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Competition, Innovation and Productivity in Australian Businesses

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Competition, Innovation and Productivity in Australian Businesses

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INQUIRIES

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CONTENTS

COMPETITION, INNOVATION AND PRODUCTIVITY IN AUSTRALIAN BUSINESSES: A FIRM-LEVEL ECONOMETRIC ANALYSIS

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ABSTRACT

This paper investigates two important relationships relating to firm behaviour and performance using econometric methods. First, the relationship between product market competition and innovation is examined, and then the association between innovation and productivity is separately investigated. Data from the Australian Bureau of Statistics' Business Longitudinal Database are used in the analysis. Cross-sectional modelling is employed to investigate the association between competition and innovation, with further models exploring the link between innovation and productivity. For every measure of competition considered except one, the results of the modelling are consistent with an anti-Schumpeterian relationship between competition and innovation – that is, firms appear more likely to innovate if they face stronger competition. The results examining the relationship between innovation and productivity, although weaker than those between competition and innovation, suggest that innovation is associated with better productivity outcomes.

KEY POINTS

- Economic theory in the area of competition and innovation suggests that there are many possible relationships between the two. This paper tests a Schumpeterian relationship (where increased competition is associated with less innovation), and an 'anti-Schumpeterian' relationship (where increased competition is associated with more innovation).
- For all but one of the competition measures used, the results indicate that stronger competition is associated with a higher propensity for firms to innovate – that is, an anti-Schumpeterian view.
    - Having more competitors, having a lower price-cost margin (a measure of mark-up over cost), being an exporter, and reporting downward pressure on profit margins in order to remain competitive, are all associated with a significantly higher probability of being an innovator.

- The models also indicate that a greater market share and larger firm size (as measured by the number of employees) are positively associated with innovation.
    - Other empirical studies, where these characteristics have served as the only competition measures, have sometimes interpreted such a finding as evidence of a Schumpeterian relationship.
    - The result found in this paper is discussed in the context of the wider set of other competition variables employed here.
- Statistically significant associations are also found between certain competition-related variables and the presence of a larger number of different types of innovation being completed and a higher degree of novelty of those innovations. For example:
    - firms that have a lower price-cost margin and those that report facing downward pressure on profit margins to remain competitive are both more likely to undertake a larger number of different types of innovation,
    - firms that are exporters and firms with a higher market share are both more likely to undertake innovations with a higher degree of novelty.
- A large degree of dependence is found between the probabilities of different innovation types being completed by a firm.
- The modelling also indicates a positive and statistically significant association between each of four types of innovation (goods and services, organisational process, operational process, and marketing) and higher productivity reported by the firm.
- Data limitations give rise to two important caveats to the findings of this paper:
    - the lack of a sufficient time dimension to the data results in only cross-sectional (snap-shot) analysis being viable – this precludes conclusions regarding causality and its direction.
    - much of the data is in the form of subjective judgements by survey respondents.
- Nevertheless, this paper provides useful ‘snapshots’ of the association between competition and innovation, and between innovation and productivity in Australian businesses. The results are consistent with much of the established literature, and are distinguished from that literature by greater industry coverage and a variety of different competition measures.

1. INTRODUCTION

This paper investigates two important relationships between firm behaviour and performance using econometric methods. First, the relationship between product market competition and innovation is examined, and then the association between innovation and productivity is separately investigated.

The relationship between competition and innovation is a complex one. Competition evolves over time as firms enter and leave the market, as new products and processes are introduced, and as firms employ different strategies with regard to their competitors. In an effort to better capture the complexity of product market competition and the variety of business responses to changes in such competition, a number of different competition indicators are used in this analysis: market share, number of competitors, price-cost margin, export status, and whether or not a business reports downward pressure on its profit margins in order to remain competitive (further details on these and other variables used in the analysis are provided in Section 3).

Innovation and the evolution of productivity are also complex processes. At any point in time, firms evaluate their competitive position and make strategic decisions about whether and how to engage in innovation. Decisions to invest in innovation activity will in general meet with varying degrees of success and have different implications for the evolution of productivity.

To now there has been relatively little analytical scrutiny of the relationships between competition, innovation and productivity at the firm level in Australia, largely due to a lack of suitable data. However, the recently developed Australian Bureau of Statistics' (ABS) Business Longitudinal Database (BLD) – a dataset of firm characteristics, tax and trade information – provides new opportunities for firm-level analysis in Australia, and is the data source employed for analysis in this paper.

There is a wealth of theoretical literature on the link between competition and innovation. The main two long-established competing theories are: the 'Schumpeterian' theory, that greater levels of competition faced by firms lead to less innovation, and the 'anti-Schumpeterian' theory, that greater levels of competition lead to more innovation.

A more recent theory developed by Aghion *et al.* (2005) suggests that both Schumpeterian and anti-Schumpeterian responses to competition can occur depending on the technological diversity of the particular product market in question. Where the product market is characterised by firms of similar technological sophistication, an increase in competition will lead to a greater innovation effort – the so-called 'escape competition effect'. However, where firms are widely dispersed in terms of technological sophistication, an increase in competition (among technological leaders) will lead to a decrease in innovation effort. The balance of these technological market characteristics across the various product markets in an economy determines whether an increase in competition will generally be expected to increase or decrease the aggregate flow of innovation. If competition is at a relatively low level, an increase in competition is more likely to lead to an increase in innovation, but if the level of competition is already high, an increase in competition is more likely to decrease aggregate innovation. In this way the relationship between aggregate innovation and the level of competition follows an inverted 'U' shape.

The Aghion model is an important development as it allows for the reconciliation of what until recently appeared to be inconsistent theories. However, this model can not be tested in this paper as it has not been possible to identify product markets and their associated technological dispersion using the data available.

There is also a wealth of empirical literature that has examined the link between competition and innovation, but with many more overseas studies than Australian works. A variety of competition and innovation measures have been employed in these investigations, some of which have been incorporated into this paper. Based on the difficulty of measuring competition and the variety of ways firms might respond to competitive pressures, several different competition measures are used simultaneously in the regressions included in this paper to obtain a more complete picture of how firms react in the face of competition.

The nature of the relationship between innovation and productivity has also been the subject of much empirical work. Many studies have found innovation to be an important driver of productivity at the firm level. The link between innovation and productivity is examined in this paper using proxies for productivity, as good measures of productivity at the firm level are difficult to obtain. There are many reasons why firms competing in the same product market may be subject to different input prices and may price their outputs differently. As such it is not possible to properly deflate revenues (and input costs) to obtain the volume measures necessary for reliable productivity estimates.[1]

Discrete choice modelling techniques are employed in view of the categorical nature of the innovation and productivity data in the BLD. Also, the limited time dimension to the data (because the BLD is yet quite young) constrains the modelling to a cross sectional analysis of the relationship between competition and innovation. Binary, ordered, and multivariate probit models are used to test what characteristics of firms (including in particular, various competition measures) are associated with the propensity to innovate in general, and to undertake different types of innovations and innovations with different degrees of novelty. Discrete choice modelling

1 This problem is examined in great detail by Foster *et al.* (2005).

methods are used to examine the association between innovation measures and productivity outcomes.

These techniques test the relationships of interest and provide estimates of the magnitude of the changes in the probability of a firm conducting a particular type of innovation associated with given changes in relevant firm characteristics – for example the change in the likelihood of a particular type of innovation when selected competition measures are changed.

This paper is analytical in nature and does not consider any policy related implications of the analytical findings.

2. LITERATURE[2]

This section examines some of the theoretical and empirical literature on the relationship between competition, innovation and productivity. Particular attention is paid to the competition, innovation and productivity measures used in this literature in order to facilitate comparison with the measures used in this paper.

Although inquiry into aspects of the competition/innovation relationship goes back much further, the work generally cited as the seminal contribution to the subject is that of Schumpeter (1942) in which it was argued that stronger competition leads to less innovation activity. The basic reasoning behind the theory is that the incentive to innovate arises from the potential profits accruing to the innovating firm, and that such profits will be higher where firms have a degree of market power. This view was supported by the empirical work of Scherer (1965) in which a positive relationship between patenting activity and firm size was identified. Another size-related argument takes the position that innovation activity involves significant additional cost and higher than usual risk, and larger firms with greater market share are generally better equipped to manage the expense and risk of innovation, whereas smaller firms may not be able to survive the financial consequences of even a single unsuccessful innovation. That is, smaller firms with relatively little collateral and relatively small pools of liquid equity assets are likely to find funding of innovation more difficult, as well as lacking the risk attenuating benefits of having a number of diverse innovation activities.

More contemporary models of Schumpeterian theory include Salop's 'Circular Model' (Salop, 1977) and the Dixit–Stiglitz model (Dixit and Stiglitz, 1977) in which firms facing similar costs of entry choose whether to enter the market or not, and innovation is modelled as a differentiated good (that is, a product that faces higher demand relative to the other goods in the market at the same price). Where there is strong competition in the market, the benefit from innovating (having a more strongly differentiated good) is lower compared to the situation where competition is weaker. Essentially, the post-entry rent is smaller for innovators in the presence of higher levels of competition. These models therefore suggest a negative (Schumpeterian) association between competition and innovation.

On the other hand there is also a wealth of literature suggesting that, contrary to the Schumpeterian position, competition is likely to be positively associated with innovation. This 'anti-Schumpeterian' view maintains that: patents can protect innovation rewards, so broad market power is unnecessary to harness the fruits of innovation; well functioning credit and insurance markets can allow small firms to

2 For an excellent synthesis paper examining the empirics and theory of competition, innovation and productivity between Schumpeterian and anti-Schumpeterian results see Ahn (2002).

finance and bear the risk of innovation; and firms in a highly competitive market must also innovate in order to avoid being left behind and ultimately failing.

Other ‘anti-Schumpeterian’ arguments include the ‘replacement effect’ identified by Arrow (1962): when a monopolist (or near monopolist) innovates, it replaces its existing stream of rents with a new one. Entrant firms, on the other hand, increase their market share (from nothing) by entering the market with a valuable innovation. In other words, new and smaller firms that innovate have more to gain from securing new additional market share compared to larger firms that may already be close to the limits of their market. More recent work by Aghion and Schankerman (2004) revisits the Dixit–Stiglitz type model and suggests that those firms that innovate in order to lower their costs can stimulate further innovation as other firms attempt to ‘catch-up’. In other words, strong competition to reduce costs leads to greater innovation activity.

A more recent theory of competition and innovation proposed by Aghion *et al.* (2005) suggests that the relationship between competition and innovation follows an inverted-U shape. Aghion *et al.* derive a framework that incorporates elements of both Schumpeterian and anti-Schumpeterian theory to arrive at their conclusion, which is then examined empirically using data from the UK (discussed below). The Aghion *et al.* framework is an attractive theory as it allows the potential reconciliation between Schumpeterian and anti-Schumpeterian results that have been found previously.

Economic theory is mixed on the nature of the relationship between competition and innovation, as are the findings of the associated empirical work. In part, this may be because different measures of competition and innovation are used in different countries with different market structures. However, the choice of such measures and the nature of the associated results, are of interest in the design of the econometric analysis used in this study. As such, a closer examination of the more recent empirical work at the firm level is useful.

Nickell (1996) uses a panel of around 670 UK manufacturing companies over a 14 year period to conduct analysis on competition and productivity. Competition is measured (inversely) by the level of rents a firm receives, proxied by an average of sales less capital costs, normalised by value added. Productivity is measured using a form of total factor productivity. The findings indicate that greater competition is associated with higher productivity growth. While the paper does not explicitly address innovation, it does directly link competition and productivity.

Blundell, Griffith and Van Reenan (1999) use a panel of 340 firms over the period 1972 to 1982 drawn from the London stock exchange as the basis for their analysis. Competition is modelled by the firm’s market share and the degree of product market concentration (measured as the share of sales of the five largest firms in the industry in question), while innovation is measured by counting the number of patents that the firm applied for (on the basis that patent applications is a good proxy for innovation activity). The study finds a positive association between product market competition and innovation activity – an anti-Schumpeterian finding – while also finding a positive relationship between market share and the number of patents a firm applies for – a Schumpeterian finding. The authors examine a range of explanations as to why this latter finding might be so, such as the desire of high market share firms to 'pre-emptively' innovate in order to discourage entry. The phenomenon of different measures of competition leading to different signs on the relationship between competition and innovation is discussed at some length later in this paper.

In addition to a theoretical basis for the inverted-U relationship, Aghion *et al.* (2005) examine the nature of the inverted-U in a panel of 311 firms over a 21 year period. Competition is modelled by a 'Lerner measure' (an indicator that tracks the extent to which output price exceeds aggregate input price) and innovation is measured using a citation-weighted patent count. The study finds an inverted-U shaped relationship – that is, a peak in predicted citation weighted patents for a specific level of competition, tapering off on either side of that level.

Griffith, Harrison and Simpson (2006) employ a panel of twelve manufacturing *industries* over a thirteen year period to examine the relationship between competition, innovation and productivity. Competition, represented by the reduction in average firm profitability associated with the implementation of the EU single market program, is modelled with innovation, which is represented by R&D expenditure as a share of value added within an industry. Productivity is measured using a total-factor productivity variable. The study finds that the EU single market program led to increased competition which in turn was associated with increased innovation intensity and productivity growth in the manufacturing sector. This is an anti-Schumpeterian result.

Grünewald (2009) uses a panel of 1800 Swedish firms to examine the nature of competition and innovation in that country. The competition measure employed is a price-cost margin (similar in nature to the Aghion *et al.* measure) while innovation is taken to be R&D expenditure. The study finds that higher levels of competition are associated with higher R&D expenditure, but only for firms that are not severe technological laggards. No support is found for an inverted-U shaped relationship.

Polder and Veldhuizen (2010) use a panel of 234 observations at the industry level and 14,000 observations at the firm level between 1999 and 2006 to investigate the relationship between competition and innovation in the Netherlands. Competition is again represented by a mark-up measure (like Aghion *et al.* and Grünewald) and alternatively by a profit elasticity measure.[3] Innovation is measured by R&D as a share of firm value added. The study finds an inverted-U relationship at both the industry and firm level when the profit elasticity measure is used as the competition measure.

The literature on the analysis of the relationship between competition, innovation and productivity in Australia, especially at the firm level, is considerably sparser than the overseas literature.

Rogers (2004) uses 4500 firm-level observations from the ABS Growth and Performance Survey (GAPS) in a cross-sectional, discrete choice context to identify those factors associated with a firm being more likely to innovate. The study finds that firm size and whether the firm innovated previously are positively associated with the probability of a firm innovating, but that market share (measured in two different ways) is not significant in explaining innovation activity.

Wong *et al.* (2007) use the 2003 ABS innovation survey linked with the Economic Activity Survey (EAS) datasets for multiple years as well as incorporating unpublished business income tax and business activity statement data from the ATO. These datasets contain information on firm characteristics and innovation activity, and are used with tax return information in a Crepon, Duguet and Mairesse (CDM) - type model to examine those factors that affect innovation inputs, innovation outputs and productivity. While the authors emphasise that their results are indicative and exploratory only (due to the short period of data examined), they include a finding that firms with higher market share and larger firms are more likely to innovate.

Griffiths and Webster (2009) analyse a panel of 4802 Australian firms over a sixteen year period to investigate how external factors (such as competition) and internal (firm-specific) factors affect R&D expenditure. They find that most variation in R&D expenditure at the firm level is related to internal, unspecified, time-invariant characteristics that are specific to the firm. The authors conclude that even over a very long time period, drivers of innovation may not easily be separately identified from firm-specific indicators.

Implications for this paper

The range of different methods and measures employed in the literature investigating the relationship between competition, innovation and productivity suggests there is no clear, 'off-the-shelf' best practice to apply to this question in general, and in this study in particular.

In the various studies cited above, competition has been measured using price mark-up measures, the degree of market share held by firms, and the level of product

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3 The ratio of the proportionate change in profits resulting from, and expressed as a fraction of, a given proportionate change in sales.

market competition measured by subjective survey information. Typically, most studies use a single competition measure in their empirical analysis. However, given the variety of apparently contradictory results, some possibly related to the competition measure used, the question arises as to whether the nature and extent of product market competition is too complex to be fully captured by a single indicator, and whether some measures of competition might be picking up the effects of different aspects of competitive activity. For example: short-term predatory behaviour by a relatively large firm may be associated more with lower rather than higher price-cost margins; price-cost margins may be controlled by regulation; and the number of competitors faced may be controlled by operational licensing. In light of these and similar considerations, this paper investigates the value of using several competition measures simultaneously (that is a 'vector' of product market competition indicators) in order to capture the potentially multi-dimensional nature of competitive activity.[4]

Innovation has typically been measured by patent data, R&D expenditure, or R&D as a proportion of value added. However, many innovations do not lend themselves to patenting, and much innovation expenditure is not classified as R&D expenditure. The BLD data used in this analysis includes a variety of innovation measures that, although subjective and categorical, provide for a broader and more inclusive approach to exploring the characteristics that are associated with innovative behaviour at the firm level in Australia.

Because in a large firm-level dataset it is virtually impossible to obtain firm specific input and output price data, productivity in the literature has typically been proxied by a variety of quasi-productivity measures, often a mix of price and productivity components.[5] In this study a proxy measure of productivity derived from tax data is employed, as is a survey based subjective productivity improvement indicator – firms report a categorical productivity change (decrease, no change, or increase) from the previous year.

