Does Innovation Make (SME) Firms More Productive?

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1. Introduction

There is no shortage of dialogues and commentaries extolling the need for more innovation to regenerate sagging national productivity growth. However, hard evidence on whether or not innovation makes a difference is largely absent because most firm-level studies are drawn from cross-sectional data which cannot disentangle cause and effect.[1]

This paper advances this state of the art by bringing a dynamic element to the modelling. We use a panel of approximately 7 000 Australian small to medium-sized enterprises (SMEs), over a five-year period, to estimate the effect of introducing a new product, or new managerial, operational or marketing method on the firm's future productivity. In our context, we define these as changes that were new *to the firm*, rather than new *to the world*. Over and above innovation, we also test for whether collaborative arrangements with external parties make further contributions to firm productivity.

We begin this paper with a review of the accepted stylised facts concerning firm-level innovation and productivity. We then describe and estimate our model. We find that firms that introduced an innovation saw their (total factor) productivity rise by 2.7 percentage points annually over the subsequent years relative to other firms in their industry. Those firms that accompanied their innovations with an innovation-oriented collaboration raised their productivity by an additional 3.3 percentage points.

2. Background

There is a clear deductive case that change, spearheaded by improved knowledge, is necessary to enhance economic wellbeing. If knowledge is static, marginal returns to investment into more of the same plant, equipment or worker skills will eventually diminish to zero. Unless new-to-the-world, and subsequently new-to-the-firm, products and methods of production are realised, firm-level productivity will plateau and our standard of living will stagnate. By contrast, the returns to accumulated knowledge are unbounded for it is difficult to imagine a limit to advances in our stock of knowledge.

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1 See Hall (2011) for a review. Temporal or combined cross-sectional and time series firm-level estimations are more common for research and development and productivity studies (Hall, Mairesse and Mohnen (2010) found 45 such studies).

Two stylised facts stand out from the literature. First, persistent and large differences exist between firms in output per worker, even after allowing for the magnitude of tangible capital.[2] Second, these differences – and their persistence – are correlated with research and development (R&D) spending,[3] innovation activity,[4] collaboration,[5] and managerial acumen.[6] Both facts have been found across many countries, across and within industries, and when using pooled and fixed effects estimation methods.

Although suggestive, the estimated models behind this literature are, by and large, quite mechanical. Typically, they only explain between 15 and 20 per cent of the variation in firm output.[7] By mechanical we mean that the explanatory variables are merely counts of employed workers or (deflated) accounting values of past investments in plant, equipment and real estate.[8] To the man in the street, this model might seem too superficial. Even a casual observer of firms would expect two firms – of the same size and operating in the same market – to have different growth paths and profit outcomes. Although luck plays its inevitable role, common sense dictates that the dynamism of managers, the choice of products to develop, the choice of markets to seek and the choices about which internal processes to adopt also have a hand in firm performance. And this hand can be great.

The persistent differences between firms imply that these 'intangible' factors of production are difficult to buy off-the-shelf and are therefore not simply eroded by competition. Although managerial acumen and the insight about how to manage change are scarce, these skills can be hired, albeit within an imperfect market. Similarly, blueprints for technologies and products'

2 See Bartelsman and Doms (2000) and Syverson (2011) for surveys; Palangkaraya, Stierwald and Yong (2009) for Australian evidence; and Lokshin, Belderbos and Carree (2008) and Raymond *et al* (2013) for recent international evidence.

3 R&D typically only covers part of the spectrum of innovative activities. It usually correlates with upstream technological activities surrounding product and process innovation but misses organisational, managerial and marketing innovations. It is also a very poor indicator of innovation in many industries, especially the primary and services sectors where innovation expenditure is often defined informally. Nonetheless, analyses using R&D data provide valuable information that cannot be gleaned elsewhere. In an extensive review of 58 firm-level studies, Hall *et al* (2010) report that the evidence consistently finds that R&D spending by firms increases firm-level productivity. The average estimated elasticity is 0.08, which suggests that a 100 per cent increase in R&D spending per worker will raise output per worker by 8 per cent, *ceteris paribus*.

