1.28]	[-1.56]
$hcnt_{t-1}$	-0.13	-0.15
	[-1.12]	[-1.55]
amttot_berd		0.41**
		[2.46]

[5] We also note recent evidence that strongly supports investment in collaboration. Recent reviews have attempted to quantify these benefits. A review by Universities Australia (2020) suggests a return of $4.47 per dollar invested in collaboration. Similarly, the Department of Education's *Review of Research Policy and Funding Arrangements* (2015) suggests that businesses may increase efficiency from engaging in collaborative research, relative to uncollaborative research, by a factor of three.

[6] There are several policies that may provide effective at enhancing this form of collaboration. Through the taxation system, the R&DTI can be amended to include a premium for research collaboration with Australian publicly-funded research institutions. This approach has been considered and supported by recent reviews of the Australian R&D ecosystem (Ferris et al. 2016; Tanewski et al., 2021). More directly, the Government may provide collaboration vouchers to businesses, both subsidising research activities and requiring collaboration with research institutions (Tanewski et al., 2021). In foreign jurisdictions, these vouchers have been shown to be highly effective (Cornet et al. 2006, SQW, 2019; Sala et al., 2016; Bravo-Biosca, 2020; Roelandt and van der Wiel, 2020).

Year FE	Yes	Yes
Industry FE	Yes	Yes
Pseudo R^2	0.24	0.26
Num. obs.	2,243	2,243

This table reports the results of Poisson regressions estimating the effect of collaborative R&D arrangements on patent filings. The dependent variable *p_filed* is the number of patents filed in the following three years. The primary explanatory variable is *coopjres_bcs*, a binary indicator variable equal to one for companies that that report collaborative R&D arrangements, and equal to zero otherwise. Pseudo R^2 are McFadden R^2. Standard errors are clustered by company, and z-statistics are presented in brackets. Intercepts are absorbed.

Table 5: Association between collaborative R&D agreements with research institutions on patent filings

	p_filed	
	Model 1	**Model 2**
col_uni	3.84^{**}	4.39^{***}
	[2.29]	[5.69]
taxoffset	2.63^{**}	1.19
	[2.23]	[1.49]
govt_subsidies	0.04	-0.13
	[0.26]	[-2.46]
$revenue_{t-1}$	-2.94^{**}	-1.90^{***}
	[-2.25]	[-2.92]
ch_sales_{t-1}	-0.08	-0.49
	[-0.13]	[-2.01]
roa_{t-1}	-2.00	3.93^{***}
	[-1.21]	[5.00]
$loss_{t-1}$	-2.07	0.74
	[-0.94]	[0.95]
$assets_{t-1}$	-0.38	-2.26^{***}
	[-0.57]	[-6.16]
$hcnt_{t-1}$	0.04	-0.11
	[0.04]	[-0.39]
amttot_berd		2.06^{***}
		[8.90]
Year FE	Yes	Yes
Industry FE	Yes	Yes
Pseudo R^2	0.60	0.75
Num. obs.	851	851

This table reports the results of Poisson regressions estimating the effect of collaborative R&D arrangements with research institutions on patent filings. The dependent variable *p_filed* is the number of patents filed in the following three years. The primary explanatory variable is *col_uni*, a binary indicator variable equal to one for companies that that report collaborative R&D arrangements with research institutions, and equal to zero otherwise. Pseudo R^2 are McFadden R^2. Standard errors are clustered by company, and z-statistics are presented in brackets. Intercepts are absorbed.