While the BLD provides for analysis based on a range of competition, innovation and productivity measures, it is still a relatively new dataset, and as such the longitudinal component is (at the time of this analysis) not yet well populated. The lack of a substantial time-series dimension to the data constrains the analysis in this paper. The models in Section 3 that relate competition and innovation are limited to only one year of information. Three years of data is available to estimate the models of Section 4 that relate innovation and productivity. Accordingly, cross-sectional analyses rather than panel data models are employed in the econometric work.

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4 Tests indicate that multicollinearity among the various competition measures used here is not problematic for model estimation. Correlation (Spearman) measures are included in Appendix A.

5 In this regard see the revealing findings in Foster *et al.* (2005).

3. COMPETITION AND INNOVATION

This section details the data, models and results from the econometric analysis of the relationship between competition and innovation. First, the data and measures constructed from the BLD are discussed, followed by a brief presentation of the econometric models. Finally, the model estimates are presented and discussed.

The data[6]

Information included in the BLD is drawn from business characteristics data sourced from the ABS Business Characteristics Survey (BCS) and financial data sourced from two main administrative sources: the Australian Taxation Office (ATO) and the Australian Customs and Border Protection Service (Customs). Most of the items included in the BCS are categorical in nature. The BLD is comprised of several panels – sets of firms that are surveyed annually for up to five years – designed so as to allow longitudinal analysis of firm activity. The first year of the first panel of firms was collected for 2004–05, with new panels starting in each successive year. At the time of writing, data was available for the 2005–06, 2006–07 and 2007–08 years.[7]

In addition to the longitudinal component, firms are surveyed to create a (weighted) representative sample to perform cross-sectional analysis. This cross-sectional sample is augmented by questions in the BCS that are asked in alternating years. In 2005–06 and 2007–08, extra questions regarding firm use of IT were included. In 2006–07, supplementary questions regarding firm innovation activity were included. Once fully populated, the BLD will comprise several longitudinal datasets containing both characteristics and financial data. The sample design is based on the use of consecutive panels that represent the Australian business population at the point in time that each panel is introduced into the BLD.

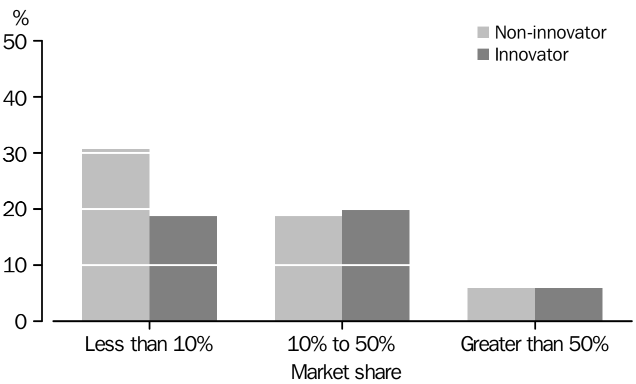
The cross-section from 2006–07 is used for analysis of the relationship between competition and innovation. It includes the detailed 'innovation module' from the BCS – that is, it is the only year that includes the full set of information about a firm's innovation behaviour: detailing both the different types of innovations undertaken and the novelty of those innovations, both of which are of interest. Also, the 2006–07 cross-section includes the 'innovation scope': a cross-sectional sample of firms that is designed to be representative of innovating firms in the general business population (apart from firms in Agriculture, Forestry and Fishing) – specifically, 9724 firm observations that form a representative sample for unbiased analysis of firm-level innovation.

6 Additional descriptive statistics are available in Appendix A. For more information regarding the BLD, see ABS (2009).
7 The BLD follows the earlier ABS development of a Business Longitudinal Survey, which ran from 1994 to 1999.

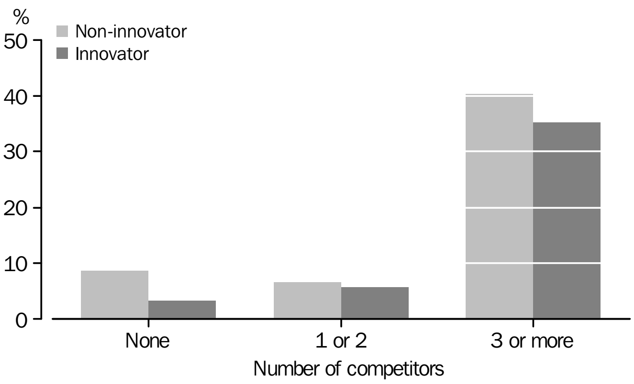
A variety of competition-related measures are drawn from the BLD, ranging from responses to survey questions, to variables constructed from tax information. These include categorical data on: measures of the firm's market share, the number of competitors it faces, and whether or not it feels hampered by the need to keep profit margins low in order to remain competitive. A price-cost margin (described in detail on page 13) is also computed from the tax data.

The market share information is drawn directly from the BCS question of how much market share a firm perceives itself to hold, with response categories of 'less than ten percent', 'ten to fifty percent' or 'greater than fifty percent'. The majority of firms report holding less than ten percent market share, but there are sufficient observations of firms with higher degrees of market share to allow the variable to be of use in the analysis (figure 3.1). Inspection of this data reveals that a greater proportion of firms reporting the higher market-share responses are innovators relative to those firms reporting lower market share responses.[8]

3.1 Distribution of market share

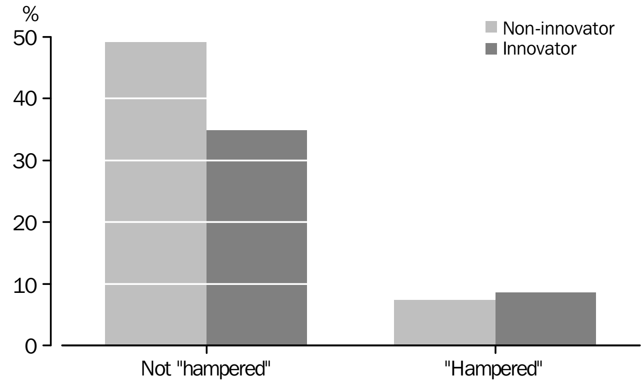


3.2 Number of competitors faced by firm



8 The figures display the sample distributions, by innovators and non-innovators, for each of the firm characteristics examined in the econometric analysis. Because the data are not weighted they do not necessarily reflect the corresponding population proportions.

3.3 Distribution of firms 'hampered'



The variable relating to number of competitors is also drawn directly from the BCS component of the BLD, with categories: 'no competitors', '1 or 2 competitors' and '3 or more competitors'. A clear majority of firms reported having three or more competitors (figure 3.2). Those firms reporting 'no competitors' have a lower proportion of innovators relative to the other categories.

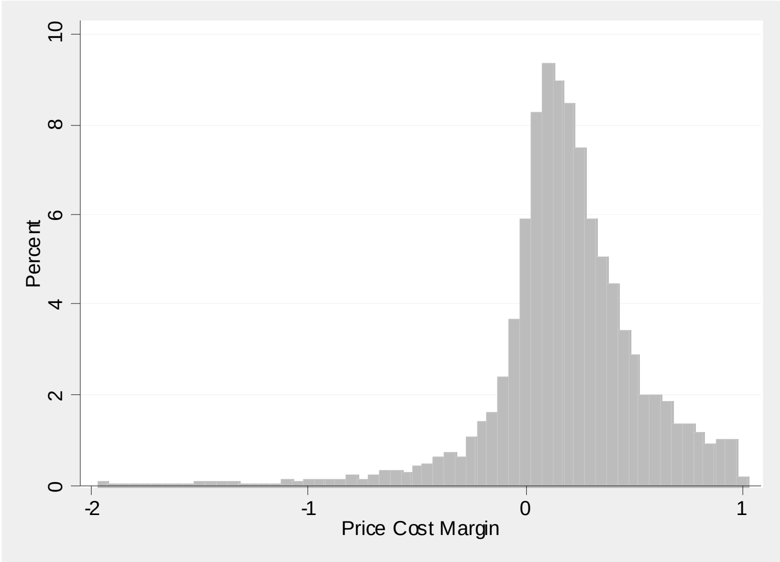
Another variable of interest is whether the firm declared its 'business operations to be hampered by the need to keep profit margins low due to strong competition' – a question also from the BCS. For brevity and convenience, firms that respond positively to this question are henceforth simply referred to as 'hampered'. Most firms respond negatively to the question, that is, they are not 'hampered' (figure 3.3). In the sample data, innovators represent a higher proportion of 'hampered' than of not 'hampered'.

The only continuous (and essentially objective) competition variable is the price-cost margin, derived from the tax data included in the BLD. It is defined as the sales income of a firm less intermediate input and wage expenses, expressed as a share of sales income – effectively a measure of accounting profit per dollar of sales. The rationale behind this variable is that firms with significant market power would be able to charge a higher mark-up, and that as competition increases, the ability to charge such mark-ups is competed away – although the price elasticity of demand will also play a role, as firms facing a high price elasticity may have little scope to mark up prices regardless of their competitive position.[9]

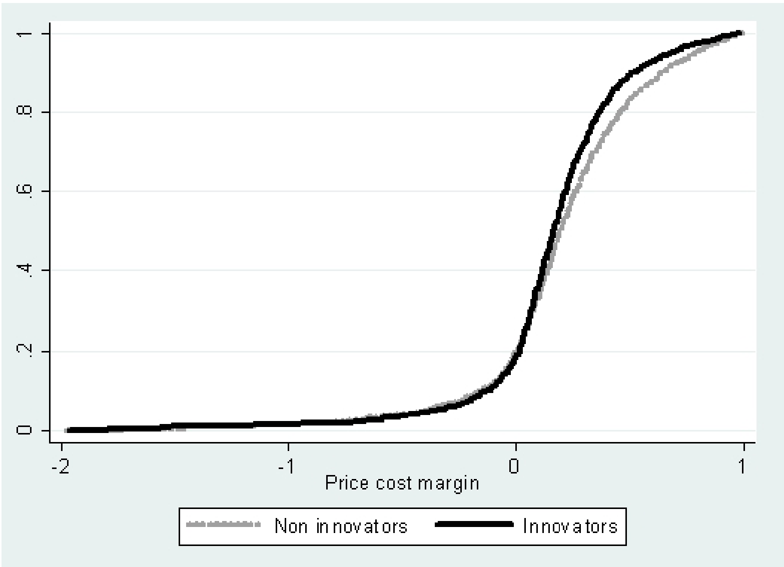
The distribution of price-cost margins suggests that the most common values are small and positive, although there is a long tail of firms with a negative PCM (figure 3.4). Based on the cumulative distribution of price cost margins for innovators and non-innovators, it appears that in the sample data non-innovators have a higher price cost margin relative to innovators.

9 While a higher mark-up will be reflected, *ceteris paribus*, in a higher value for this variable, so too will a larger capital stock – this is a weakness of this measure. However, this measure (and variants) is quite commonly used in the literature (for example, Aghion *et al.* (2005), Grünewald (2009) and Polder and Veldhuizen (2010)). Including book value of capital in the regressions proved not to be significant in this study.

3.4(a) Price Cost Margin – Sample distribution for all firms

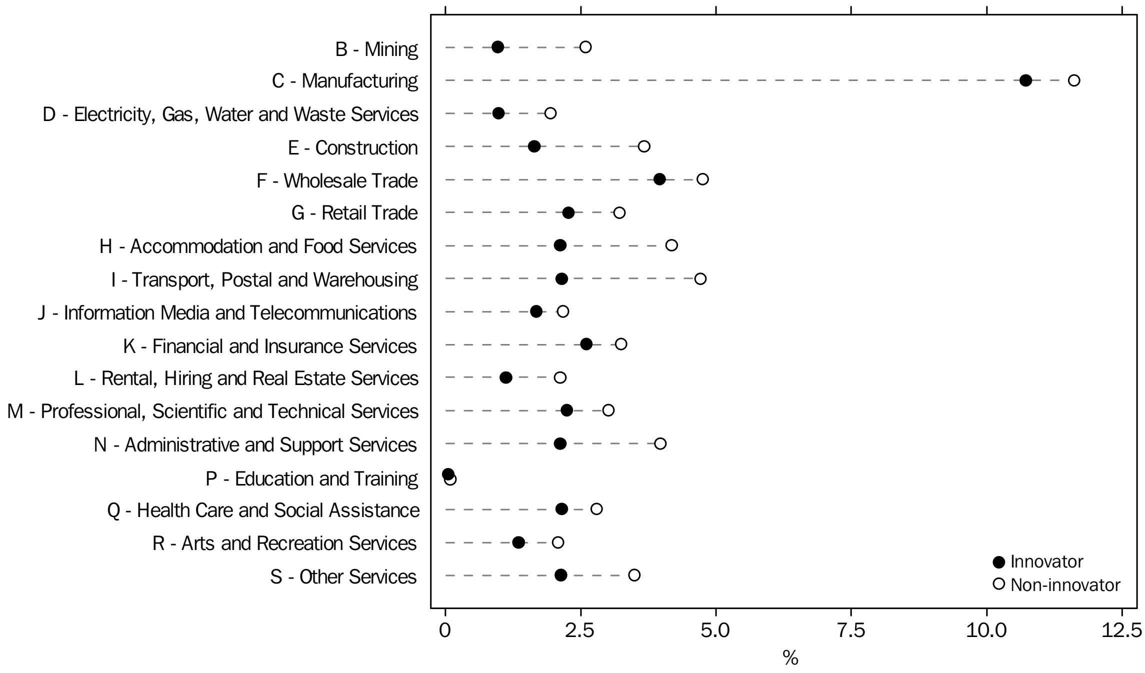


3.4(b) Price Cost Margin – Cumulative sample distributions for innovators and non-innovators

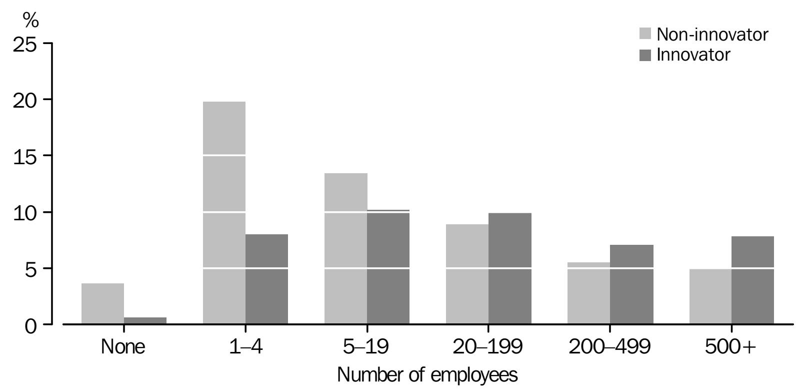


In addition to the competition measures, a number of other variables are used in the modelling: an indicator of the industry division to which the firm belongs (on an ANZSIC06 basis – figure 3.5) and its employment size by category (figure 3.6). These are survey design variables for the BLD, and, as only unweighted regressions are used here, it is important that they are included, although, on *a priori* grounds they are also likely to be structurally relevant variables. The manufacturing division has the highest proportion of innovators (47%), but not a substantially different proportion compared to wholesale trade (45%), finance and insurance services (44%) and information media and communications services (43%). Also, larger firms have a higher proportion of innovators relative to smaller firms.

3.5 Industry of operation

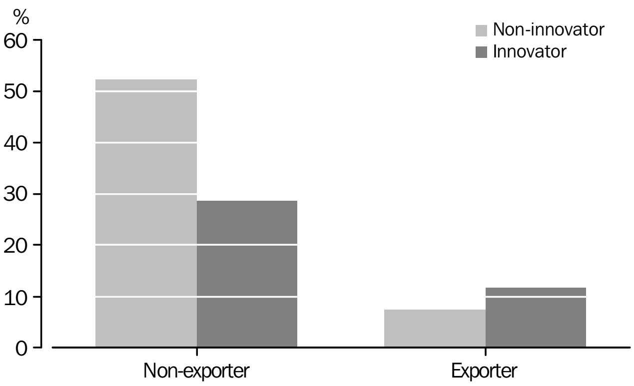


3.6 Business size

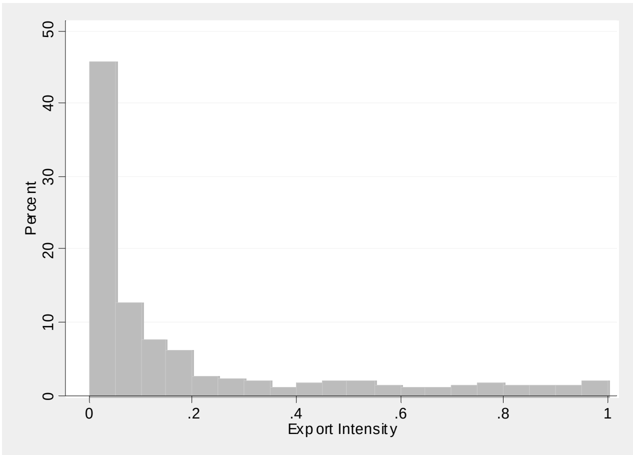


Whether or not a firm exports, and the share of its export sales in total sales are also variables of interest. Other studies (for example DITR, 2006) have shown export status to be significantly associated with innovation status, providing a *prima facie* reason for including such a variable (at least to avoid possible bias in other estimates). Also, the export exposure of a firm is another type of product market competition indicator. The BCS provides information on the export status of firms, while Business Activity Statements in the tax data provide information on total sales. Export sales are available from the linked trade data. Figure 3.7 shows that relatively few firms in the sample are exporters and that the export intensity of these firms is relatively low and strongly skewed.