4 Studies that use more general measures of innovation are fewer and more recent than the R&D studies. However, most rely on cross-sectional datasets that are typically based on specially designed surveys of innovation activities. Griffith, Harrison and Van Reenen (2006) use a cross-section of Community Innovation Survey data from 1998 to 2000 for four countries, and find that product innovation is correlated with productivity in France, Spain and the United Kingdom but not Germany. Hall, Lotti and Mairesse (2009) find similar results for Italy; Halpern and Muraközy (2012) find that product innovation is correlated with productivity in Hungary. Panel estimations have only recently appeared. Bartelsman, Dobbelaere and Peters (forthcoming) show a positive effect of product innovation on labour productivity – an effect that is stronger for the most productive firms – using data from a sample of over 20 000 firms from Germany and the Netherlands between 2000 and 2008. They find no overall effect for process innovation and a negative effect of process innovation on the most productive firms. Bloom, Sadun and Van Reenen (2012) find evidence consistent with the view that the productive use of IT depends on complementary management practices. Raymond *et al* (2013) use two measures of innovation: a binary measure of whether an innovation has taken place and an intensity measure of the share of sales attributable to new products. Using a sample of about 3 000 firms from the Netherlands and France, they find clear results that innovation raises productivity. Furthermore, they observe a pattern in the data that suggests that, in the short run, innovation reduces labour productivity as firms adjust to their new production routines. Bartel, Ichniowski and Shaw (2007) use data on 290 distinct valve products made during 1999 to 2003 and find a clear positive effect of IT innovation on productivity. Hubbard (2003) also finds a positive impact of IT use on productivity in the trucking industry.

5 See Belderbos, Carree and Lokshin (2004).

6 See Green (2009) and Bloom and Van Reenen (2010).

7 Aiello and Ricotta (2014) find in their estimations for Italian firms that labour and tangible capital explain less than 20 per cent of the variation in firm output. Despite this, it is common in the literature to assume *a priori* that labour and tangible capital exhibit constant returns to scale (e.g. Lokshin *et al* 2008).

8 Strictly, tangible assets also include cash.

brands can be bought and sold via the intellectual property market. By contrast, firm-specific characteristics are less easy to buy and sell. These characteristics include:

- the synergies between skilled and experienced staff who are needed to forge change through an organisation
- know-how
- the presence of complementary teams within the firm
- governance structures appropriately tailored for the firm's position
- strategic informal contacts with external parties.

Given the observed clustering of successful innovators, it is also conceivable that the external environment – that is, local knowledge infrastructure and the depth of the labour market for innovation-savvy workers – matters. In this respect, knowledge infrastructure comprises the local institutions that support the generation, sharing and translation of ideas into commercial products. This includes mechanisms designed to compensate knowledge originators for the spillovers they create, such as: R&D tax credits; government procurement contracts for high-risk ventures; public investment into inter-firm and university-industry collaboration; and royalties from intellectual property.

Ultimately, policymakers want to know which factor from the list of potential factors is the most important driver of the 'unexplained' 80–85 per cent of firm performance. Encouraging firms that lack the necessary supporting internal and external factors to innovate without addressing these issues could be counterproductive. Policymakers need to answer: what effect would the adoption of an innovation strategy have on the firm performance of non-innovators? Alternatively: if innovation (either new to the firm or new to the world) systematically raises firm productivity, why do not all firms do it? Or, if it systematically lowers firm productivity, why do any firms do it?

Although we have derided the mechanical nature of existing productivity models, we find that models incorporating innovation can be just as empty and sterile. Including innovation as an explanation for productivity differences gets us only so far. Understanding the magic that makes some firms take the plunge – and some of these succeed – is still a work in progress.

3. Empirical Framework

To estimate if, and how, innovative activity affects productivity, we first need to estimate the productivity of each firm, while making sure there is no reverse causality (feedback from productivity to a firm's decision on whether to innovate or not). We follow the existing literature by specifying that the output of each firm *i* in year *t* (Y_{it}) can be represented by a common across-firm Cobb-Douglas production function of the form:

$$Y_{it} \equiv J_{it} K_{it}^{\alpha_k} L_{it}^{\alpha_l} \tag{1}$$

where J_{it} denotes the Solow or production residual, K_{it} denotes the tangible capital stock and L_{it} denotes the size of employment. J_{it} has also been called the intangible capital stock. We do not need a coefficient or exponent for J_{it} because it is not defined in natural units such as dollars or people. Using the corresponding lower case letters to denote the logarithmic values of the inputs and output above, Equation (1) can be rewritten as:

$$y_{it} \equiv j_{it} + \alpha_k k_{it} + \alpha_l l_{it}. \tag{2}$$

We assume that the log of the current production residual (j_{it}) is determined by the firm's measured ability (A_{it}) such that:

$$j_{it} = \beta A_{it} + \theta_i + u_{it} \tag{3}$$

where θ_i and u_{it} denote unobserved time-invariant firm-specific and random effects, respectively. We would expect that θ_i includes slow-changing managerial and worker skills.