Conclusions and Recommendations

In this report we outline the link between innovation, exports and productivity in Australian micro-, small- and medium-sized enterprises by estimating a series of production functions to obtain a better understanding of how productivity differs across different types of private companies. There is limited research in the small business literature that examines how innovation and exports affect the productivity of different categories of SMEs and whether innovation translates into productivity gains, especially among smaller businesses. While results reveal that average productivity growth of all private companies (including SMEs) increased by a mediocre 2.04 per cent across all industries in Australia between 2006 and 2018, providing support to Australian Treasury and OECD research that shows differing variations and patterns in the slowdown of productivity growth across OECD member countries, we also demonstrate there is substantial heterogeneity in productivity across different types of private companies. These productivity variations, which exist among different private entities by size, age and industry sectors, indicate that productivity gains are more challenging for resource-constrained smaller and younger firms compared to larger and older firms. Similarly, we observe that private company innovators, exporters and companies operating in export-heavy industries are significantly more efficient than companies that are non-innovators and non-exporters, with modelling showing that exporters decrease their productivity gap from the efficient frontier by at least 3 points.

To augment our understanding of the link between innovation and technical efficiency in private companies, we consider whether external collaborations can provide important support to innovation and R&D, premised on the basis that these external collaborations can be translated into productivity gains for private companies. Our modelling demonstrates that external collaboration arrangements are a valuable vehicle for supporting private company innovation and R&D and that such external collaborative research endeavours may constitute an important lever in improving labour productivity in Australia.

As the Productivity Commission inquiry is interested in considering issues and reform areas that would most likely enhance productivity growth, we believe that both state and federal governments in Australia should do more to directing policies toward encouraging a broader cross-section of private companies, especially micro- and small-businesses, to innovate and export. Results presented in this report show that micro- and small-businesses should not be regarded to be marginal entities with no growth options. While many micro-and small-businesses in Australia do not innovate and export, however, those that do demonstrate significantly higher productivity gains compared to those that do not innovate and export. More importantly, as micro- and small-businesses that innovate and export are also associated with more competitive industries, policies directing innovation and exports among a broader cross-section of SMEs could increase the Australian economy's competitiveness by inducing SMEs to improve their performance via more widespread innovation and export activities.

We note that as SMEs operate under different constraints compared to large firms and for SMEs to successfully exploit innovation opportunities, firms need the right combination of financial and human capital resources. To overcome these resource-constraints, we suggest external collaborations can provide important support to SME innovation and R&D. More importantly, in today's complex and knowledge-intensive environment such external collaborations not only complement resource constraints, but they can assist SMEs in acquiring missing knowledge to encourage innovation and growth outcomes. As our results support this proposition, government policies focussed on R&D should further support collaborative R&D, especially among smaller businesses and for companies partnering with Australia's world class teaching and research institutions. While incentive for such collaboration can be provided through the existing R&DTI tax subsidy for research activity, we strongly recommend policymakers to consider the application of research collaboration vouchers, which have been shown to both support additional research and innovation activities and encourage value adding collaboration between business and research institutions, establishing strong cultures of collaboration that improve innovation.

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Appendix A: Other variable definitions

Variable	Definition
amttot_berd	The natural logarithm of one plus the dollar value (in thousands) of reported business expenditure on research and development [amttot_berd].
assets	The natural logarithm of one plus the dollar value (in thousands) of total assets [c_totlasst].
govt_subsidies	The natural logarithm of one plus the dollar value (in thousands) received from the Commonwealth and State and Local governments [scecom_berd & scesal_berd; missing replaced with 0].
hcnt	The natural logarithm of the number of staff employed [hcnt].
loss	Binary indicator variable equal to one for companies with ROA < 0 and zero otherwise.
p_certified	The natural logarithm of the number of patents certified during the year [p_certified].
p_filed	The natural logarithm of the number of patents applied for during the year [p_filed]
post	Binary indicator variable equal to one for the years 2012 and beyond, and zero otherwise.
revenue	The natural logarithm of one plus the dollar value (in thousands) of total revenue [c_totlinc; turnover; d_inctotal_eas]
roa	The ratio total profit [c_toprolos] divided by total assets [c_totlasst].
salary	The natural logarithm of one plus the dollar vale (in thousands) of salaries and wages paid during the year [wage].
taxoffset	An indicator variable equal to one for years where a company claims tax deductions/offsets for R&D expenditure, and zero otherwise.