3.7(a) Exporting firms and export intensity – Sample distribution for all firms



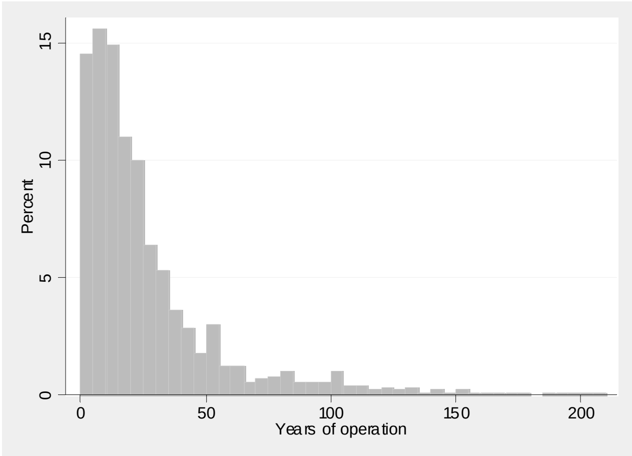
3.7(b) Exporting firms and export intensity – Export intensity of exporters only



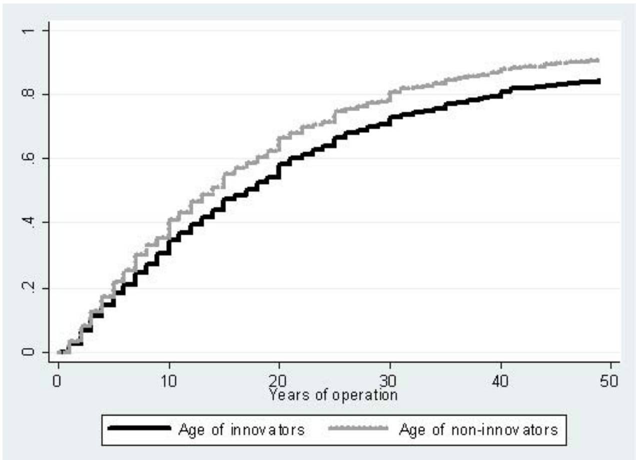
Business age might be expected to be correlated with the accumulation of types of knowledge capital and hence be associated with the propensity to innovate. BCS data on how long firms (regardless of ownership) have been operating is used as the measure of business age in this analysis. Under this definition, the average age of firms is roughly twenty years, with the distribution showing strong skewness towards younger firms (figure 3.8). Observations of implausibly old firms (where the company indicates it has been operating prior to 1788) have been removed from the data. On the basis of the sample data, it appears that innovators are somewhat more likely to be older firms relative to non-innovators.

The degree of foreign ownership is also included in the analysis for similar reasons (figure 3.9). The BCS asks respondents to indicate the proportion of the business that is foreign owned, in the categories of 'zero percent', 'greater than zero and less than ten percent', 'ten to fifty percent' and 'greater than fifty percent'. A little over 85 per cent of firms in the dataset report having zero foreign ownership with most of the rest (around 10 per cent) reporting greater than 50 per cent foreign ownership.

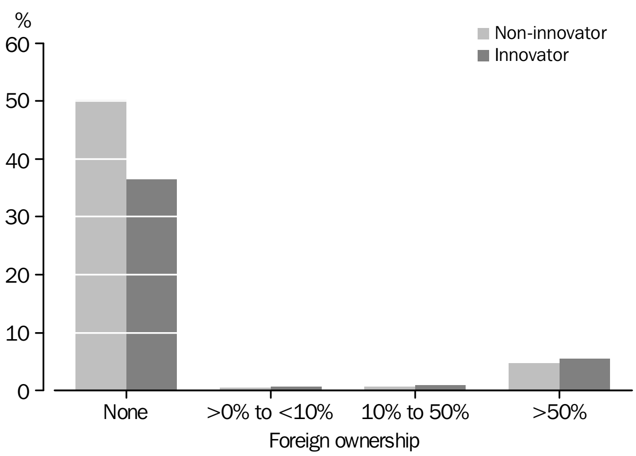
3.8(a) Age of operation of firms – Sample distribution for all firms



3.8(b) Age of operation of firms – Cumulative distribution for firms older than one year



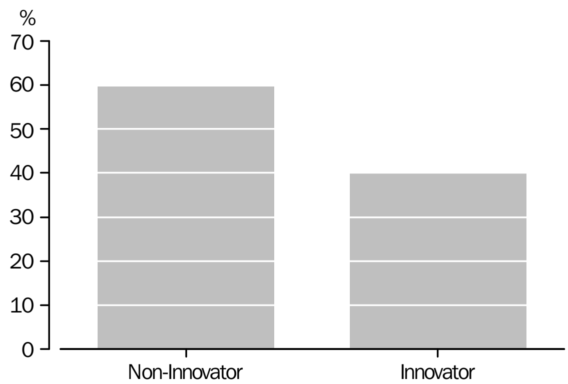
3.9 Degree of foreign ownership



A variety of innovation variables are available in the BLD. For each of the years there are simple binary indicators of whether a firm is an innovator or not, and of the types of innovation a firm has undertaken, from which 'type' and 'number of types' variables are constructed. There are also questions on the level of novelty of the firm's innovations.

While we freely use the term 'innovation' here, it should be noted that in the BCS survey instrument the notes to guide respondents in answering the 'innovation' questions actually ask about "new or improved goods, services, processes or methods which were introduced during the year ended …". We interpret a positive response to having introduced such new goods, services, processes or methods as an indication that the firm was 'an innovator'. Broadly speaking, about forty percent of firms in the dataset are 'innovators' in this sense (figure 3.10).

3.10 Innovators vs Non-Innovators:

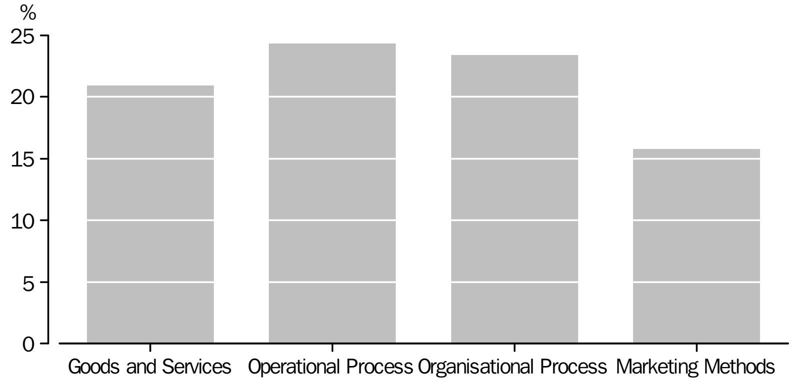


The BCS identifies each of four types of innovation that a firm can complete:

- New or significantly improved goods and services;
- Operational process innovation, 'a significant change for this business in its methods of producing or delivering goods or services';
- Organisational process innovation, 'a significant change in this business's strategies, structures or routines which aim to improve the performance of this business'; and
- Marketing methods innovation, 'a significant change in a design, promotion or sales method aimed to increase the appeal of this business's goods or services or to enter new markets'.

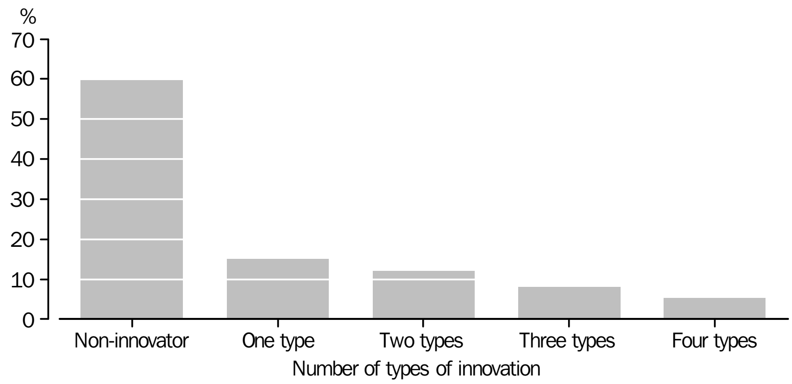
Generally speaking, the most prevalent type of completed innovation was an 'operational process' type, while 'marketing method' was the least common type of completed innovation (figure 3.11).

3.11 Different types of innovations completed by firms



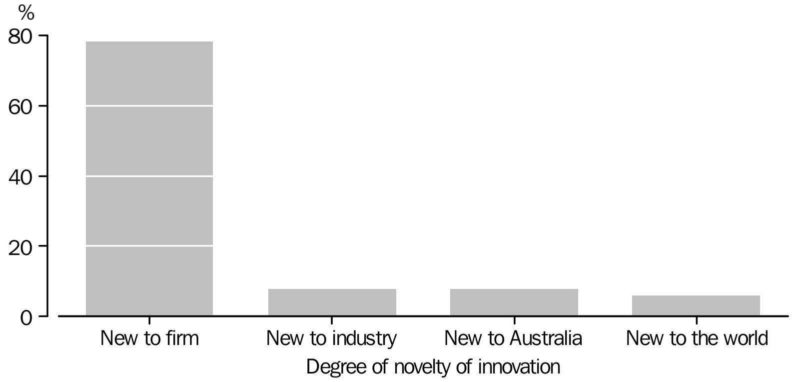
The number of different types of innovation that a firm undertakes can be viewed as an innovation diversity indicator, though certainly not a comprehensive one (for example, one firm might undertake several quite distinct 'goods or services' innovations while another firm might undertake one goods or services innovation and one marketing innovation. However it would not be reasonable on this basis alone to conclude the latter to be a more diverse innovator than the former). Nevertheless, it is of some interest to investigate the characteristics of firms that complete a greater rather than lesser number of these four innovation types. Ordered probit modelling is used to investigate this issue. Most firms are non-innovators, and the proportion of firms completing a particular number of innovation types decreases for each additional innovation type completed (figure 3.12).

3.12 Number of types of innovation a firm completes



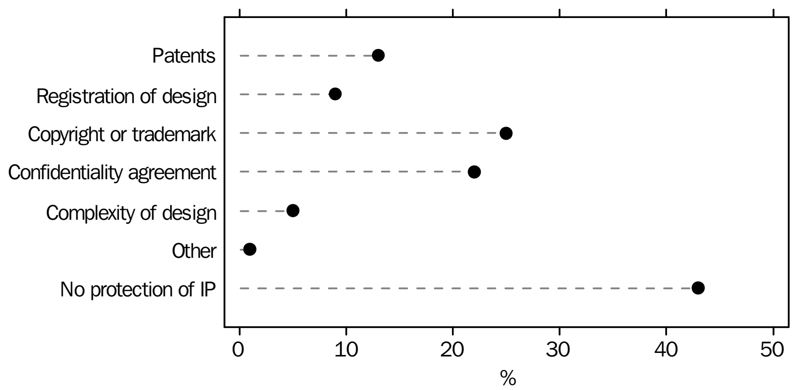
The BCS asks those respondents identifying themselves as having innovated in the year in question, about the degree of novelty of those innovations. The categories of novelty are: 'new to the firm', 'new to the industry', 'new to Australia' and 'new to the world'. Most innovating firms complete only innovations that are classified as 'new to the firm' (figure 3.13). The highest degree of novelty among the innovations a firm completes is also of interest, as it reflects the position of an innovating firm on the spectrum from 'adopter', through 'adaptor' and on to 'frontier innovator'.

3.13 Highest degree of novelty of innovation completed by firms



Finally, the different methods of protecting intellectual property (IP) employed by innovating firms are of interest in modelling of the number of types and highest degree of novelty of innovations. Figure 3.14 shows the distribution of use of different strategies of intellectual property protection that innovating firms adopted. This information is used only in the ordered probit models examining the number of types of innovation completed and the highest degree of novelty that was achieved.

3.14 Methods of IP protection amongst innovating firms[10]



The competition, innovation and other business characteristic measures described above form the data for the econometric modelling. Given the categorical nature of the dependent variables (*viz.* innovation, innovation type, number of types of innovation and highest degree of novelty of innovation) a variety of discrete choice models are employed to investigate the relationship between competition and innovation.

10 Reports the proportion of innovating firms that declared using each type of IP protection, or declared that no method of IP protection was employed.

The models

Binary probit, multivariate probit and ordered probit models are used in the econometric analysis of competition and innovation.[11] A single binary probit model is used to analyse the propensity of a firm to innovate (regardless of innovation type). Then, four separate binary models are estimated, one for each different type of innovation. It is of interest to compare and contrast the marginal effect estimates of the various conditioning variables across these models for different types of innovation. Such comparisons naturally lead to the question of whether certain types of innovation go hand-in-hand with others. To properly address this question, the various types of innovation should be considered in a *system* of equations. One way to do this is to use a multivariate probit model.

The multivariate probit model brings together each of the binary probits that examine whether a firm completes a particular type of innovation into a single system of equations that allows for the unobservable terms which affect reported innovation by type to be correlated with one another. The dependent variable in the model therefore consists of a four dimensional innovation outcome vector with each component of the vector (either zero or one) corresponding to the firm's type-specific innovation status. Once estimated, the multivariate probit model can be used to predict the conditional probability of a firm displaying any combination of innovation type outcomes, taking into account the estimated extent of correlation between one type of innovation and another – for example, the likelihood of a firm being both an operational process innovator and an organisational process innovator (conditioned on any chosen set of firm characteristics). It also allows for the computation of the predicted probability of being an innovator of a particular type conditional on being an innovator of another particular type (for example the probability of being a marketing innovator conditional on being a goods and services innovator).

As the name suggests, ordered probit models allow analysis of outcomes that have some sort of ordering present in the data. In the case of the innovation variables used here, there are two that have such ordering: the highest degree of novelty of a firm's innovations, and the number of different types of innovation conducted by a firm (one indicator of firm-level innovation diversity). By using an ordered probit model, the results can provide information about the conditional likelihood of an innovating firm having a given highest level of novelty, or of completing a particular number of types of innovation.

For each of the models and dependent variables (first column of table 3.15) the set of explanatory variables is the same (second column of table 3.15).

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11 A full description of equations, models and notes is included in Appendix B.

3.15 Models and variables used in the competition-innovation stage

Dependent variables (and model used)	*Explanatory variables (common to each model)*
Is the firm an innovator? (model #1 – binary probit)	The degree of market share that a firm holds.
Is the firm a goods and services innovator? (model #2 – binary probit)	The number of competitors that a firm faces.
Is the firm an operational process innovator? (model #3 – binary probit)	The price-cost margin of the firm.
Is the firm an organisational process innovator? (model #4 – binary probit)	The number of employees a firm has.
Is the firm a marketing methods innovator? (model #5 – binary probit)	The age of the firm.
What combination of innovation types does a firm undertake? (model #6 – multivariate probit)	The degree of foreign ownership of the firm.
How many different types of innovation does a firm undertake? (model #7 – ordered probit)	The export status of the firm.
What is the highest degree of novelty of innovation a firm undertakes? (model #8 – ordered probit)	The export intensity of the firm.
	Whether the firm is 'hampered'.
	The industry within which the firm operates.

Many of the explanatory variables are categorical in nature, so they are included in the model as sets of 'dummy' variables: that is, switches that indicate a particular state for each outcome (for example, a dummy variable is used for five of the six outcomes for employment size displayed in figure 3.6, with one omitted as the base category). The price-cost margin, age, and export intensity of the firm are all continuous variables.

The results

Estimation of the models shows that all but one (export intensity) of the competition variables described above have a statistically significant association with the likelihood of a firm being an innovator.[12] That is, the level of product market competition that a firm faces appears to be strongly associated with the likelihood of innovation activity – but the nature of the results is mixed, suggesting both Schumpeterian and anti-Schumpeterian aspects depending on the measure of competition.

Estimation of the simple binary probit (model 1 in table 3.16) shows all but one of the competition measures to be statistically significant, with substantial effects on the propensity to innovate. The market share variable indicates that a higher market

12 Full tables of results that include the results for all the variables included in the models (such as foreign ownership and industry division of operation, which are not detailed here for brevity's sake) are listed in Appendix C.

share, all other things being equal, is associated with a higher propensity to innovate – a result that is Schumpeterian in nature (and similar to that of Wong *et al.,* 2007 and Scherer, 1965). On the other hand, the variable measuring the number of competitors is positively associated with innovation, suggesting an anti-Schumpeterian outcome. (This is a similar result to that of Blundell *et al.,* 1999 discussed in the earlier section on the literature.) On the face of it this appears somewhat perplexing. However, some possible explanations are discussed in Box 3.1.

3.16 Summary of results for the binary probit model

	Innovator – Model #1 (binary probit)[13]		*Marginal effect*[14] *percentage points*	*(proportionate change)*
10–50% market share	0.207	***	8	(22%)
50%+ market share	0.313	***	12	(34%)
1 or 2 competitors	0.411	***	15	(56%)
3+ competitors	0.426	***	16	(58%)
PCM	–0.159	***	–6	(–15%)
1–4 employees	0.535	***	16	(103%)
5–19 employees	0.829	***	27	(173%)
20–199 employees	1.068	***	37	(234%)
200–499 employees	1.279	***	45	(287%)
500+ employees	1.533	***	54	(346%)
Exporting Business	0.404	***	16	(40%)
Export intensity	–0.149		–6	(–14%)
‘Hampered by competition’	0.208	***	8	(20%)
Constant	–1.426	***	na	
Number of observations	5,044			
Wald chi-squared (33)	465.15			
Prob > chi-squared	0.000			

Being ‘hampered’ is strongly associated with innovation activity, suggesting that firms facing profit pressures due to competition are more likely to be innovators than firms not facing such pressures. This result is consistent with the estimated coefficient on the PCM measure, which implies that smaller margins are associated with a higher propensity to innovate. The coefficients on these variables therefore point to a strong, anti-Schumpeterian relationship between mark-up and innovation activity.