Substituting Equation (3) into Equation (2) yields our augmented Cobb-Douglas function:

$$y_{it} = \beta A_{it} + \alpha_k k_{it} + \alpha_l l_{it} + \theta_i + u_{it}. \tag{4}$$

The problem with directly estimating Equation (4) is that analysts rarely have reliable measures of the level of *A*. Very occasionally we might have a monetary measure of the investment laid out on these stocks of intangibles,[9] but almost inevitably we do not have a measure of how much was spent or when the changes were effective.[10] Rather, datasets derived from survey questions typically provide measures of attempts to *change A* – that is, innovation. We denote innovation by *N*.

A further complication in the estimation process is knowing the appropriate interval between the introduction of a change and its ensuing effect on intangible capital stock. These time lags could vary by the type of change, the magnitude of the change, the industry of the firm or the technology introduced. In the immediate investment phase of an innovation, the effect on the stock of usable intangible capital could well be negative. Therefore, when we calculate the year-by-year effects, we may be averaging the effects over different phases (i.e. a negative, neutral and positive phase) of the life cycle of different innovations. So we recast Equation (3) as the current innovation *N* on the production residual with a lag of length *n*:[11]

$$\overline{j_{it+n}} - j_{it} = \beta N_{it} + \varepsilon_{it} \tag{5}$$

where $\overline{j_{it+n}}$ is the average production residual over *n* forward years. Although defining the model in this way stabilises the estimates, it makes the intuitive interpretation of β difficult. Strictly, β represents the average step-change in the productivity residual from year 0 to the average of years 1 to 4. However, given the average number of years in our dataset for $\overline{j_{it+n}}$ is 2.0, we will quote a value of β in terms of both the 'raw' estimate and the year-on-year approximation.

With substitution from Equation (2), the left-hand side of Equation (5) is equivalent to:

$$\overline{j_{it+n}} - j_{it} \equiv \left(\overline{y_{it+n}} - \alpha_k \overline{k_{it+n}} - \alpha_l \overline{l_{it+n}}\right) - \left(y_{it} - \alpha_k k_{it} - \alpha_l l_{it}\right). \tag{6}$$

9 For a discussion of how this problem relates to the accounting system, see Hunter, Webster and Wyatt (2012).

10 To the extent intangible investments are time-invariant (at least over a certain period), their effects will be conflated with the firm-specific fixed effects. There are often data limitations, as in this study, in terms of the length of the period covered or missing responses in some of the years which make it difficult to estimate Equation (4) directly using a dynamic panel model, such as found in Arellano and Bond (1991), Olley and Pakes (1996) or Blundell and Bond (2000).

11 To derive Equation (5) from Equation (3) consider, for example, the case of $n = 1$. Using Equation (2) and the definition of $\overline{j_{it+n}}$, we get that $\overline{j_{it+n}} - j_{it} = \overline{j_{it+1}} - j_{it} = j_{it+1} - j_{it} = \beta\left(A_{it+1} - A_{it}\right) + \left(u_{it+1} - u_{it}\right) = \beta N_{it} + \varepsilon_{it}$ where N_{it} is innovation introduced by the firm in period *t*. Note that in estimation, we use $N_{it} = A_{it} - A_{it-1}$ to reduce the extent of endogeneity (feedback effect) from the dependent variable $\left(\overline{j_{it+n}} - j_{it}\right)$ to N_{it}.

Our aim is to estimate the β in Equation (5). To do that we first need to estimate the change in the production residual from Equation (6). Then we regress the estimated $\overline{j_{it+n}} - j_{it}$ on innovation (N_{it}), as shown in Equation (5). By construction, we expect no feedback effect from net output (estimated using later period data) on N (measured from earlier period data). However, this proposition is testable.

We can expand Equation (5) by disaggregating firm-level innovation (N) into firm-level innovation in: the range of products (P_{it}); managerial processes (M_{it}); operational procedures (O_{it}); and marketing methods (D_{it}), such that:

$$\overline{j_{it+n}} - j_{it} = \beta_p P_{it} + \beta_m M_{it} + \beta_o O_{it} + \beta_d D_{it} + \varepsilon_{it}. \quad (5a)$$

Furthermore, we can also expand Equation (5) by including the effect of prior collaborations on changes to intangible capital stock by including a prior collaboration variable (C_{it}) in the estimation.

$$\overline{j_{it+n}} - j_{it} = \beta_p N_{it} + \beta_c C_{it} + \varepsilon_{it}. \quad (5b)$$

Equations (5), (5a) and (5b) are our main estimating equations.

4. The ABS Data

Our empirical analysis uses an unpublished, confidential Australian Bureau of Statistics (ABS) dataset of over 7 000 Australian SMEs for the period 2005/06 to 2011/12. In this dataset, Business Characteristics Survey data is linked by Australian business number to the corresponding business income taxation and business activity taxation data (the taxation data is from the Australian Taxation Office (ATO)). To contain respondent burden, firms are rotated out of the survey after five years and replaced by a new cohort. The response rate for the survey was approximately 95 per cent in all years.[12] After we exclude firms from agriculture, forestry and fishing, we are left with 23 380 firm-year observations. For the analysis of these data, the data extraction and execution of our programs was undertaken by officers of the ABS who removed all identifiers from the outputs before release.

The advantage of this dataset is twofold: size and diversity. With the exception of R&D studies, most existing studies use datasets that are either cross-sectional, small or unrepresentative. Although suggestive, one cannot draw strong causality conclusions from these studies – a causal analysis should, as a minimum, include both cross-sectional and time-series dimensions. Second, the explanatory and dependent variables in the ABS dataset are drawn from separate sources. As it is much harder to find patterns in data drawn from independent sources, any statistically significant results have an additional degree of robustness. It is too easy to find correlations in data reported by the same respondent.

We define our time of analysis to be the survey sequence year, not calendar year, due to the cohort rotation. This means we model the effect of a change in innovation (N) in year 0 on the average yearly growth in productivity over the subsequent one to four years (bearing in mind we are using an unbalanced panel of up to five years).

Table A1 compares our sample with the estimated population of SME firm counts. It shows an over-representation of mining and manufacturing firms and an under-representation in construction,

12 Firms are directed by the Australian Government to complete the survey and the response rate is very high.

retail trade, professional, scientific & technical services, and health care & social assistance firms. Aside from these differences, the sample is broadly representative. Table A2 shows that nearly two-thirds of firms were private companies, one in five were trusts and one in ten were partnerships.

A full description of the variables used in the estimations is presented in Table A3. Briefly: the value of output is total sales less material inputs; the value of the tangible capital stock is non-current assets; and employment is the number of persons working in the firm during the last pay period. To control for cross-industry effects in the productivity estimates, we normalise each variable in the production function with respect to the industry average for each year. For variables denoted in current prices, such as output and tangible capital, the normalisation also substitutes for the need for industry-specific price deflators (Klette 1999).[13] Flow variables refer to activity up until year-end 30 June and stock variables are as of 30 June. The first stage, Equation (2), only includes (normalised) output, capital stock and employment.

In the second stage (Equations (5), (5a) and (5b)) we regress $\overline{j_{it+n}} - j_{it}$ against prior measures of innovative activities. We measure the explanatory variable – innovation – in three different ways:

- a binary variable for whether or not the business introduced any new or significantly improved goods and services, operational processes, organisational and managerial processes or marketing methods
- the mean number of types of innovations introduced (from a possible 19 types)[14]
- a factor comprising: the four types of business innovation listed above; the number of types of innovations introduced; whether the firm had been involved in a collaboration; whether the firm had collaborated for the purpose of innovation; and the extent of business focus on innovation.

All innovation variables relate to the firm's activity in the year to 30 June.

In Equation (5a), we disaggregate innovative activity into the four main types listed in the first bullet point above. In Equation (5b), we test for the effect of prior collaboration in two possible ways. First, whether the firm was involved in a collaborative arrangement for any purpose such as marketing, joint buying, manufacturing, supply chain access or R&D. Second, whether the business collaborated specifically for the purposes of innovation (given the firm had introduced an innovation). We are able to disaggregate the second measure according to whether the partners were in Australia or overseas, or were from a research-oriented organisation (science-based collaboration) or not. All collaboration variables relate to the firm's activity in the year to 30 June.

Table 1 presents the mean and standard deviation for these variables for the first and last years of our dataset. The mean value of output was \$1.14 million in 2005/06 and \$1.41 million in 2011/12. The mean

13 The alternative is using either a combination of broader GDP or sector price deflators or nominal values. Our estimates are robust to whether or not we use nominal values.

14 Separately identified innovations comprise new or significantly improved: goods; services; methods of manufacturing or producing goods or services; logistics, delivery or distribution methods for goods and services; supporting activities for business operations; other operational processes; knowledge management processes; the organisation of work; business practices for organising procedures; methods of organising work responsibilities and decision-making; significant changes in relations with others; methods of organising external relations with other firms or institutions; other organisational/managerial processes; the design or packaging of a good or service; media or techniques for product promotion; sales or distribution methods/methods of product placement or sales channels; methods of pricing goods or services; and other market innovation.

value of tangible capital stock was $0.96 million and $1.05 million. Average employment was close to 17 people in both years.