13 Here and in all subsequent tables, *** denotes a coefficient is significant at the 1% level, ** the 5% level, and * the 10% level.

14 Calculated while holding all other variables fixed at their average values. Categorical variables are incremented from a value of zero to unity in the specific category in question. Results are reported as the percentage point change followed by the proportionate change in parentheses. In the case of continuous variables, the marginal effect is the value of the partial derivative of the probability of being an innovator with respect to that variable, evaluated at the mean. Marginal effects are calculated using code bundled with Long and Freese (2006).

Export status is also strongly and positively associated with the propensity to innovate. However, export intensity is negatively, though not significantly, associated with a propensity to innovate, suggesting that entering export markets for the first time may be more demanding of innovation than increasing export intensity once already an established exporter.

The size of the firm is also found to be strongly associated with a firm's innovation status. All else equal, larger firms are predicted to be more likely than smaller firms to innovate. This result is consistent with nearly all the empirical literature, both in Australia and internationally.[15]

The most interesting application of the models is to assess the impact of a change in a given characteristic on the predicted probability of being an innovator. Such calculations have to be conducted at a particular chosen value for each of the conditioning variables. Where the given characteristic of interest is a categorical variable the predicted probability of being an innovator is computed at the base value of zero for this characteristic and then at the incremented value of unity, and the difference in these predicted probabilities is then computed (with all other conditioning variables held fixed at their 'average' values across all firms).

For continuous variables the marginal effects are computed as the partial derivative of the probability of being an innovator with respect to that variable, evaluated at the mean. 'Marginal' effects for the conditioning variables are reported in the tables.

For more specific types of firms, the impact of changes in a conditioning variable of interest should be calculated directly rather than relying on the indicative 'marginal' effects provided in the tables. By way of a specific example, take the case of a manufacturing firm with 1–4 employees, less than 10 per cent market share, three or more competitors, profitability not 'hampered' by competition, an average PCM mark-up, average age, a non-exporter, and with no foreign ownership. The predicted probability of such a firm being an innovator, according to the binary probit model described in table 3.2, is 31%. This predicted probability can now be compared for example with the predicted probability of a much larger firm with 500+ employees but with all other characteristics unchanged, being an innovator. The model predicts the probability of this much larger firm innovating to be closer to 70%, an absolute increase of 39 percentage points and a proportionate change of more than one hundred per cent. Such impact analyses are helpful in gaining a more concrete appreciation of the quantitative effect of changes in various conditioning variables on the predicted probability of particular firm types being an innovator.

15 This is investigated in greater detail by comparing the estimated effects of the size coefficient of different size categories against one another in formal tests for each of the innovation types. This output is provided in Appendix C.

BOX 3.1: POSSIBLE EXPLANATIONS FOR OPPOSITE EFFECTS OF MARKET SHARE AND OTHER COMPETITION-RELATED VARIABLES

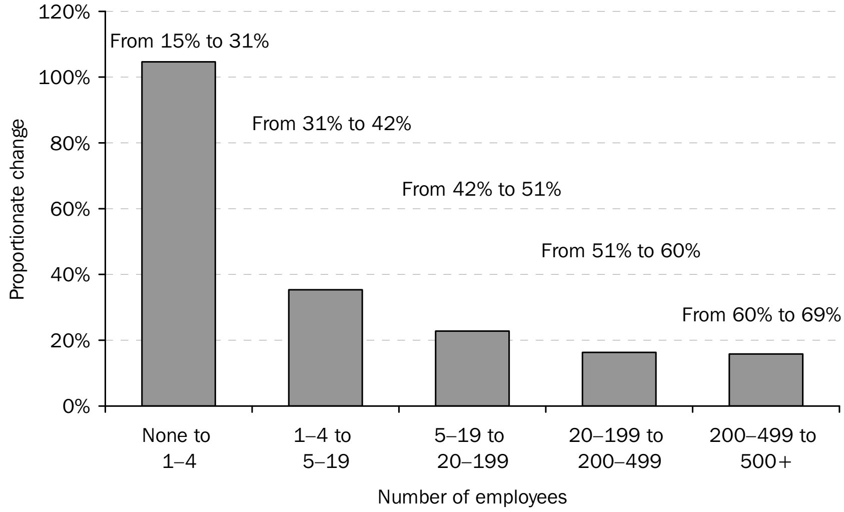
The coefficients reported in table 3.2 imply that an increase in market share, usually interpreted to indicate a drop in competition, is associated with a higher likelihood of innovation, while for each of the other statistically significant competition variables, changes usually associated with an increase in competition are predicted to be associated with a higher likelihood of innovation. How might this apparent inconsistency be arising?

The sign of the estimated coefficients in the model indicate the direction of change in predicted probabilities resulting from a given change in the selected explanatory variable, with all other conditioning variables held fixed. Thus, the opposite effects in question simply imply that with all other competition variables held fixed, an increase in market share is expected to be associated with an increased likelihood of innovation. First of all, does it even make sense to impose an increase in market share with all other competition variables held fixed? Well, businesses with the same number of competitors and the same number of employees could have very different market shares if they operate in different product markets of different size. In that case the business operating in the smaller product market might be expected to have higher market share. However, with the same PCM, such a result could reflect a more concentrated (although not necessarily less competitive) market, and the result found here could reflect an association between innovation and concentration, rather than innovation and competition.

Another possible explanation lies in the categorical nature of some of the explanatory variables. For example, the 'all other things equal' constraint in the interpretation of coefficients is very weak for some variables. For example, holding the business size category fixed within the 20 to 199 category allows for a great deal of variation in business size. The impact of market share, holding categorical business size fixed, may still be influenced by substantial variation in business size within that category. Similar arguments apply to the 'number of competitors' category 'three or more'. Although only categorical data are available for number of competitors, continuous data on number of employees are available (categorical variables for employment are used in the main models as it was categorical classes that were used in the sample survey design). However, even in the presence of a continuous employment variable in the regressions, the coefficient on the market share variable remained positive and statistically significant.

Further, it may be the case that the model is picking up 'reverse causality'. That is, it could be that innovation leads to the firm increasing its market share – the act of innovating is a competitive act designed to seize market share from competitors. Unfortunately, the model as it stands cannot provide guidance as to the direction of causality – does higher market share lead to greater likelihood of innovation or does innovation lead to higher market share, or both. To address issues of causality, time series models must be employed rather than the cross-sectional methods employed in this paper. Such analysis of causal effects will become more viable as the time series dimension of the BLD populates more fully in the future.

3.17 The proportionate increases in the probability of innovating as firm size increases



Pursuing the above example further, the proportionate change in the probability of innovating resulting from moving from one size category to the next (with other variables fixed as described above) is set out in figure 3.17.

The *proportionate* increase in the predicted probability of being an innovator resulting from an increase in employee numbers from no employees to 1–4 employees is 103%. As the size categories increase, the proportionate increase in the predicted probability of innovating as a result of shifting from one size category to the next gradually declines. The corresponding absolute difference in the probabilities also tends to decline at 16%, 11%, 9%, 9%, and 9% respectively. This finding is similar to that found by Scherer (1965).

Results regarding different types of innovation

The characteristic of being an innovator can be nuanced, by considering the various different types of innovation. To this end, four separate binary probits are modelled (one for each type of innovation) using the same set of conditioning variables as for the simple binary innovator/non-innovator model just discussed (model 1). One might expect the factors that are important in explaining whether a firm innovates in general to be similarly important in explaining whether the firm completes a particular type of innovation, an expectation that is generally met by the results in table 3.18.

Larger market share is found to be important in explaining the likelihood of firms innovating in goods and services, operational process and organisational process innovations, but does not appear relevant in explaining the choice to engage in marketing methods innovation.

3.18 Summary of results for different types of innovation

	Goods and services (model 2)				*Organisational process (model 4)*			
	Coeff.		*M.E. (pp (%))*		*Coeff.*		*M.E. (pp (%))*	
10–50% market share	0.182	***	5	(29%)	0.155	***	4	(24%)
50%+ market share	0.336	***	10	(57%)	0.244	***	7	(39%)
1 or 2 competitors	0.440	***	11	(94%)	0.298	***	7	(56%)
3+ competitors	0.403	***	10	(84%)	0.326	***	8	(63%)
PCM	–0.160	**	–5	(–22%)	–0.217	***	–6	(–30%)
1–4 employees	0.447	***	9	(111%)	0.325	**	6	(78%)
5–19 employees	0.636	***	14	(176%)	0.706	***	15	(213%)
20–199 employees	0.729	***	17	(211%)	1.027	***	26	(362%)
200–499 employees	0.931	***	24	(296%)	1.233	***	34	(470%)
500+ employees	1.181	***	33	(413%)	1.128	***	30	(414%)
Exporting Business	0.400	***	13	(62%)	0.132	**	4	(19%)
Export intensity	–0.250		–7	(–35%)	–0.039		–1	(–5%)
'Hampered by competition'	0.213	***	6	(31%)	0.147	***	4	(21%)
Constant	–1.776	***	na		–1.826	***	na	
Number of observations	5,044				5,044			
Wald chi-squared (33)	295.36				328.17			
Prob > chi-squared	0.000				0.000			

	Operational process (model 3)				*Marketing methods (model 5)*			
	Coeff.		*M.E. (pp (%))*		*Coeff.*		*M.E. (pp (%))*	
10–50% market share	0.178	***	5	(27%)	0.059		1	(10%)
50%+ market share	0.230	***	7	(36%)	0.026		1	(4%)
1 or 2 competitors	0.221	**	6	(37%)	0.319	***	6	(73%)
3+ competitors	0.258	***	7	(44%)	0.409	***	8	(99%)
PCM	–0.123	**	–4	(–17%)	–0.242	***	–6	(–38%)
1–4 employees	0.405	***	8	(100%)	0.598	***	8	(212%)
5–19 employees	0.693	***	15	(202%)	0.812	***	13	(335%)
20–199 employees	0.997	***	26	(335%)	0.817	***	13	(339%)
200–499 employees	1.073	***	28	(371%)	1.093	***	22	(540%)
500+ employees	1.499	***	45	(589%)	1.105	***	22	(549%)
Exporting Business	0.363	***	12	(54%)	0.214	***	5	(36%)
Export intensity	–0.395	**	–12	(–53%)	0.106		2	(17%)
'Hampered by competition'	0.239	***	7	(34%)	0.226	***	6	(38%)
Constant	–1.584	***	na		–2.061	***	na	
Number of observations	5,034				5,044			
Wald chi-squared (32 & 33)	379.68				237.56			
Prob > chi-squared	0.000				0.000			

The number of competitors is also statistically significant and positively associated with the propensity to innovate for each of the different innovation types. This again highlights the similar results between greater market share and a larger number of competitors (and other competition variables) discussed previously in Box 3.1. The results regarding the firm being 'hampered' and its price-cost margins are similar in nature: the greater the price-cost margin the less likely the firm is to innovate in each of the four types of innovation. Similarly, if a firm describes itself as 'hampered', it is more likely to innovate in each of the four types of innovation.

The binary export status variable remains important in explaining the propensity to innovate in each type of innovation activity, while the export intensity measure is statistically insignificant except in the operational process innovation model where the estimated coefficient is negative (and quite large in absolute value) and statistically significant (at the 5% level). Jointly considering the coefficients of export status and export intensity, model 3 indicates a strong association between becoming an exporter and operational process innovator, but with this association attenuating as export intensity increases.

Finally, firm size has a significant and positive association with innovation propensity for all four innovation types. This is again consistent with most of the empirical literature.

Multivariate probit results

The multivariate probit model (model 6) allows the prediction of all possible combinations of outcomes from the system of binary probits. That is, based on any given value for the conditioning variables, the model can provide the predicted likelihood of innovating in each of the different types of innovations and in any combination of those types. The ability to compute these probabilities from a single model is extremely useful. The only downside is that techniques used to derive the multivariate normal distribution are computationally intensive. The model estimates all four (innovation type) sets of coefficients simultaneously along with the variance-covariance matrix of the associated multivariate standard normal distribution. A summary of the results of the multivariate probit are shown in table 3.19.

3.19 Multivariate probit results[16]

	Goods and services		Organisational Process		Operational Process		Marketing methods	
10–50% market share	0.193	***	0.160	***	0.185	***	0.068	
50%+ market share	0.357	***	0.255	***	0.242	***	0.056	
1 or 2 competitors	0.459	***	0.303	***	0.208	**	0.342	***
3+ competitors	0.420	***	0.338	***	0.256	***	0.434	***
PCM	–0.167	***	–0.209	***	–0.129	**	–0.232	***
1–4 employees	0.442	***	0.393	**	0.568	***	0.634	***
5–19 employees	0.627	***	0.765	***	0.841	***	0.837	***
20–199 employees	0.730	***	1.091	***	1.153	***	0.856	***
200–499 employees	0.921	***	1.298	***	1.245	***	1.132	***
500+ employees	1.188	***	1.177	***	1.620	***	1.126	***
Exporting Business	0.414	***	0.160	**	0.382	***	0.242	***
Export intensity	–0.272		–0.055		–0.333	**	0.061	
'Hampered by competition'	0.211	***	0.150	***	0.238	***	0.222	***
Constant	–1.810	***	–1.919	***	–1.765	***	–2.140	***
Number of observations	5,005							
Wald chi-squared (131)	863.97							
Prob > chi-squared	0.000							

The combinations of innovation types completed can be represented by the vector $\{a, b, c, d\}$ where:

- $a = 1$ if the firm completes a goods and services innovation, and 0 otherwise;
- $b = 1$ if the firm completes an organisational process innovation, and 0 otherwise;
- $c = 1$ if the firm completes an operational process innovation, and 0 otherwise;
- $d = 1$ if the firm completes a marketing innovation, and 0 otherwise.[17]

The model can predict the probability of being an innovator (1 – Pr{0,0,0,0}), the probability of being an innovator of a particular type (for example, the probability of goods and services innovator = $\sum_{\forall b,c,d} \Pr\{1, b, c, d\}$), and the probability of innovating in a particular number of types of innovation (for example, innovating in exactly n types would have the probability = $\sum_{\forall (a+b+c+d=n)} \Pr\{a, b, c, d\}$ while the probability of innovating in at least n types would be = $\sum_{\forall (a+b+c+d \geq n)} \Pr\{a, b, c, d\}$).

16 Stata code from Capellari and Jenkins (2003, 2006) was used to run the multivariate probit regressions using 71 draws. Results were robust for a range of different starting values.

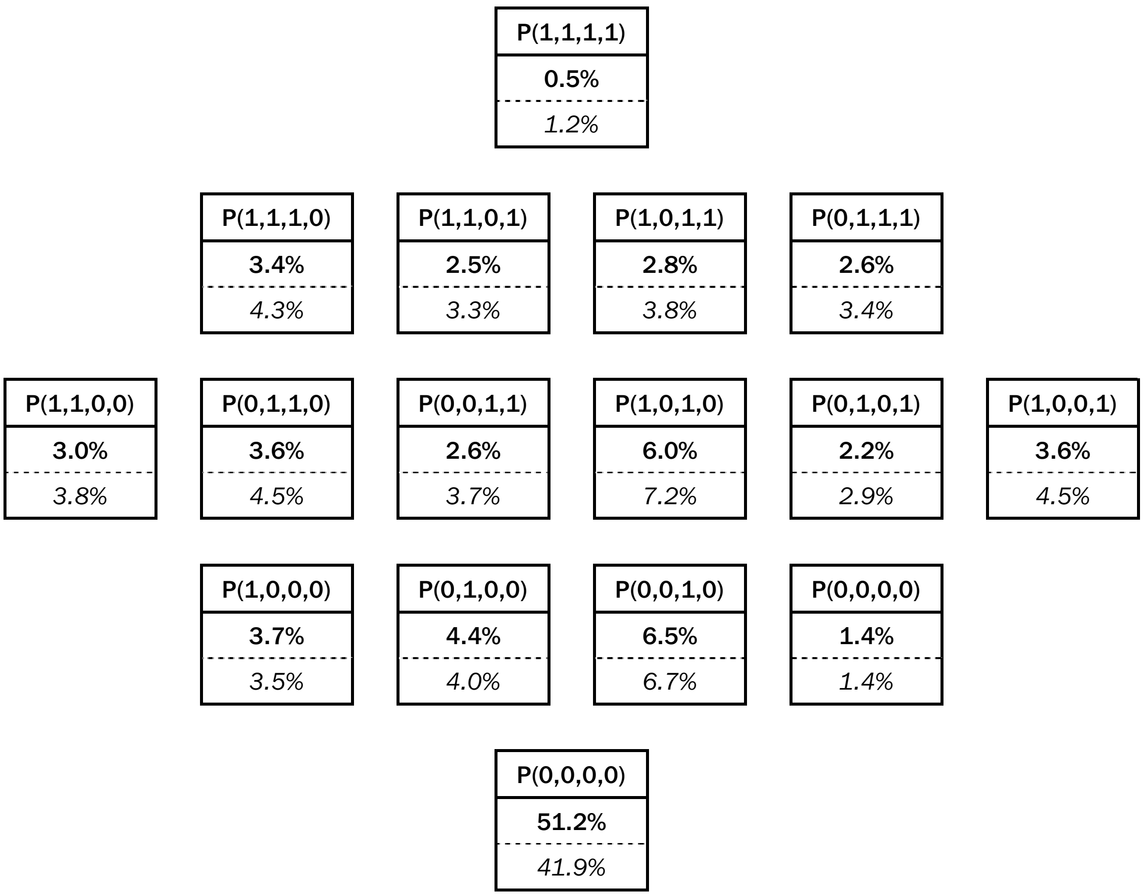
17 For example, the outcome where a firm is an innovator in goods and services and marketing (but no other types) would be written as {1, 0, 0, 1}, a firm that innovates in all innovation types as {1, 1, 1, 1}, and a non innovator as {0, 0, 0, 0}.