About half of all firms had introduced an innovation (either new to the firm or new to the world) in the last 12 months. The type of innovation introduced was evenly split between: new good or service; operational processes; organisational and/or managerial processes; and marketing. In 2005/06, 12 per cent of SMEs had participated in at least one collaboration; 17 per cent had done so in 2011/12. About 10 per cent had participated in an innovation-specific collaboration (in both 2005/06 and 2011/12). Of these innovation-oriented collaborations, most were with Australian-based organisations and very few were with science-based organisations.[15]

Table 1: Summary of Dataset Statistics

Variable	2005/06 sample		2011/12 sample	
	Mean	Standard deviation	Mean	Standard deviation
Output (A$m)	1.14	1.75	1.41	2.26
Tangible capital stock (A$m)	0.96	2.32	1.05	2.45
Employment	16.91	22.02	16.72	21.74
Change in intangible capital stock	0.61	0.78	0.58	0.73
Innovation business focus	1.34	1.04	1.39	1.04
Innovation introduced	0.50	0.50	0.47	0.50
Innovation diversity	0.07	0.10	0.07	0.11
New good or service	0.26	0.44	0.22	0.41
Operational processes	0.30	0.46	0.24	0.43
Organisational/management processes	0.27	0.44	0.27	0.44
Marketing method	0.20	0.40	0.24	0.42
Collaboration – any	0.12	0.33	0.17	0.38
Collaboration – innovation	0.09	0.29	0.11	0.31
Innovation introduced and collaborated (Australia)	0.07	0.26	0.03	0.16
Innovation introduced and collaborated (overseas)	0.02	0.14	0.003	0.06
Innovation introduced and collaborated (science-based)	0.01	0.09	0.002	0.04

Notes: 2005/06 sample consists of 1 697 observations; 2011/12 sample consists of 2 332 observations
Sources: ABS; ATO; Authors' calculations

15 To accommodate selection bias resulting from innovations that fail and subsequently force the firm to close, we exclude all firms which disappear from the survey before the last year of the dataset (2011/12).

5. Results

The results from estimating the first stage, Equation (2), are presented in Table 2. They show output elasticities with respect to measured tangible capital stock and employment at 0.058 and 0.390, respectively. As shown in columns 2 and 3 of Table 2, these estimates are slightly higher if we exclude the not-for-profit sector and outliers.

Table 2: First-stage Fixed-effects Estimation
Dependent variable is the value of output, years 1 to 4

Explanatory variables	Full sample	Excluding firms in not-for-profit sector[(a)]	Excluding firms in not-for-profit sector and outliers[(a)(b)]
Log (value of tangible capital stock)	0.058***	0.061***	0.136***
	(0.012)	(0.013)	(0.018)
Log (level of employment)	0.390***	0.399***	0.476***
	(0.019)	(0.020)	(0.024)
Observations	15 195	14 474	8 384
R^2-within	0.059	0.061	0.117
Groups	7 527	7 166	4 512
ρ	0.811	0.808	0.905

Notes: Variables have been normalised with respect to the corresponding 2-digit ANZSIC industry average in each year; *, ** and *** denote coefficient estimates are statistically significant at the 10, 5 and 1 per cent levels respectively; standard errors are in parentheses; constant included
(a) Not-for-profit sector comprises: administrative and support services; public administration and safety; and education and training
(b) Any firm with an annual change in the value of output, value of tangible capital stock or employment in the top or bottom 5 per cent of observations is called an outlier

Sources: ABS; ATO; Authors' calculations

Before we continue to the second stage of the estimation, it is worth making a comment about the size of these estimates, which at first glance seem to imply diseconomies of scale. Much discussion has occurred in the literature about why panel estimations of standard Cobb-Douglas production functions do not give something approximating constant-returns-to-scale technology. However, we believe elasticities of this order are economically logical given that constant returns to scale assumes that *all* inputs change *pari passu*. As discussed above, labour and tangible assets do not constitute all the fundamental factors of production. There are other very important intangible factors such as managerial talent, know-how, synergies in the workplace and the governance of the business. Accordingly, we expect that we would observe diminishing returns if we increase only the combination of (head counts of) labour and tangible assets, *ceteris paribus*. Nonetheless, for our purposes, we only need an unbiased measure of the mean fixed effect plus a random error term $\left(\overline{j_{it+n}}\right)$ for each firm. These residuals relate to productivity in years 1 to 4, and have been normalised for industry.