An example is helpful. Consider a firm with the following characteristics:

- 10–50% market share
- 1–2 competitors
- PCM = 0.20
- 5–19 employees
- Is a manufacturer
- Non exporter, not ‘hampered’, and zero foreign ownership.

Based on these characteristics, the model predicts probabilities for each possible outcome, P(*a,b,c,d*), as shown in **bold** in figure 3.20. For example, the outcome (0,0,0,0) – non-innovator – has a predicted probability of occurrence of 51.2%.

3.20 Predicted probabilities of different innovation outcomes using the multivariate probit model



The probabilities of each possible outcome, but this time for a firm with the same characteristics *except that it is now 'hampered' by competition*, are also presented below, in italics. Comparing these newly calculated probabilities with the former case provides predictions of how the probability of particular innovation activity occurring is expected to change as a result of changing from 'not hampered' to 'hampered'.[18]

For example:

- as a result of the change in status from 'not hampered' to 'hampered', the predicted probability of being an innovator changes from 48.8% (1 minus the probability of being a non-innovator) to 58.1%, which is a proportionate increase of about 19%, while
- the predicted probability of being a goods and services innovator changes from 25.5% (the sum of all the probabilities with unity in the first co-ordinate) for the unhampered firm to 31.6% for the hampered firm, a proportionate increase of about 24%.

Note that these changes are not uniform. Moving to being 'hampered' shifts density from the non-innovator and '1-type only' innovator outcomes towards the 'higher' innovation outcomes. This can be seen more generally by examining how the change in being hampered is associated with the number of innovation types completed by the firm (table 3.21):[19]

3.21 Number of innovation types completed[20]

Number of innovation types completed	*Probability (not hampered)*	*Probability (hampered)*	*Proportionate change*
0	51.2%	41.9%	–18.2%
1	16.0%	15.6%	–2.5%
2	21.0%	26.6%	26.7%
3	11.3%	14.8%	31.0%
4	0.5%	1.2%	140.0%

Finally, from the results of the multivariate probit it is possible to compute the predicted probability of a given innovation outcome conditional upon any other specified innovation outcome. For example, the probability of the above 'unhampered' firm being a goods and services innovator *given* that it is a marketing innovator is 51.6% (equal to the probability it is both a 'goods and services' innovator and a 'marketing' innovator, divided by probability it is a 'marketing' innovator). If the

18 This, and other scenarios with 'shocks' to the other competition variables, are presented in Appendix B.
19 Notice that the number of innovation types completed by the firm corresponds with the horizontal 'tiers' in figure 3.16, and the predicted probability of a specific number of types to the sum of the predicted probabilities across the relevant horizontal tier.
20 Note that the probabilities associated with the number of innovation types completed sum to unity.

firm is hampered, then this conditional probability is predicted to be only very slightly higher at 52.9%. In this way the impact of changes in the modelled firm characteristics on the predictions of such conditional probabilities can also be computed.

Ordered probit model results

Two ordered probit models are estimated in this paper to investigate the association between firm characteristics, particularly those influenced by competition, and (a) the number of different types of innovation completed by innovating businesses, and (b) the degree of novelty of innovations conducted by innovating businesses. This analysis is conducted for innovating firms only, as it seeks information on the nature of innovation. In the first ordered probit model, the dependent variable of interest is the number of different types of innovations a firm completes (1 for completing just one type of innovation, 2 for completing two different types of innovation, and so on up to 4 for completing all four types of innovation). In the second ordered probit model, the dependent variable is the highest degree of novelty a firm achieves (1 if the highest degree of novelty is new to the firm, 2 if the highest degree of novelty is new to the industry, 3 if new to Australia and 4 if new to the world). The explanatory variables for both these models consist of all those used in the binary probits and multivariate probit (discussed earlier), plus indicators of whether or not a firm employs certain methods of intellectual property protection to safeguard the prospective returns to its innovations.[21] The results for each model are shown in table 3.22.

The first of these two models (model 7) finds three IP protection methods to have a positive and statistically significant association with a greater number of different types of innovation being completed. According to the model, using ‘registration of design’, ‘secrecy/confidentiality agreements’ and/or completing an innovation that has ‘complexity of design’ are each associated with a higher predicted probability of the firm completing more innovation types compared with firms that use no method of IP protection. Of the remaining explanatory variables, only the price cost margin and the declaration of being ‘hampered’ are statistically significant. A lower price-cost margin and the presence of profit constraint to remain competitive are associated with a higher predicted probability of completing a greater number of innovation types. The marginal effects of changes in the significant explanatory variables on the predicted probabilities of the four different outcomes are presented in table 3.23.

21 Recall that these methods of IP protection are discussed in the data section in figure 3.14.

3.22 Ordered probit models with innovators only in the sample

	Number of innovation types completed (model 7 – innovators only)		*Highest degree of novelty of innovation (model 8 – innovators only)*	
Patents	0.0007		0.1988	
Registration of design	0.5067	***	0.4502	***
Copyright or trademark	0.0849		–0.0050	
Secrecy/Confidentiality Agreement	0.4710	***	0.3614	***
Complexity of design	0.2755	**	0.6245	***
Other method to protect IP	0.3061		0.4339	
10–50% market share	0.0297		0.0800	
50%+ market share	0.0765		0.3168	**
1 or 2 competitors	0.0782		–0.1231	
3+ competitors	0.1362		–0.0865	
PCM	–0.1826	**	0.0066	
1–4 employees	0.1387		–0.2416	
5–19 employees	0.1838		–0.3748	
20–199 employees	0.2428		–0.4671	
200–499 employees	0.3317		–0.1896	
500+ employees	0.3516		–0.9622	
Exporting Business	–0.0051		0.3267	***
Export intensity	–0.1861		0.1894	
'Hampered by competition'	0.1888	***	0.1363	*
Constant 1	0.0360		0.5520	*
Constant 2	0.8697	***	0.9250	***
Constant 3	1.6243	***	1.3435	***
Number of observations	2076		1734	
Wald chi-squared (39 & 38)	186.13		181.95	
Prob > chi-squared	0.000		0.000	

The marginal effects provide an indication of the magnitude of effects associated with those variables found to be statistically significantly associated with the number of innovation types completed. For example: the model predicts that the use of registration of design increases the probability of innovating in 3 types of innovation by 8 percentage points (a proportional increase of 38%) and the probability of innovating in all 4 types of innovation by 12 percentage points (a proportional increase of (115%). The use of registration of design reduces the predicted probability of innovating in the other numbers of types of innovation, indicating that the likelihood of innovating in a greater number of types is increasing. Broadly speaking, these results show that there is a strong association between protecting IP in these ways and completing a greater number of types of innovation.

3.23 Marginal effects of significant explanatory variables in number of innovation types completed

	1 type [22]		*2 types*		*3 types*		*All 4 types*	
	pp	*(%)*	*pp*	*(%)*	*pp*	*(%)*	*pp*	*(%)*
Registration of design	–17	(–46%)	–2	(–5%)	8	(38%)	12	(115%)
Secrecy / confidentiality agreement	–17	(–44%)	–1	(–2%)	7	(37%)	10	(100%)
Complexity of design	–10	(–26%)	0	(–1%)	4	(22%)	6	(56%)
PCM	7	(18%)	–1	(–2%)	–3	(–16%)	–3	(–32%)
'Hampered by competition'	–7	(–19%)	0	(1%)	3	(16%)	4	(35%)

The ordered probit examining the highest degree of novelty completed by innovators yields similar results with respect to the IP protection variables, 'Registration of design', 'secrecy/confidentiality agreements' and 'complexity of design' are all positively and statistically significantly associated with a higher degree of novelty of innovation. Of the remaining variables, only two are significantly associated with higher degrees of innovation novelty. A large market share (50% or more) and being an exporter are both strongly associated with higher degrees of novelty. The strong positive association between being an exporter and having a higher degree of novelty of innovation is not unexpected. As exporters compete in a global market, it might be expected that such innovations would, in general, be more likely to be new to the world than those of non-exporters. The marginal effects of changes in the significant explanatory variables on the predicted probabilities of the four different outcomes are presented in table 3.24.

3.24 Marginal effects of significant explanatory variables in highest degree of novelty completed

	New to the firm		*New to industry*		*New to Australia*		*New to world*	
	pp	*(%)*	*pp*	*(%)*	*pp*	*(%)*	*pp*	*(%)*
Registration of design	–14	(–17%)	4	(46%)	4	(72%)	6	(129%)
Secrecy / confidentiality agreement	–11	(–13%)	3	(38%)	3	(56%)	4	(92%)
Complexity of design	–21	(–25%)	5	(60%)	6	(102%)	10	(204%)
50%+ market share	–9	(–11%)	3	(36%)	3	(53%)	4	(89%)
Exporting business	–10	(–12%)	3	(34%)	3	(50%)	4	(79%)

22 'pp' refers to the percentage point change and '%' the proportionate change. Rows may not sum to zero due to rounding. The marginal effects are calculated while holding all other variables fixed at their average values. Categorical variables are incremented from a value of zero to unity in the specific category in question. Results are reported as the percentage point change followed by the proportionate change in parentheses. In the case of continuous variables, the marginal effect is the value of the partial derivative of the probability of the outcome in question with respect to that variable, evaluated at the mean.

Several types of IP protection are significantly associated with higher predicted probability of innovating in more novel innovations (as was the case in table 3.23), especially complexity of design. For example, the model predicts that firms that use complexity of design to protect the IP of their innovation are 60% more likely to complete innovations that are new to the industry, 102% more likely to complete innovations that are new to Australia, and 204% more likely to complete innovations that are new to the world. While these are large proportional increases because the base probability of the more novel sorts of innovation are low to begin with, it is of interest to note that 'complexity of design' is associated with a 10 percentage point higher probability of an innovating firm completing a new to the world innovation. This is a very large predicted change given the low number of new to the world innovators that operate in Australia.

The absence of any scope to test for causality in the models estimated in this paper is of particular relevance in the case of the ordered probit model of innovation novelty described above. On prior grounds alone, a causal link from innovation novelty to the use of IP protection mechanisms seems more likely than a causal link from IP protection mechanisms to innovation novelty – new to the world innovations would seem much more likely to benefit (*ex post*) from IP protection than innovations that are simply new to the firm (and therefore likely to be 'owned' by some other party).

Summary

Our cross-sectional modelling has generally found the competition-related variables to have an important statistical association with innovation activity at the firm level (the partial exception being in the ordered dependent variable models – which focus on aspects of the nature of innovation – where relatively few competition variables are statistically significant). Higher levels of market share are associated with a greater propensity to innovate – a Schumpeterian-type result, and one that is consistent with some previous Australian empirical work. All the other competition-related variables included in the modelling indicate an anti-Schumpeterian relationship – that increasing competition is associated with a higher likelihood of innovation by the firm. The inclusion of multiple competition variables in the analysis has enabled a more 'complete' multi-dimensional look at the relationship between competition indicators and firm-level innovation activity. Overall, the weight of evidence supports an anti-Schumpeterian relationship, but not exclusively so.

4. INNOVATION AND PRODUCTIVITY

The preceding section detailed the data, models and estimation results for the relationship between competition and innovation. This section provides similar details but on the relationship between innovation and productivity. The data and the construction of variables not already discussed in the preceding section are detailed first before moving on to the models employed and the estimation results and their interpretation.

The data[23]

Three years of data from the BLD (2005–06, 2006–07 and 2007–08) are used for the econometric analysis examining the relationship between innovation and productivity. The observations are pooled in order to provide a larger number of data-points.[24] The larger dataset across multiple years allows for utilisation of a limited time dimension in the analysis. A one year lag of the innovation measures is used in the analysis of the innovation/productivity relationship, reflecting the generally held view that innovation leads on to productivity growth, but with some delay.

Two measures of productivity are investigated for the analysis in this paper. The first is a subjective measure of productivity derived from responses to the BCS – surveyed firms are asked how their productivity changed relative to the previous year with the options of choosing ‘improved’, ‘declined’ or ‘stayed the same’. While productivity is not explicitly defined in the survey (which may introduce some spurious variation where there are differences between firms’ interpretation of the term ‘productivity’), this subjective measure provides an alternative to the more objective (but potentially compromised) measure of productivity discussed below. Most firms report no change in their assessment of productivity, while fewest firms report a decline (figure 4.1). Firms that innovated in the previous year appear more likely to have reported a productivity improvement in the current year.

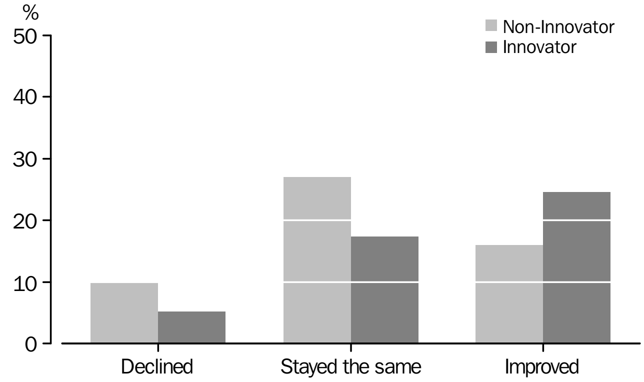
The alternative measure of productivity employed in the analysis is a more ‘objective’ proxy measure of multifactor productivity derived from tax information. This measure is created by dividing value added by the sum of primary factor input costs.[25]

23 As in the previous section, full descriptive statistics are available in Appendix A.

24 This larger pool of data is not available for analysis of the competition/innovation relationship as the more complicated measures of competition and innovation required for that analysis are available only for the 2006–07 year.

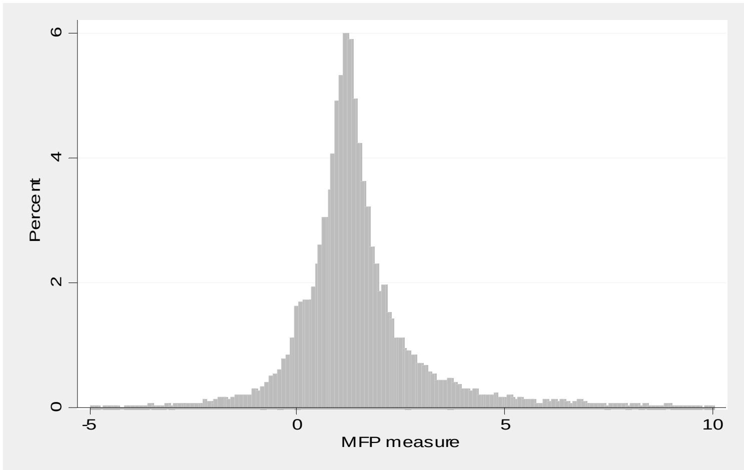
25 Factor costs are proxied by using the sum of book-value depreciation and ten percent of book-value non-current assets as a proxy for the cost of capital services, and wages as a proxy for labour costs.

4.1 Firm responses to how productivity changed compared to the previous year



It should immediately be noted that this is not a 'true' multifactor productivity measure, as both the numerator and denominator are nominal (no firm-level price series are available for deflation) and the nominal cost of labour and of capital are only quite general approximations to the true costs.[26] Productivity is generally measured as a growth term, rather than a level, but as there are insufficient data to generate productivity growth figures this relatively simple 'levels' measure provides the approximation for productivity at the firm level for one of the cross-sectional models employed here.

4.2 The objective, nominal measure of MFP derived from tax data[27]



26 The numerator of the MFP measure can be represented as an index of output prices multiplied by an index of output volumes, while the denominator could be represented as an index of factor input prices multiplied by an index of factor input volumes. The MFP measure used here therefore resembles the product of a 'true' MFP index and the ratio of an index of output prices to an index of input prices, with this later ratio looking like an inverse competition measure. Thus the proxy MFP measure used here can be directly influenced by variation in 'true' MFP and/or variation in the ratio of output to input prices. This means that an association between innovation and this proxy productivity measure could be influenced by variations in competition. By lagging innovation in our regressions we hope to avoid picking up the competition/innovation relationship already examined in the previous section, although there may also be a lagged relationship between competition/innovation and productivity.

27 Note that the full range of values is not shown in this figure: the top and bottom 1% of observations are trimmed for ease of presentation.