From Table 2, in the full sample, we calculate the log of the production residual for firm *i* in year 0 as:

$$j_{i0} = y_{i0} - 0.058 * k_{i0} - 0.390 * l_{i0} - constant.$$ [16]

We use the difference $\left(\overline{j_{i1,2,3,4}} - j_{i0}\right)$ as the dependent variable in the estimation of Equations (5), (5a) and (5b).

The second stage – Equations (5), (5a) and (5b) – comprises: two measures of overall innovative activity; four disaggregated measures of innovation; and five measures of collaboration. Since the model has been specified in logs, the β coefficients shown in Tables 3 to 5 give the semi-elasticity (percentage point change in output).

As shown in column (1) in Table 3, introducing an innovation in year 0 increased productivity (production residual) by 5.4 percentage points. This increment of 5.4 represents the change between year 0 and the average of years 1 to 4. Given that the average time span was 2.0 years, we can say that the introduction of an innovation leads to an annual productivity increase of 2.7 percentage points. For example, if the production residual of a non-innovator increased by 1 percentage point a year, the residual for the innovator would increase by 3.7 percentage points a year. Column (2) indicates that introducing all 19 sub-types of innovation, compared with no innovation at all, would predict a rise in productivity of about 30 percentage points (or 15 percentage points per year).[17] These findings are echoed by column (3), which uses the innovation factor as the explanatory variable.

Columns (4) and (5) use the presence of collaborative arrangements as a predictor of productivity growth. They show that collaboration for any reason has no effect on productivity, but collaboration for the purpose of innovation raises productivity by 8.2 percentage points (or 4.1 percentage points per year).

Bearing in mind that the four disaggregated types of innovation are not mutually exclusive, we find that only goods and services and marketing methods innovation had an impact on productivity. Column (6) shows that good or service innovation had a positive and significant effect on productivity (a rise of 6.5 percentage points, or 3.2 percentage points per year) but the coefficients for the other forms of innovation are not statistically significant. The null finding for operational processes and organisational and managerial innovation does not rule out the possibility that these forms of innovation have an effect. There could be an effect that evaporates within a shorter time window or only emerges after the five-year window.

16 We use stored values and calculate to seven decimal places.

17 Because our model is semi-log and the right-hand side variables are levels, the coefficients can be read directly as semi-elasticities.

Table 3: Second-stage Fixed-effects Estimation – Innovation

Percentage points

	(1) Equation (5)	(2) Equation (5)	(3) Equation (5)	(4) Equation (5b)	(5) Equation (5b)	(6) Equation (5a)
Innovation introduced (1/0)	5.4*** (1.9)					
Innovation diversity (0 to 1)		27.9*** (9.4)				
Innovation (factor)			3.5*** (1.1)			
Collaboration (any reason)				2.2 (2.7)		
Collaboration (innovation)					8.2*** (3.0)	
Type of innovation introduced						
New good or service (1/0)						6.5** (2.6)
Operational processes (1/0)						–3.1 (2.6)
Organisational/ management processes (1/0)						3.0 (2.6)
Marketing method (1/0)						4.0 (2.6)
Observations	7 140	7 140	7 141	7 141	7 141	7 140
R^2	0.001	0.001	0.016	0.001	0.001	0.002

Notes: Change in production residual between year 0 and the average of years 1 to 4; variables have been normalised with respect to the corresponding 2-digit ANZSIC industry average in each year; *, ** and *** denote coefficient estimates are statistically significant at the 10, 5 and 1 per cent levels respectively; standard errors are in parentheses; constant included

Sources: ABS; ATO; Authors' calculations

Table 4 tests for the effects of collaboration over and above the effect of introducing an innovation. As can be seen in column (1), there are no additional effects from collaborating for any reason. However, if the collaboration was for the purposes of innovation the average production residual increases by 6.7 percentage points, or 3.3 percentage points per year (column (2)). Collaborating with an Australian-based partner raises average yearly productivity growth by 8.9 percentage points or 4.4 percentage points per year (column (3)) but there is no effect arising from an overseas partner or a science-based organisation (column (4)).

Table 4: Second-stage Fixed-effects Estimation – Collaboration
Percentage points

	(1) Equation (5b)	(2) Equation (5b)	(3) Equation (5b)	(4) Equation (5b)
Innovation introduced	5.3*** (1.9)	4.5** (2.0)	4.7** (2.0)	5.4*** (1.9)
And collaboration (any reason)	0.9 (2.7)			
And collaboration (innovation)		6.7** (3.1)		
And collaboration (Australia)			8.9** (4.3)	
And collaboration (overseas)			–8.2 (9.5)	
And collaboration (science-based)				2.9 (13.1)
Observations	7 140	7 140	7 140	7 140
R^2	0.001	0.002	0.002	0.001

Note: See notes to Table 3

Sources: ABS; ATO; Authors' calculations

We started this article with a discussion of how these mechanical productivity estimations have limited power to explain why some firms innovate and succeed and others do not. We conjectured that this limited power is because qualitative factors, such as managerial skill and the energy and dynamism of staff, matter for the success of innovation. Although we do not have data on these factors, information on the degree of competition in the firm's product market may shed some light. If the degree of competition drives how well the firm converts innovation into productivity growth, then we have a small step towards understanding what makes firms succeed.

We define a dummy variable for being in a competitive market which is equal to one if the firm exports, has at least one product market competitor, or is foreign owned. It is zero otherwise.

Table 5 presents the main innovation and collaboration results according to a sample split on this competitive market variable. It reveals that innovation is only successful in a competitive market. However, this result is qualified by the small sample size of the 'not competitive' group. Of more interest is the size and significance of the 'collaboration for the purpose of innovation' variable. It is large (22.9 percentage points, or 11.4 percentage points per year) and significant for firms that are not in competitive product markets. This suggests that collaboration for innovation may substitute for inexperience or lack of skill by management.

Table 5: Second-stage Fixed-effects Estimation – Competition

Percentage points

	(1)		(2)		(3)		(4)		(5)	
	Competitive	Not competitive	Competitive	Not competitive	Competitive	Not competitive	Competitive	Not competitive	Competitive	Not competitive
Innovation introduced (1/0)	4.9** (2.0)	5.7 (7.5)								
Innovation diversity (0 to 1)			25.4*** (9.7)	34.9 (4.77)						
Innovation (factor)					3.1*** (1.1)	4.5 (4.8)				
Collaboration (any reason)							2.0 (2.8)	–0.4 (11.8)		
Collaboration (innovation)									7.1*** (3.1)	22.9* (12.8)
Observations	6 542	598	6 542	598	6 542	598	6 542	598	6 542	598
R^2	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.005	0.001	0.001

Note: See notes for Table 3

Sources: ABS; ATO; Authors' calculations

6. Conclusion

Until now, there have been no large-scale firm-level econometric analyses of the effects of innovation (and collaboration) on firm productivity for Australia. Our headline conclusion is that SME firms that previously introduced innovations had an annual productivity increase that was 2.7 percentage points higher than non-innovating firms over the subsequent year. Furthermore, innovating firms with Australian-based collaborations raised their productivity by 4.4 percentage points per year.

Given the nexus between profits and productivity, one might well ask: why don't all firms innovate? Why doesn't competition force all firms to be active and aggressive promoters of new products and ways of operating? One explanation is that competition is simply missing in many markets. Managers may know what would improve performance but lack the incentives from competition or the owners of the business to implement them.

However, competition, or lack thereof, may not be the only explanation. Economic theory tells us that some factors of production can be difficult to replicate; some firms possess these and others do not. A factor that is not easily imitated will not be eroded by competition. The managerial literature is more advanced and nuanced on this point. According to Bloom *et al* (2013), managers might not innovate because they do not realise that they are inefficient or, if they do, they may not know how to implement the necessary changes. A complicated constellation of complementary activities may be needed for success, such as: particular collaborations; specialist in-house skills; intellectual property; marketing activities; capital investments; and training for employees. Identifying what these factors are is the Holy Grail and the subject of our ongoing research.

Appendix A: Data Summary

Table A1: Counts of SME Firms

Industry (ANZSIC06)	ABS population count		ABS BCS-BAS-BIT sample (used in first-stage estimation)	
	June 2012	Share of total	2005/06 to 2011/12	Share of total
Mining	3 712	0.5	995	4.2
Manufacturing	49 472	6.4	3 740	15.8
Electricity, gas, water and waste services	2 727	0.4	376	1.6
Construction	135 640	17.6	1 849	7.8
Wholesale trade	41 422	5.4	2 125	9.0
Retail trade	80 251	10.4	1 455	6.2
Accommodation and food services	58 630	7.6	1 566	6.6
Transport, postal and warehousing	40 448	5.2	1 884	8.0
Information media and telecommunications	7 229	0.9	1 130	4.8
Financial and insurance services	33 136	4.3	452	1.9
Rental, hiring and real estate services	32 361	4.2	1 270	5.4
Professional, scientific and technical services	111 746	14.5	1 645	7.0
Administrative and support services	36 218	4.7	1 048	4.4
Public administration and safety	3 744	0.5	11	0.0
Education and training	11 735	1.5	33	0.1
Health care and social assistance	50 195	6.5	343	1.5
Arts and recreation services	9 072	1.2	1 037	4.4
Other services	48 782	6.3	1 699	7.2
Not known	14 668	1.9	995	4.2
Total	771 188	100.0	23 653	100.0