There is a small but non-trivial density (around 10 percent) of negative productivity values, indicating the presence of observations with negative value added (that is, some firms have costs of intermediate inputs greater than sales). It is not unusual to observe some poorly performing firms, especially ones that might be close to failure, displaying this characteristic. There are also some large values of ten or more (slightly less than 4% of observations).[28]

The models[29]

Two models were used to examine the relationship between innovation and productivity. The first uses firm responses to the BCS question on whether firm productivity declined, stayed the same, or increased. Because responses are categorical, discrete-choice modelling is again employed in the form of an ordered probit with the dependent variable taking the value 0 if productivity declined, 1 if productivity stayed the same and 2 if productivity improved.[30]

The alternative approach uses the measure of MFP derived from the tax data, described above and in figure 4.2 Ordinary least squares is used in this model to explain the variation in the level of the derived MFP measure, based on firms' innovation status in each of the four innovation types, as well as on employment size and industry of operation.

Results[31]

The model estimates presented in table 4.1 indicate that each of the innovation types is statistically significantly associated with the higher outcomes of the reported productivity variable. That is, for each type of innovation, a firm is less likely to report a decline, and more likely to report an increase in productivity if it also innovated in the previous year, compared to a firm that did not innovate. Estimated coefficients for each innovation type are reported in table 4.3 and the corresponding marginal effects on the predicted probabilities of reporting a decline in productivity and of reporting an increase in productivity, in the following year, are presented in table 4.4.

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28 One other possible explanation for the extreme values observed is that this measure does not take into account changes in inventories.
29 Again, full specifications of the models are detailed in Appendix B.
30 These ordinal values have no useful cardinal interpretation here and simply play the role of ordered labels.
31 Selected results are presented here. Full tables of econometric results are included in Appendix C.

4.3 Results from the ordered probit model using discrete subjective productivity variables

	Reported productivity change	
Lag of goods and services innovation	0.2294	***
Lag of organisational process innovation	0.0604	**
Lag of operational process innovation	0.1508	***
Lag of marketing methods innovation	0.0841	***
Constant 1	–0.4807	***
Constant 2	0.8916	***
Number of observations	14,677	
Wald chi-squared (29)	1752.09	
Prob > chi-squared	0.000	

4.4 Expanded marginal effects from the ordered probit model

	Reported productivity change			
	Productivity declined (pp %)		*Productivity improved (pp %)*	
Lag of goods and services innovation	–5	(–31%)	9	(26%)
Lag of organisational process innovation	–1	(–9%)	2	(7%)
Lag of operational process innovation	–3	(–21%)	6	(17%)
Lag of marketing methods innovation	–2	(–12%)	3	(9%)

As a guide to the magnitude of impact effects, the modelling predicts that a small firm that does not innovate has a predicted probability of about 17% of reporting a decline in productivity. However, an otherwise identical firm that is a goods and services innovator is predicted to have only a 12% probability of reporting a decline in productivity. As far as productivity improvement is concerned, a small manufacturer that is not an innovator is predicted to have about a 34% chance of reporting increased productivity, whereas if it is a goods and services innovator, this probability increases to around 43%.

The second model, using the derived MFP measure, provided much weaker and more mixed evidence of an association between innovation and productivity. Goods and services innovation was still associated with improvements in productivity, but was significant only at the 10% level while operational process innovation was *negatively* associated with productivity, again only at the 10% level of significance. The other two innovation types were not significant (see Appendix C). The poor statistical significance, variable signs on the coefficients, and *prima facie* problems of nominal values in the proxy MFP measure, particularly in the numerator, lead us to question the robustness of this model. Further work is needed to relate an objective productivity measure generated from tax information with innovation propensity at the firm level.

Summary

The modelling revealed a statistically significant and positive association between all types of innovation and the likelihood of survey respondents perceiving their productivity to have improved. This positive association was particularly strong in the case of goods and services, and operational process innovations. Furthermore, there is evidence to suggest that firms that are not innovators are more likely to report a decline in productivity than those that are innovators.

5. CONCLUSION

This paper uses the ABS Business Longitudinal Database to examine the relationship between competition, innovation and productivity in the context of the established theoretical literature. Two main theories of how competition and innovation interact: Schumpeterian and 'anti-Schumpeterian' are examined in the Australian case, with the evidence pointing strongly, but not entirely unambiguously, to an anti-Schumpeterian relationship. That is, the analysis finds that most of the competition-related indicators used here are strongly and positively associated with an increase in the propensity to innovate – the only exception being that of the market share indicator, which is a result found in other studies too.

Amongst the population of innovators, a larger market share and the propensity to export are identified as factors associated with a higher degree of novelty of innovation being completed, while a lower profit margin and a declaration to be 'hampered by competition' are both found to be associated with firms completing a greater number of different types of innovation. Some (but not all) intellectual property protection methods are found to be associated with firms achieving a higher degree of novelty of innovations and completing a greater number of innovations.

In terms of innovation and productivity at the firm level, a positive and statistically significant association is found between completing an innovation in any one of the four types of innovation, and reporting a productivity improvement in the following year. The association between 'goods and services' and 'operational process' type innovations and improved productivity is particularly strong.

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APPENDIXES

A. DATA

A.1 Descriptive statistics of variables for the 2006–07 cross-section

Variable	*Obs.*	*Mean*	*St. dev.*	*Min.*	*Max.*
Price cost margin (innovation scope)	6,420	0.1814	0.3605	–1.9738	0.9986
Age of business – years (innovation scope)	8,225	25.4621	28.0950	0	209
Export intensity – proportion (innovation scope)	5,288	0.0265	0.0607	0	0.9996
Market share					
Less than 10%	8,634	0.4935			
10% to 50%	8,634	0.3867			
Greater than 50%	8,634	0.1198			
Number of competitors					
No competitors	8,719	0.1199			
1 or 2 competitors	8,719	0.1247			
3 or more competitors	8,719	0.7555			
Hampered by competition					
Not ‘hampered’	8,511	0.8388			
Hampered’	8,511	0.1612			
Division of operation					
B – Mining	9,724	0.0356			
C – Manufacturing	9,724	0.2233			
D – Electricity, Gas, Water and Waste Services	9,724	0.0293			
E – Construction	9,724	0.0531			
F – Wholesale Trade	9,724	0.0872			
G – Retail Trade	9,724	0.0550			
H – Accommodation and Food Services	9,724	0.0630			
I – Transport, Postal and Warehousing	9,724	0.0687			
J – Information Media and Telecommunications	9,724	0.0387			
K – Financial and Insurance Services	9,724	0.0585			
L – Rental, Hiring and Real Estate Services	9,724	0.0324			
M – Professional, Scientific and Technical Services	9,724	0.0527			
N – Administrative and Support Services	9,724	0.0611			
P – Education and Training	9,724	0.0014			
Q – Health Care and Social Assistance	9,724	0.0495			
R – Arts and Recreation Services	9,724	0.0343			
S – Other Services	9,724	0.0563			
Size of business					
No employees (sole trader)	8,954	0.0428			
1–4 employees	8,954	0.2783			
5–19 employees	8,954	0.2361			
20–199 employees	8,954	0.1891			
200–499 employees	8,954	0.1261			
500+ employees	8,954	0.1277			
Export status					
Non-exporter	9,724	0.8100			
Exporter	9,724	0.1900			
Foreign ownership					
No foreign ownership	8,851	0.8668			
Greater than zero and less than 10%	8,851	0.0130			
10% to 50%	8,851	0.0174			
Greater than 50%	8,851	0.1028			

A.2 Spearman correlation rank coefficient table of some of the explanatory variables used in the competition-innovation analysis

	Market share	*# of competitors*	*PCM*	*Size*	*Export status*	*Export intensity*	*Hampered*
Market share	1						
# of competitors	–0.2819	1					
PCM	0.0203	–0.0823	1				
Size	0.1777	0.1205	–0.1247	1			
Export status	0.0126	0.0482	–0.0867	0.1851	1		
Export intensity	0.0480	0.0388	–0.0990	0.2021	0.6800	1	
Hampered	–0.0448	0.1327	–0.0960	0.0588	0.0193	0.0297	1

A.3 Descriptive statistics of variables for the 2006–07 and 2007–08 pool used in innovation-productivity analysis:

Variable	*Obs.*	*Mean*	*St. dev.*	*Min.*	*Max.*
Multifactor productivity measure	11,736	1.7902	2.9978	–6.3220	31.1780
Division of operation					
A – Agriculture, Forestry and Fishing	29,385	0.1489			
B – Mining	29,385	0.0328			
C – Manufacturing	29,385	0.1902			
D – Electricity, Gas, Water and Waste Services	29,385	0.0123			
E – Construction	29,385	0.0548			
F – Wholesale Trade	29,385	0.0840			
G – Retail Trade	29,385	0.0534			
H – Accommodation and Food Services	29,385	0.0554			
I – Transport, Postal and Warehousing	29,385	0.0599			
J – Information Media and Telecommunications	29,385	0.0272			
K – Financial and Insurance Services	29,385	0.0229			
L – Rental, Hiring and Real Estate Services	29,385	0.0220			
M – Professional, Scientific and Technical Services	29,385	0.0495			
N – Administrative and Support Services	29,385	0.0462			
O – Public Administration and Safety	29,385	0.0001			
P – Education and Training	29,385	0.0017			
Q – Health Care and Social Assistance	29,385	0.0387			
R – Arts and Recreation Services	29,385	0.0284			
S – Other Services	29,385	0.0465			
Z– Missing industry information	29,385	0.0250			

Note that Agriculture, forestry and fishing (AFF) information not available for use in the analysis of competition-innovation, but *is* available for use in innovation-productivity analysis. Cross-sectional estimates regarding estimation are not available for the AFF industry in the BLD for the 2006–07 innovation scope year, however once the analysis is extended to the pooled sample of multiple years of data, the preservation of the scope is no longer necessary. As such, AFF as an industry dummy is used in the innovation-productivity analysis.

B. MODELS[32]

Competition–Innovation

Let $\boldsymbol{x}$ be defined as the vector of explanatory variables used in the analysis. Then $\boldsymbol{x}$ is:

$$\boldsymbol{x} = \begin{cases} \text{Dummy variable for market share 10-50\%} \\ \text{Dummy variable for market share} > 50\% \\ \text{Dummy variable for number of competitors being 1 or 2} \\ \text{Dummy variable for number of competitors being 3 or more} \\ \text{Price Cost Margin} \\ \text{Dummy variable for } 1-4 \text{ employees} \\ \text{Dummy variable for } 5-19 \text{ employees} \\ \text{Dummy variable for } 20-199 \text{ employees} \\ \text{Dummy variable for } 200-499 \text{ employees} \\ \text{Dummy variable for } 500+ \text{ employees} \\ \text{Dummy variable for export status} \\ \text{Export intensity} \\ \text{Dummy variable for } >0 \text{ and } <10\% \text{ foreign ownership} \\ \text{Dummy variable for } 10\%-50\% \text{ foreign ownership} \\ \text{Dummy variable for } >50\% \text{ foreign ownership} \\ \text{Dummy variable for being 'hampered'} \\ \text{Dummy variables for each industry division (excluding manufacturing)} \end{cases}$$

Dependent variables are:

$$y_{inn} = \begin{cases} 1 & \text{if firm is an innovator} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{gs} = \begin{cases} 1 & \text{if firm is a goods and services innovator} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{opp} = \begin{cases} 1 & \text{if firm is an operational process innovator} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{org} = \begin{cases} 1 & \text{if firm is an organisational process innovator} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{mkm} = \begin{cases} 1 & \text{if firm is a marketing innovator} \\ 0 & \text{otherwise} \end{cases}$$

32 Much of this appendix is adapted from Greene (2008) and Wooldridge(2002).

Models 1–5 are binary probit models, where the probability of $y=1$ conditional on the independent vector variable $\boldsymbol{x}$, is given by the cumulative standard normal distribution:

$$\Pr(y=1 \mid x) = \int_{-\infty}^{x'\beta} \phi(t)dt = \Phi\left(x'\beta\right)$$

where the coefficient vector β is estimated using maximum likelihood methods.

This model is used to predict the likelihood of occurrence of y_{inn} (model 1), y_{gs} (model 2), y_{opp} (model 3), y_{org} (model 4) and y_{mkm} (model 5).

Multivariate Probit (model 6)

The multivariate probit model is a simultaneous system of several binary probits:

$$\begin{aligned}
y_1^* &= x_1'\beta_1 + \varepsilon_1, & y_1 &= \begin{cases} 1 & \text{if } y_1^* > 0 \\ 0 & \text{otherwise} \end{cases} \\
y_2^* &= x_2'\beta_2 + \varepsilon_2, & y_2 &= \begin{cases} 1 & \text{if } y_2^* > 0 \\ 0 & \text{otherwise} \end{cases} \\
&\vdots \\
y_N^* &= x_N'\beta_N + \varepsilon_N, & y_N &= \begin{cases} 1 & \text{if } y_N^* > 0 \\ 0 & \text{otherwise} \end{cases}
\end{aligned}$$

$$\begin{aligned}
E\left[\varepsilon_{\mathrm{i}} \mid x_1,\ldots,x_N\right] &= 0 \\
Var\left[\varepsilon_{\mathrm{i}} \mid x_1,\ldots,x_N\right] &= 1 \\
Cov\left[\varepsilon_i,\varepsilon_j \mid x_1,\ldots,x_N\right] &= \rho_{ij}
\end{aligned}$$

Until relatively recent times, estimation of the multivariate model in more than two dimensions has not generally been possible. This is because of the numerical complexity of estimating integrals under the multivariate normal. More recently these problems have been overcome by using *simulated maximum likelihood* methods. A set of user-written functions has recently been developed for Stata, that enables relatively straightforward estimation of the multivariate probit – the *mvprobit* and associated functions written by Capellari and Jenkins (2003) and an updated version of the program (Capellari and Jenkins, 2006) allows for calculation of the probabilities of all possible combinations of outcomes.

In this paper a multivariate probit model is used to investigate the relationship between competition and innovation. The system includes four probit equations with dependent variables being binary indicators of whether a firm is a goods and services innovator, an organisational process innovator, an operational process innovator, and/or a marketing innovator. The estimates for this model are presented in Appendix C.

The following scenarios illustrate the change in the predicted innovation outcome probabilities for a firm with specified base case characteristics when a nominated competition characteristic is changed.

The base case in all the scenarios below is a manufacturing firm with 10–50% market share, 1–2 competitors, a PCM of 0.2, and 5–19 employees. It is not an exporter, it is not hampered by the need to keep profit margins low in order to remain competitive, and has no foreign ownership.

Scenario A

The firm is the same as the base case apart from its market share, which is now set at 50% or more.

Outcome	Base case	Changed scenario
P(1,1,1,1)	0.5%	*0.7%*
P(1,1,1,0)	3.4%	*3.9%*
P(1,1,0,1)	2.5%	*2.7%*
P(1,0,1,1)	2.8%	*3.0%*
P(0,1,1,1)	2.6%	*2.8%*
P(1,1,0,0)	3.0%	*3.7%*
P(0,1,1,0)	3.6%	*4.0%*
P(0,0,1,1)	2.6%	*2.6%*
P(1,0,1,0)	6.0%	*6.6%*
P(0,1,0,1)	2.2%	*2.3%*
P(1,0,0,1)	3.6%	*4.0%*
P(1,0,0,0)	3.7%	*4.4%*
P(0,1,0,0)	4.4%	*4.7%*
P(0,0,1,0)	6.5%	*6.5%*
P(0,0,0,0)	1.4%	*1.0%*
P(0,0,0,0)	51.2%	*47.2%*

Legend:

P(0,0,0,0)	The outcome: P(*a*,*b*,*c*,*d*) *a* = 1 if a goods and services innovator *b* = 1 if an organisational process innovator *c* = 1 if an operational process innovator *d* = 1 if a marketing innovator
51.2%	The probability of the outcome for the firm with base case characteristics
47.2%	The probability of the outcome under the changed scenario

Scenario B

The firm is the same as the base case apart from its number of competitors, which is now three or more.

Outcome	Base case	Changed scenario
P(1,1,1,1)	0.5%	*0.6%*
P(1,1,1,0)	3.4%	*3.4%*
P(1,1,0,1)	2.5%	*2.6%*
P(1,0,1,1)	2.8%	*3.0%*
P(0,1,1,1)	2.6%	*2.9%*
P(1,1,0,0)	3.0%	*3.0%*
P(0,1,1,0)	3.6%	*3.8%*
P(0,0,1,1)	2.6%	*2.9%*
P(1,0,1,0)	6.0%	*5.9%*
P(0,1,0,1)	2.2%	*2.5%*
P(1,0,0,1)	3.6%	*3.8%*
P(1,0,0,0)	3.7%	*3.1%*
P(0,1,0,0)	4.4%	*4.4%*
P(0,0,1,0)	6.5%	*6.6%*
P(0,0,0,0)	1.4%	*1.6%*
P(0,0,0,0)	51.2%	*49.9%*

Legend:

P(0,0,0,0)	The outcome: P(*a*,*b*,*c*,*d*) *a* = 1 if a goods and services innovator *b* = 1 if an organisational process innovator *c* = 1 if an operational process innovator *d* = 1 if a marketing innovator
51.2%	The probability of the outcome for the firm with base case characteristics
49.9%	The probability of the outcome under the changed scenario

Scenario C

The firm is the same as the base case apart from its PCM, which is now 0.4.

Outcome	Base case	Changed scenario
P(1,1,1,1)	0.5%	*0.3%*
P(1,1,1,0)	3.4%	*3.2%*
P(1,1,0,1)	2.5%	*2.4%*
P(1,0,1,1)	2.8%	*2.7%*
P(0,1,1,1)	2.6%	*2.5%*
P(1,1,0,0)	3.0%	*2.8%*
P(0,1,1,0)	3.6%	*3.5%*
P(0,0,1,1)	2.6%	*2.4%*
P(1,0,1,0)	6.0%	*5.8%*
P(0,1,0,1)	2.2%	*2.0%*
P(1,0,0,1)	3.6%	*3.5%*
P(1,0,0,0)	3.7%	*3.7%*
P(0,1,0,0)	4.4%	*4.4%*
P(0,0,1,0)	6.5%	*6.6%*
P(0,0,0,0)	1.4%	*1.4%*
P(0,0,0,0)	51.2%	*52.7%*

Legend:

P(0,0,0,0)	The outcome: P(*a*,*b*,*c*,*d*) *a* = 1 if a goods and services innovator *b* = 1 if an organisational process innovator *c* = 1 if an operational process innovator *d* = 1 if a marketing innovator
51.2%	The probability of the outcome for the firm with base case characteristics
52.7%	The probability of the outcome under the changed scenario

Scenario D

The firm is the same as the base case except that it now declares itself to be ‘hampered’ by the need to keep profit margins low in order to remain competitive.

Outcome	Base case	Changed scenario
P(1,1,1,1)	0.5%	*1.2%*
P(1,1,1,0)	3.4%	*4.3%*
P(1,1,0,1)	2.5%	*3.3%*
P(1,0,1,1)	2.8%	*3.8%*
P(0,1,1,1)	2.6%	*3.4%*
P(1,1,0,0)	3.0%	*3.8%*
P(0,1,1,0)	3.6%	*4.5%*
P(0,0,1,1)	2.6%	*3.7%*
P(1,0,1,0)	6.0%	*7.2%*
P(0,1,0,1)	2.2%	*2.9%*
P(1,0,0,1)	3.6%	*4.5%*
P(1,0,0,0)	3.7%	*3.5%*
P(0,1,0,0)	4.4%	*4.0%*
P(0,0,1,0)	6.5%	*6.7%*
P(0,0,0,0)	1.4%	*1.4%*
P(0,0,0,0)	51.2%	*41.9%*

Legend:

P(0,0,0,0)	The outcome: P(*a*,*b*,*c*,*d*) *a* = 1 if a goods and services innovator *b* = 1 if an organisational process innovator *c* = 1 if an operational process innovator *d* = 1 if a marketing innovator
51.2%	The probability of the outcome for the firm with base case characteristics
41.9%	The probability of the outcome under the changed scenario

Scenario E

The firm is the same as the base case except it is now an exporter with export sales comprising 5% of its total sales.

P(1,1,1,1)
0.5%
1.5%

P(1,1,1,0)	P(1,1,0,1)	P(1,0,1,1)	P(0,1,1,1)
3.4%	2.5%	2.8%	2.6%
4.8%	*3.5%*	*4.3%*	*3.6%*

P(1,1,0,0)	P(0,1,1,0)	P(0,0,1,1)	P(1,0,1,0)	P(0,1,0,1)	P(1,0,0,1)
3.0%	3.6%	2.6%	6.0%	2.2%	3.6%
4.3%	*4.6%*	*3.9%*	*9.7%*	*2.4%*	*4.6%*

P(1,0,0,0)	P(0,1,0,0)	P(0,0,1,0)	P(0,0,0,0)
3.7%	4.4%	6.5%	1.4%
6.4%	*3.8%*	*7.5%*	*1.3%*

P(0,0,0,0)
51.2%
33.8%

Legend:

P(0,0,0,0)	The outcome: P(*a*,*b*,*c*,*d*) *a* = 1 if a goods and services innovator *b* = 1 if an organisational process innovator *c* = 1 if an operational process innovator *d* = 1 if a marketing innovator
51.2%	The probability of the outcome for the firm with base case characteristics
33.8%	The probability of the outcome under the changed scenario

Ordered Probit (models 7 & 8)

This model is used to estimate the effects of the independent variables on a discrete outcome that has a linear ordering. In the case of this paper, there are two variables that have such an ordering: the number of different types of innovations that a firm completes and the highest degree of novelty of innovation that a firm completes. The models are used to investigate the nature of innovations completed by the innovating firms. Both of these variables have four outcomes (zero to three) defined as follows:

$$y_{types} = \text{ The number of innovation types completed } \equiv y_{gs} + y_{opp} + y_{org} + y_{mkm}$$

$$y_{novelty} = \begin{cases} 0 \text{ if highest degree of novelty of innovation completed is 'new to the firm'} \\ 1 \text{ if highest degree of novelty of innovation completed is 'new to industry'} \\ 2 \text{ if highest degree of novelty of innovation completed is 'new to Australia'} \\ 3 \text{ if highest degree of novelty of innovation completed is 'new to the world'} \end{cases}$$

The model can be thought of as arising from a latent (unobserved) variable y^* that determines the outcome of the ordered variable:

$$y_i^* = x'\beta_i + \varepsilon_i$$

$$y = \begin{cases} 0 & \text{if } y^* \le \alpha_1 \\ 1 & \text{if } \alpha_1 < y^* \le \alpha_2 \\ 2 & \text{if } \alpha_2 < y^* \le \alpha_3 \\ 3 & \text{if } \alpha_3 < y^* \end{cases}$$

The alphas are estimated along with the coefficients on the conditioning variables and the ε_i are assumed to be independent and arise from a standard normal distribution. The probabilities of each outcome are:

$$\begin{aligned} \Pr(y=0 \mid x) &= \Phi\left(\alpha_1 - x'\beta\right) \\ \Pr(y=1 \mid x) &= \Phi\left(\alpha_2 - x'\beta\right) - \Phi\left(\alpha_1 - x'\beta\right) \\ \Pr(y=2 \mid x) &= \Phi\left(\alpha_3 - x'\beta\right) - \Phi\left(\alpha_2 - x'\beta\right) \\ \Pr(y=3 \mid x) &= 1 - \Phi\left(\alpha_3 - x'\beta\right) \end{aligned}$$

It should be noted that positive coefficients in the ordered probit will result in positive marginal effects in some categories and negative marginal effects in others, though the marginal effect will be positive for $\Pr(y=3)$ and negative for $\Pr(y=0)$. For other categories the sign of the marginal effect depends on the value of x at which it is calculated and on the alphas and betas. Indeed, the sum across all categories of the marginal effects associated with each independent variable must be zero.

Innovation and Productivity Models (models 9 and 10)

Ordered probit modelling was employed for the survey response variable regarding productivity (model 9), while ordinary least squares regression was used for the continuous measure of productivity derived from tax data (model 10).

In these models, there are fewer explanatory variables:

$$X = \left\{ \begin{array}{l} y_{gs}(t-1) \\ y_{opp}(t-1) \\ y_{org}(t-1) \\ y_{mkm}(t-1) \\ \text{Dummy variable for } 1-4 \text{ employees} \\ \text{Dummy variable for } 5-19 \text{ employees} \\ \text{Dummy variable for } 20-199 \text{ employees} \\ \text{Dummy variable for } 200-499 \text{ employees} \\ \text{Dummy variable for } 500+ \text{ employees} \\ \text{Dummy variables for each industry division (excluding manufacturing)} \\ \text{Dummy variable for year } = 2007-08 \end{array} \right\}$$

The productivity measures are defined as:

$$y_{productivity} = \begin{cases} 0 & \text{if productivity declined, as asked in the BCS survey} \\ 1 & \text{if productivity stayed the same as asked in the BCS survey} \\ 2 & \text{if productivity improved as asked in the BCS survey} \end{cases}$$

$$y_{mfp} = \left(\frac{\text{Value added}}{\text{Wages and salaries} + \text{Depreciation} + 0.1 \times \text{Non-current assets}} \right)$$

Note that 'capital services' is proxied in the tax data-derived measure as depreciation plus ten per cent of non-current assets. Ten per cent was chosen based on real rates of return to capital in the market sector for 2000–2007 calculated by Dolman (2007). Alternative measures that use five and fifteen per cent were also used in the regression analysis, but these did not yield substantially different results.

C. MODEL ESTIMATES

Competition–Innovation

C.1 Model 1

	Completed any type of innovation			
	Coefficient		*ME (pp)*	*ME (%)*
10–50% market share	0.2073	***	8	(22%)
50%+ market share	0.3133	***	12	(34%)
1 or 2 competitors	0.4107	***	15	(56%)
3+ competitors	0.4257	***	16	(58%)
PCM	–0.1586	***	–6	(–15%)
1–4 employees	0.5349	***	16	(103%)
5–19 employees	0.8287	***	27	(173%)
20–199 employees	1.0684	***	37	(234%)
200–499 employees	1.2791	***	45	(287%)
500+ employees	1.5331	***	54	(346%)
Age of business	–0.0010		0	(0%)
0–10% foreign owned	0.5608	*	22	(54%)
10–50% foreign owned	0.0918		4	(9%)
50%+ foreign owned	–0.2713	***	–10	(–25%)
Exporting Business	0.4042	***	16	(40%)
Export intensity	–0.1486		–6	(–14%)
'Hampered by competition'	0.2084	***	8	(20%)
Mining	–0.3762	***	–14	(–32%)
Electricity, Gas, Water and Waste Services	0.0147		1	(1%)
Construction	–0.3719	***	–14	(–32%)
Wholesale Trade	–0.1461	**	–6	(–13%)
Retail Trade	–0.2148	**	–8	(–19%)
Accommodation and Food Services	–0.3711	***	–14	(–32%)
Transport, Postal and Warehousing	–0.2121	***	–8	(–19%)
Information Media and Telecommunications	0.0856		3	(8%)
Financial and Insurance Services	0.2550	***	10	(23%)
Rental, Hiring and Real Estate Services	–0.1464		–6	(–13%)
Professional, Scientific and Technical Services	–0.0201		–1	(–2%)
Administrative and Support Services	–0.0801		–3	(–7%)
Education and Training	–0.5354		–19	(–44%)
Health Care and Social Assistance	–0.2209	*	–9	(–19%)
Arts and Recreation Services	–0.0532		–2	(–5%)
Other Services	–0.0168		–1	(–1%)
Constant	–1.4256	***	na	na

C.2 Models 2–5

	Goods and services			*Organisational process*		
	Coefficient	*ME (pp (%))*		*Coefficient*	*ME (pp (%))*	
10–50% market share	0.1823 ***	5	(29%)	0.1549 ***	4	(24%)
50%+ market share	0.3359 ***	10	(57%)	0.2438 ***	7	(39%)
1 or 2 competitors	0.4400 ***	11	(94%)	0.2979 ***	7	(56%)
3+ competitors	0.4027 ***	10	(84%)	0.3263 ***	8	(63%)
PCM	–0.1604 **	–5	(–22%)	–0.2166 ***	–6	(–30%)
1–4 employees	0.4473 ***	9	(111%)	0.3254 **	6	(78%)
5–19 employees	0.6358 ***	14	(176%)	0.7063 ***	15	(213%)
20–199 employees	0.7289 ***	17	(211%)	1.0269 ***	26	(362%)
200–499 employees	0.9309 ***	24	(296%)	1.2328 ***	34	(470%)
500+ employees	1.1809 ***	33	(413%)	1.1276 ***	30	(414%)
Age of business	–0.0026 **	0	(0%)	–0.0025 **	0	(0%)
0–10% foreign owned	0.6957 **	24	(119%)	0.5761 *	20	(97%)
10–50% foreign owned	0.2314	7	(35%)	0.1545	5	(23%)
50%+ foreign owned	–0.1185	–3	(–16%)	–0.1631	–4	(–21%)
Exporting Business	0.4000 ***	13	(62%)	0.1322 **	4	(19%)
Export intensity	–0.2505	–7	(–35%)	–0.0394	–1	(–5%)
'Hampered by competition'	0.2128 ***	6	(31%)	0.1470 ***	4	(21%)
Mining	–0.4667 ***	–12	(–50%)	–0.1297	–3	(–17%)
Electricity, Gas, Water and Waste Services	–0.0622	–2	(–8%)	0.2296 *	7	(36%)
Construction	–0.3570 ***	–9	(–40%)	–0.0856	–2	(–12%)
Wholesale Trade	0.0259	1	(3%)	–0.0904	–2	(–12%)
Retail Trade	–0.0714	–2	(–9%)	–0.2154 **	–5	(–28%)
Accommodation and Food Services	–0.2267 **	–6	(–27%)	–0.1773 *	–4	(–23%)
Transport, Postal and Warehousing	–0.3973 ***	–10	(–44%)	–0.0282	–1	(–4%)
Information Media and Telecommunications	0.1052	3	(14%)	0.3103 ***	10	(50%)
Financial and Insurance Services	0.0632	2	(8%)	0.4580 ***	15	(77%)
Rental, Hiring and Real Estate Services	–0.3484 ***	–9	(–40%)	0.1225	4	(18%)
Professional, Scientific and Technical Services	–0.0494	–1	(–6%)	0.1728 *	5	(26%)
Administrative and Support Services	–0.1291	–4	(–16%)	0.1832 *	5	(28%)
Education and Training	–0.7132	–16	(–68%)	–0.1116	–3	(–15%)
Health Care and Social Assistance	–0.0687	–2	(–9%)	0.1516	4	(23%)
Arts and Recreation Services	–0.0833	–2	(–11%)	0.2353 **	7	(37%)
Other Services	0.0090	0	(1%)	0.0844	2	(13%)
Constant	–1.7758 ***	0	(0%)	–1.8258 ***	0	(0%)
Number of observations	5,044			5,044		
Wald chi-squared*	295.36			328.17		
Prob > chi-squared	0.000			0.000		
Psuedo R-squared	0.060			0.067		

* The number of degrees of freedom for the Wald test for the models examining goods and services innovation, organisational process innovation and marketing innovation is 33, while a test with 32 degrees of freedom is used in the model examining operational process innovation. The reason for this is that the industry division dummy for 'education and training' (ANZSIC06 Division P) is not included in the operational process innovation model, as no firm in this division completed such an innovation.

C.2 Models 2–5 (cont.)

	Operational process				*Marketing*			
	Coefficient		*ME (pp (%))*		*Coefficient*		*ME (pp (%))*	
10–50% market share	0.1775	***	5	(27%)	0.0594		1	(10%)
50%+ market share	0.2302	***	7	(36%)	0.0261		1	(4%)
1 or 2 competitors	0.2206	**	6	(37%)	0.3190	***	6	(73%)
3+ competitors	0.2576	***	7	(44%)	0.4095	***	8	(99%)
PCM	–0.1231	**	–4	(–17%)	–0.2417	***	–6	(–38%)
1–4 employees	0.4047	***	8	(100%)	0.5980	***	8	(212%)
5–19 employees	0.6925	***	15	(202%)	0.8115	***	13	(335%)
20–199 employees	0.9968	***	26	(335%)	0.8170	***	13	(339%)
200–499 employees	1.0726	***	28	(371%)	1.0935	***	22	(540%)
500+ employees	1.4987	***	45	(589%)	1.1047	***	22	(549%)
Age of business	0.0002		0	(0%)	0.0004		0	(0%)
0–10% foreign owned	0.1648		5	(24%)	0.5456	*	16	(108%)
10–50% foreign owned	–0.1209		–3	(–16%)	0.2528		7	(45%)
50%+ foreign owned	–0.2180	**	–6	(–27%)	–0.1165		–3	(–17%)
Exporting Business	0.3631	***	12	(54%)	0.2135	***	5	(36%)
Export intensity	–0.3953	**	–12	(–53%)	0.1064		2	(17%)
‘Hampered by competition’	0.2391	***	7	(34%)	0.2262	***	6	(38%)
Mining	–0.4977	***	–14	(–50%)	–0.5581	***	–11	(–61%)
Electricity, Gas, Water and Waste Services	–0.0034		0	(0%)	–0.5277	***	–10	(–59%)
Construction	–0.2762	***	–9	(–30%)	–0.5142	***	–10	(–58%)
Wholesale Trade	–0.2382	***	–7	(–26%)	–0.0217		–1	(–3%)
Retail Trade	–0.4579	***	–13	(–47%)	–0.2277	**	–5	(–30%)
Accommodation and Food Services	–0.5182	***	–15	(–51%)	–0.0730		–2	(–10%)
Transport, Postal and Warehousing	–0.1667	*	–5	(–19%)	–0.3693	***	–8	(–45%)
Information Media and Telecommunications	–0.1825	*	–6	(–21%)	0.2511	**	7	(41%)
Financial and Insurance Services	0.0669		2	(8%)	0.0516		1	(8%)
Rental, Hiring and Real Estate Services	–0.4510	***	–13	(–46%)	0.0105		0	(2%)
Professional, Scientific and Technical Services	–0.2098	**	–7	(–23%)	–0.0539		–1	(–8%)
Administrative and Support Services	–0.3040	***	–9	(–33%)	–0.1398		–3	(–19%)
Education and Training	na		na		–0.4310		–9	(–51%)
Health Care and Social Assistance	–0.4099	***	–12	(–42%)	–0.2201		–5	(–29%)
Arts and Recreation Services	–0.3282	***	–10	(–35%)	0.1875	*	5	(30%)
Other Services	–0.2619	***	–8	(–29%)	–0.0821		–2	(–12%)
Constant	–1.5844	***	0	(0%)	–2.0606	***	0	(0%)
Number of observations	5,034				5,044			
Wald chi-squared*	379.68				237.56			
Prob > chi-squared	0.000				0.000			
Psuedo R-squared	0.073				0.058			

C.3 Additional output for models 2–5: p-values of tests of equality of coefficients on size variables

	Number of employees				
	1–4	*5–19*	*20–199*	*200–499*	*500+*
			Model 2: Goods and services		
1–4 employees	na	0.0002	0.0000	0.0014	0.0129
5–19 employees	0.0002	na	0.0794	0.0499	0.0643
20–199 employees	0.0000	0.0794	na	0.1797	0.1251
200–499 employees	0.0014	0.0499	0.1797	na	0.4379
500+ employees	0.0129	0.0643	0.1251	0.4379	na
			Model 3: Organisational process		
1–4 employees	na	0.0000	0.0000	0.0000	0.0058
5–19 employees	0.0000	na	0.0000	0.0002	0.1461
20–199 employees	0.0000	0.0000	na	0.1494	0.7279
200–499 employees	0.0000	0.0002	0.1494	na	0.7376
500+ employees	0.0058	0.1461	0.7279	0.7376	na
			Model 4: Operational process		
1–4 employees	na	0.0000	0.0000	0.0000	0.0002
5–19 employees	0.0000	na	0.0000	0.0106	0.0055
20–199 employees	0.0000	0.0000	na	0.6078	0.0837
200–499 employees	0.0000	0.0106	0.6078	na	0.1788
500+ employees	0.0002	0.0055	0.0837	0.1788	na
			Model 5: Marketing		
1–4 employees	na	0.0001	0.0003	0.0020	0.0967
5–19 employees	0.0001	na	0.9227	0.0762	0.3357
20–199 employees	0.0003	0.9227	na	0.0815	0.3448
200–499 employees	0.0020	0.0762	0.0815	na	0.9733
500+ employees	0.0967	0.3357	0.3448	0.9733	na

Each cell contains the p-value for the test of the null hypothesis that the estimated coefficients for the two firm sizes are identical. Each test is a chi-squared test with a single degree of freedom. For example, in goods and services, the hypothesis that the estimated coefficient of 200–499 employees is equal to that of 1–4 employees is rejected at the five per cent level of significance (a p-value of 0.0014). However, the null hypothesis that the estimated coefficient of 200–499 employees is the same as that of 500+ employees cannot be rejected at the five per cent level of significance (a p-value of 0.4379).