Notes: 1–199 employees, excludes agriculture, forestry and fishing; BCS = Business Characteristics Survey; BAS = business activity statement; BIT = business income tax

Sources: ABS; ATO

Table A2: ABS BCS-BAS-BIT Sample by Type of Legal Organisation

Type of legal organisation	Per cent
Public (limited)	0.7
Private (proprietary limited)	63.3
Partnership	11.7
Trust	23.1
Other	0.8
Total	100.0

Notes: See notes to Table A1; 2008 TOLO Classification
Sources: ABS; ATO

Table A3: Variable Definition – ABS BCS-BAS-BIT Sample
(*continued next page*)

Variable	Source	Definition	Scale
Sales	BAS	Total sales; A$ million	2.45
Material inputs	BIT	Cost of sales for tax purposes; A$ million	1.49
Tangible capital stock	BIT	Non-current (derived) assets; includes assets that the company holds for at least one year, e.g. cars, land, buildings, office equipment, computers, bonds, stocks, notes, patents, trademarks, and goodwill; A$ million	0–41.5
Employment	BCS	Number of persons working for this firm during last pay period	0–250
Innovation business focus	BCS[(a)]	Business focus = innovation focus > 0	0/1
Innovation introduced	BCS[(a)]	Introduced any new or significantly improved: good or service; operation processes; organisational/managerial processes; marketing methods	0/1
Innovation diversity	BCS[(a)]	Number of different types of innovations introduced	0–19
New good or service	BCS	Introduced any new or significantly improved: goods; services	0/1
Operational processes	BCS	Introduced any new or significantly improved: methods of manufacturing or producing goods or services; logistics, delivery or distribution methods for goods or services; supporting activities for business operations; other operational processes	0/1

Table A3: Variable Definition – ABS BCS-BAS-BIT Sample
(*continued next page*)

Variable	Source	Definition	Scale
Organisational/ management processes	BCS	Introduced any new or significantly improved: knowledge management processes; organisation of work; business practices for organising procedures; methods of organising work responsibilities and decision-making; significant changes in relations with others; methods of organising external relations with other businesses or institutions; other organisational/managerial processes	0/1
Marketing method	BCS	Introduced any new or significantly improved: design or packaging of a good or service; media or techniques for product promotion; sales or distribution methods/methods of product placement or sales channels; methods of pricing goods or services; other market innovation	0/1
Innovation introduced – science-based	BCS[a]	Introduced an innovation and sources of ideas/information were: universities or other higher education institutions; government agencies; private non-profit research institutions; commercial laboratories/R&D enterprises	0/1
Innovation introduced – non-science-based	BCS[a]	Introduced an innovation and not science-based as defined above	0/1
Collaboration – any	BCS	Has a cooperative ('collaborative' from 2007/08 onwards) arrangement (any type)	0/1
Collaboration – innovation	BCS	Introduced an innovation and collaborated for innovation	0/1
Innovation introduced and collaborated (Australia)	BCS[a]	Introduced an innovation and collaborated within Australia for innovation	0/1
Innovation introduced and collaborated (overseas)	BCS[a]	Introduced an innovation and collaborated overseas for innovation	0/1
Innovation introduced and collaborated (not stated)	BCS	Introduced an innovation and collaborated (location not stated) for innovation	0/1

Table A3: Variable Definition – ABS BCS-BAS-BIT Sample
(*continued*)

Variable	Source	Definition	Scale
Innovation introduced and collaborated (science-based)	BCS[(a)]	Introduced an innovation and collaborated with a science-based organisation (as defined above) for innovation	0/1
Innovation introduced and collaborated (non-science-based)	BCS[(a)]	Introduced an innovation and collaborated with a non-science-based organisation (as defined above) for innovation	0/1
Captive market/ no effective competition	BCS[(a)]	Number of competitors = captive market/no effective competition	0/1
Foreign-owned	BCS	Business reports any degree of foreign ownership	0/1
Core skills – engineering, IT, science and research professionals	BCS[(a)]	Skills used in undertaking core business activities include all of engineering, IT, scientific and research professionals	0/1
Business years in operation	BCS	Years of operation	0–100

Note: (a) These BCS items are derived from directly collected data items; all variables relate to the firm's activity in the year to June 2012

Source: ABS

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