C.4 Model 6: Multivariate probit

	Goods and services		*Organisational process*	
	Coefficient	*p-value*	*Coefficient*	*p-value*
10–50% market share	0.1926	0.00	0.1596	0.00
50%+ market share	0.3571	0.00	0.2548	0.00
1 or 2 competitors	0.4585	0.00	0.3033	0.00
3+ competitors	0.4202	0.00	0.3382	0.00
PCM	–0.1672	0.01	–0.2091	0.00
1–4 employees	0.4419	0.00	0.3927	0.01
5–19 employees	0.6274	0.00	0.7645	0.00
20–199 employees	0.7302	0.00	1.0914	0.00
200–499 employees	0.9214	0.00	1.2984	0.00
500+ employees	1.1878	0.00	1.1771	0.00
Age of business	–0.0024	0.02	–0.0025	0.02
0–10% foreign owned	0.6656	0.02	0.5553	0.05
10–50% foreign owned	0.2336	0.27	0.1669	0.42
50%+ foreign owned	–0.1200	0.26	–0.1836	0.09
Exporting Business	0.4140	0.00	0.1597	0.01
Export intensity	–0.2720	0.15	–0.0553	0.74
'Hampered by competition'	0.2109	0.00	0.1496	0.00
Mining	–0.4425	0.00	–0.0990	0.49
Electricity, Gas, Water and Waste Services	–0.0332	0.80	0.2551	0.06
Construction	–0.3722	0.00	–0.0936	0.35
Wholesale Trade	0.0195	0.79	–0.0871	0.27
Retail Trade	–0.0809	0.41	–0.2039	0.05
Accommodation and Food Services	–0.2330	0.01	–0.1754	0.06
Transport, Postal and Warehousing	–0.3945	0.00	–0.0026	0.98
Information Media and Telecommunications	0.1059	0.30	0.3105	0.00
Financial and Insurance Services	0.0886	0.37	0.4664	0.00
Rental, Hiring and Real Estate Services	–0.3264	0.01	0.1514	0.17
Professional, Scientific and Technical Services	–0.0462	0.63	0.1686	0.08
Administrative and Support Services	–0.1217	0.24	0.1869	0.06
Education and Training	–0.1670	0.70	0.3591	0.36
Health Care and Social Assistance	–0.0746	0.57	0.1396	0.29
Arts and Recreation Services	–0.0814	0.45	0.2546	0.02
Other Services	0.0126	0.88	0.1084	0.21
Constant	–1.8105	0.00	–1.9194	0.00
Number of observations	5,005			
Wald chi-squared (131)	863.97			
Prob > chi-squared	0.0000			

C.4 Model 6: Multivariate probit (cont.)

	Operational process		*Marketing*	
	Coefficient	*p-value*	*Coefficient*	*p-value*
10–50% market share	0.1851	0.00	0.0685	0.15
50%+ market share	0.2419	0.00	0.0557	0.51
1 or 2 competitors	0.2081	0.02	0.3424	0.00
3+ competitors	0.2558	0.00	0.4343	0.00
PCM	–0.1293	0.04	–0.2319	0.00
1–4 employees	0.5679	0.00	0.6341	0.00
5–19 employees	0.8409	0.00	0.8370	0.00
20–199 employees	1.1528	0.00	0.8561	0.00
200–499 employees	1.2449	0.00	1.1320	0.00
500+ employees	1.6195	0.00	1.1258	0.00
Age of business	0.0001	0.94	0.0006	0.56
0–10% foreign owned	0.1002	0.76	0.5582	0.06
10–50% foreign owned	–0.1306	0.51	0.2518	0.24
50%+ foreign owned	–0.2346	0.03	–0.1305	0.24
Exporting Business	0.3817	0.00	0.2424	0.00
Export intensity	–0.3325	0.03	0.0607	0.73
'Hampered by competition'	0.2379	0.00	0.2217	0.00
Mining	–0.4398	0.00	–0.5208	0.00
Electricity, Gas, Water and Waste Services	0.0026	0.98	–0.5050	0.01
Construction	–0.2875	0.00	–0.5414	0.00
Wholesale Trade	–0.2267	0.00	–0.0410	0.60
Retail Trade	–0.4375	0.00	–0.2149	0.04
Accommodation and Food Services	–0.5178	0.00	–0.0781	0.42
Transport, Postal and Warehousing	–0.1391	0.11	–0.3515	0.00
Information Media and Telecommunications	–0.1973	0.06	0.2428	0.02
Financial and Insurance Services	0.0970	0.31	0.0750	0.47
Rental, Hiring and Real Estate Services	–0.4099	0.00	0.0299	0.80
Professional, Scientific and Technical Services	–0.2074	0.04	–0.0599	0.56
Administrative and Support Services	–0.2878	0.00	–0.1340	0.22
Education and Training	na	na	–0.0297	0.95
Health Care and Social Assistance	–0.4238	0.00	–0.2090	0.15
Arts and Recreation Services	–0.3037	0.01	0.1834	0.09
Other Services	–0.2223	0.01	–0.0635	0.49
Constant	–1.7648	0.00	–2.1403	0.00
Number of observations				
Wald chi-squared (131)				
Prob > chi-squared				

C.5 Off-diagonal terms in the variance-covariance matrix

	Goods and services	*Organisational process*	*Operational process*
Organisational process	0.528		
Operational process	0.623	0.715	
Marketing	0.587	0.586	0.561

Likelihood ratio test of all off-diagonal terms being zero is a chi-squared test statistic with six degrees of freedom = 2504.08. The p-value of the test statistic is less than one percent. It should also be noted that each off-diagonal term is statistically significantly different from zero at the one per cent level of significance.

C.6 Models 7 and 8: Ordered probit with innovators only

	Number of innovation types		*Highest degree of novelty of innovation*	
	Coeff	*P>z*	*Coeff*	*P>z*
Patents	0.0007	0.996	0.1988	0.186
Registration of Design	0.5067	0.000	0.4502	0.003
Copyright or Trademark	0.0849	0.218	–0.0050	0.957
Secrecy / Confidentiality Agreement	0.4710	0.000	0.3614	0.000
Complexity of Design	0.2755	0.039	0.6245	0.000
Other method to protect IP	0.3061	0.194	0.4339	0.155
10–50% market share	0.0297	0.583	0.0800	0.288
50%+ market share	0.0765	0.390	0.3168	0.014
1 or 2 competitors	0.0782	0.515	–0.1231	0.442
3+ competitors	0.1362	0.228	–0.0865	0.568
PCM	–0.1826	0.019	0.0066	0.952
1–4 employees	0.1387	0.953	–0.2416	0.509
5–19 employees	0.1838	0.436	–0.3748	0.306
20–199 employees	0.2428	0.308	–0.4671	0.204
200–499 employees	0.3317	0.233	–0.1896	0.640
500+ employees	0.3516	0.282	–0.9622	0.107
Age of business	–0.0012	0.300	0.0035	0.053
0–10% foreign owned	0.2903	0.319	0.5267	0.125
10–50% foreign owned	0.0577	0.802	–0.0187	0.959
50%+ foreign owned	–0.0713	0.587	–0.6925	0.289
Exporting Business	–0.0051	0.941	0.3267	0.000
Export intensity	–0.1861	0.288	0.1894	0.463
'Hampered by competition'	0.1888	0.001	0.1363	0.084
Mining	–0.4312	0.023	–0.7736	0.005
Electricity, Gas, Water and Waste Services	–0.2759	0.109	0.0046	0.984
Construction	–0.0571	0.640	0.0279	0.870
Wholesale Trade	0.0478	0.605	0.0133	0.910
Retail Trade	–0.3060	0.017	–0.1448	0.910
Accommodation and Food Services	0.0146	0.908	–0.0374	0.439
Transport, Postal and Warehousing	–0.2200	0.054	–0.7459	0.830
Information Media and Telecommunications	0.1468	0.229	0.2169	0.001
Financial and Insurance Services	–0.0832	0.486	–0.3010	0.188
Rental, Hiring and Real Estate Services	–0.1896	0.170	–0.1156	0.058
Professional, Scientific and Technical Services	–0.1843	0.129	–0.0132	0.561
Administrative and Support Services	–0.1186	0.295	–0.2602	0.933
Education and Training	–1.4718	0.000	na	na
Health Care and Social Assistance	0.0272	0.855	0.0544	0.127
Arts and Recreation Services	0.0887	0.517	–0.3159	0.108
Other Services	–0.1599	0.096	–0.1992	0.166
Constant 1	0.0360	0.446	0.5520	0.077
Constant 2	0.8697	0.001	0.9250	0.009
Constant 3	1.6243	0.000	1.3435	0.000
Number of observations	2,076		1,734	
Wald chi-squared (39 & 38)	186.13		181.95	
Prob > chi-squared	0.000		0.000	
Psuedo R-squared	0.036		0.071	

Note that this set of tables shows the results for the ordered probit models explaining the number of innovation types and highest degree of novelty of innovation for firms that are innovators only. These 'intellectual property' variables cannot be used in the full sample of the ordered probit regression, as they only apply to innovating firms.

C.7 Model using survey responses and derived measures for productivity (models 9 & 10)

	Subjective productivity		*Objective productivity*
	Coefficient	*ME (pp (%))*	*Coefficient*
Lagged goods and services innovation	0.2294 ***	0.14 (8%)	0.1786 *
Lagged operational process innovation	0.1508 ***	0.09 (5%)	–0.1533 *
Lagged organisational process innovation	0.0604 **	0.04 (2%)	–0.0518
Lagged marketing innovation	0.0841 ***	0.05 (3%)	–0.0097
1–4 employees	0.2296 ***	0.14 (8%)	–0.5444 **
5–19 employees	0.4257 ***	0.27 (14%)	–0.9936 ***
20–199 employees	0.5899 ***	0.37 (20%)	–1.1241 ***
200–499 employees	0.8140 ***	0.50 (27%)	–0.2335
500+ employees	0.9910 ***	0.60 (32%)	–0.5285
Agriculture, Forestry and Fishing	–0.1333 ***	–0.08 (–4%)	–0.5105 ***
Mining	0.1691 ***	0.11 (6%)	0.0015
Electricity, Gas, Water and Waste Services	0.1875 **	0.12 (6%)	–0.3302
Construction	–0.0087	–0.01 (0%)	0.3661 **
Wholesale Trade	0.1426 ***	0.09 (5%)	0.5159 ***
Retail Trade	0.1126 **	0.07 (4%)	0.4379 **
Accommodation and Food Services	0.0306	0.02 (1%)	0.4845 ***
Transport, Postal and Warehousing	0.1523 ***	0.10 (5%)	0.0941
Information Media and Telecommunications	0.1823 ***	0.11 (6%)	0.0155
Financial and Insurance Services	0.0863	0.05 (3%)	0.2056
Rental, Hiring and Real Estate Services	0.0739	0.05 (2%)	0.0188
Professional, Scientific and Technical Services	0.3109 ***	0.20 (10%)	0.3410 *
Administrative and Support Services	0.0470	0.03 (2%)	0.4205 *
Public Administration and Safety	0.3905	0.25 (13%)	–0.6455 **
Education and Training	0.0443	0.03 (1%)	0.5184
Health Care and Social Assistance	–0.0085	–0.01 (0%)	0.4310
Arts and Recreation Services	–0.0609	–0.04 (–2%)	0.1419
Other Services	0.0637	0.04 (2%)	0.3139 *
Missing Industry Information	–0.0758	–0.05 (–3%)	–0.3848
Year 2008 dummy	–0.0578 ***	–0.04 (–2%)	0.3109 ***
Constant 1	–0.4807 ***	na	2.3517 ***
Constant 2	0.8916 ***	na	na
Model	Ordered Probit		OLS
Number of Observations	14,677		7,414
Wald chi-squared (29)	1752.09		na
Prob > chi-squared	0.000		na
Psuedo R-squared	0.064		na
F(29, 7384)	na		6.270
Prob > F	na		0.000
R-squared	na		0.027

C.8 Auxiliary model testing industry specific PCM coefficients

	Any innovation completed	
	Coefficient	*P>z*
10–50% market share	0.2077	0.000
50%+ market share	0.3148	0.000
1 or 2 competitors	0.4160	0.000
3+ competitors	0.2393	0.000
PCM – Mining	–0.3562	0.335
PCM – Manufacturing	–0.1054	0.354
PCM – Electricity, Gas, Water and Waste Services	–0.3572	0.264
PCM – Construction	–0.4225	0.145
PCM – Wholesale Trade	–0.1723	0.361
PCM – Retail Trade	0.0256	0.930
PCM – Accommodation and Food Services	–0.6420	0.006
PCM – Transport, Postal and Warehousing	0.1042	0.656
PCM – Information Media and Telecommunications	–0.1382	0.489
PCM – Financial and Insurance Services	–0.1120	0.608
PCM – Rental, Hiring and Real Estate Services	0.0618	0.809
PCM – Professional, Scientific and Technical Services	–0.2489	0.391
PCM – Administrative and Support Services	–0.2278	0.367
PCM – Education and Training	–1.8524	0.373
PCM – Health Care and Social Assistance	0.0169	0.953
PCM – Arts and Recreation Services	–0.2120	0.375
PCM – Other Services	–0.0455	0.840
1–4 employees	0.5395	0.000
5–19 employees	0.8252	0.000
20–199 employees	1.0754	0.000
200–499 employees	1.3014	0.000
500+ employees	1.5449	0.000
Age of business	–0.0010	0.273
0–10% foreign owned	0.5766	0.056
10–50% foreign owned	0.0978	0.637
50%+ foreign owned	–0.2710	0.006
Exporting Business	0.4035	0.000
Export intensity	–0.1470	0.373
'Hampered by competition'	0.2065	0.000
Mining	–0.3202	0.048
Electricity, Gas, Water and Waste Services	0.0626	0.647
Construction	–0.3134	0.003
Wholesale Trade	–0.1364	0.079
Retail Trade	–0.2296	0.020
Accommodation and Food Services	–0.2676	0.005
Transport, Postal and Warehousing	–0.2545	0.007
Information Media and Telecommunications	0.0914	0.374
Financial and Insurance Services	0.2504	0.025
Rental, Hiring and Real Estate Services	–0.1928	0.120
Professional, Scientific and Technical Services	0.0107	0.930
Administrative and Support Services	–0.0590	0.589
Education and Training	0.2883	0.963
Health Care and Social Assistance	–0.2503	0.071
Arts and Recreation Services	–0.0365	0.729
Other Services	–0.0314	0.735
Constant	–1.4420	0.000
Number of observations	5,044	
Wald chi-squared (49)	469.32	
Prob > chi-squared	0.000	
Psuedo R-squared	0.076	

The test of the null hypothesis that all the coefficients are –0.158 on the PCM measure (the value found for the restricted equation, which is the same as model 1) yields a test statistic of 10.04 under the chi-squared distribution with 17 degrees of freedom. The critical value to reject the null at a ten-per cent level of significance is 27.59. As the test statistic does not exceed the critical value, the null hypothesis cannot be rejected at the 10% level of significance. This suggests that industry specific coefficients for the price cost margin are unnecessary.

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