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What's driving innovation in small businesses in Australia? The case of the food industry*

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There is strong evidence that innovation is a primary driver of a nation's economic growth. As Australia continues to compete in the global economy, it is imperative that businesses should be innovative to improve their performance. In this paper, we evaluate the status and main drivers of innovation in small businesses in the food sector in Australia. Discrete choice modelling and bootstrapping procedures are applied to a panel of firm-level data collected through the ABS Business Characteristics Survey (2006–2007 to 2010–2011 for the Australian Bureau of Statistics' Business Longitudinal Database Confidential Unit Record File) to investigate the factors affecting the likelihood of small food businesses to innovate. Results show that businesses are more likely to innovate if they collaborate, have higher information and communication technology intensity, and use science, technology, engineering and mathematics skills. We also found that small food businesses, even at the subsector level, do combine different types of innovation when innovating. The propensity to innovate also increases for small businesses that have flexible working arrangements, face moderate-to-strong market competition, operate overseas and seek finance through debt and equity. The relative importance of these factors was found to vary between agricultural and nonagricultural food subsectors.

Key words: Australia, collaboration, science technology engineering and mathematics skills, information and communication technology, innovation.

1. Introduction

The Australian Government is strongly committed to developing an internationally competitive and productive environment for small businesses. Small businesses[1] play a significant role in the Australian economy,

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[1] The concept of a *small business* is quite intuitive, and there is no consistently used definition. The OECD defines it as a firm with generally fewer than 50 employees (OECD 2005b). This study employs the ABS definition of an actively trading business with less than 20 employees. Categories of businesses include the following: nonemploying business–sole proprietorships without employees; microbusinesses (businesses employing fewer than five people), including nonemploying businesses; and small businesses (businesses employing five or more, but fewer than 20, people) (ABS 2002).

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accounting for almost half of the employment in the private nonfinancial sector and over one-third of production (Australian Bureau of Statistics (ABS) 2015b). They account for the majority of the Australian business counts (97.5 per cent) in 2016–2017 (ABS 2018) and are believed to be the critical players in Australia's economy, underpinning growth and innovation, and providing jobs for millions of Australians (Australian Government 2015). A recent study by Hendrickson *et al.* (2015) established that young small and medium enterprises (SMEs) made the highest contribution (40 per cent) to net job creation in Australia over the period 2006 to 2011.

Along with these small businesses, the Australian Government considers the food and agribusiness industry an important part of the Australian economy because it makes significant contributions to the economies of regional areas in employment, business and service opportunities (Department of Industry, Innovation and Science (DIIS) 2017). Australia's food and agribusiness industry production was around A$ 54 billion of industry value added in 2014–2015 which is equivalent to 3.3 per cent of the total GDP. Its labour productivity has increased at an annual rate of 2.4 per cent over the past five years since 2010. The industry's exports were worth A$ 40.8 billion in 2015 (Chaustowski and Dolman 2016). With this industry spending nearly A$ 728 million on research and development (R&D) related to food, beverage and agricultural machinery manufacturing, an important question is as follows: Have the small food businesses been engaging in any form of innovation activities that are useful in improving their performance?

Innovation remains vital to the expansion and international competitiveness of Australia's economy and, as Australia continues to compete in the global economy, Australian businesses such as the small food businesses need to be innovative for job creation and income growth (DIISR 2009, 2018a). Innovation statistics in selected growth sectors[2] in Australia show that only 32.7 per cent of all businesses in food and agribusiness were engaged in any innovative activity in 2013–2014 of which 28.2 per cent successfully introduced and implemented innovation (ABS 2015d). This was lower than the overall proportion of business innovators in Australia, which was 48.3 per cent in that period. In addition, the innovation rate for Australian small businesses employing 5–19 persons was 59.9 per cent in 2013–2014 (ABS 2015c). Evidently, there is a need to encourage small businesses in the food and agribusiness industry to innovate to become more competitive and productive. To unleash the potential of small food businesses to innovate, grow and create more jobs, it is imperative to examine more closely what drives them. This is what the current study seeks to achieve.

Central to the vision of providing the right economic incentives to enable businesses – big and small – to grow, the Australian Government through the

[2] The food and agribusiness growth sector includes food-related production, food processing and the major inputs into these sectors, but not the wholesale and retail sale of these goods (ABS 2015d).

Industry Innovation and Competitiveness Agenda[3] has identified food and agribusiness as an area of competitive strength and prioritised it as a growth sector (Department of the Prime Minister and Cabinet 2014). A key initiative in the agenda was establishing Industry Growth Centres and, in the case of the Australian food and agribusiness sector, the Food and Agribusiness Growth Centre, known as Food Innovation Australia Ltd (FIAL), which was established to build capability and encourage collaboration and innovation in the industry involved (DIIS 2017). For the growth centre's plans, activities or strategies to drive innovation, productivity and competitiveness and help food and agribusiness businesses build stronger futures for themselves, and it is essential to provide empirical evidence of factors that drive these businesses to innovate. Empirical studies on the determinants of innovation in the Australian food sector are nonexistent, so a study on small food businesses in Australia using firm-level data is desirable to support the above-mentioned agenda.

In the light of the above discussion, this study aims to evaluate the status and main drivers of innovation in small businesses in the food industry in Australia using a discrete choice model with panel data. In particular, we examine how large the impacts of these key drivers are on business innovation, and what are the implications of the findings for the government's innovation agenda and initiatives. What is compelling in this work is the use of the food industry sample in the five waves, (2006–2007 to 2010–2011, of the ABS Business Longitudinal Database (BLD)), a unique extract of longitudinal microdata that have never been used by any previous researcher to analyse business innovation or performance in small businesses in the Australian food industry using panel data. The data also allowed us to go deeper and analyse the food industry subsectors. Another remarkable contribution of our study is the estimation of robust standard errors for the impact measures called 'average partial effects' via simulation using modern bootstrapping procedures as well as analysing their distribution. This empirical study also adds to the literature on the analytical use of the ABS confidentialised business survey microdata.

The paper proceeds as follows. Section 2 presents a review of the relevant literature which formed the basis for the hypotheses and conceptual framework of this study. Section 3 describes the data and the methodology used in the empirical analysis. Sections 4 and 5 provide the findings and conclusions.

2. Literature review and framework

This section examines the theoretical and empirical literature on innovation that describes the key determinants and relationships examined in this study.

[3] More information regarding the Industry Innovation and Competitiveness Agenda and Growth Centres can be found at the DIIS website: www.industry.gov.au.

The choice of the key determinants is limited to the information being collected in the ABS Business Characteristics Survey (BCS) and what has been used in the previous ABS cross-sectional studies on innovation. Particular attention is given to the food industry studies on innovation by other countries and those previous ABS and DIIS innovation analyses (mostly cross-sectional). Included also are the conceptual framework, some definitions and the hypotheses to be tested.

2.1 Defining innovation

This study uses the Organisation for Economic Co-operation and Development (OECD) definition of *innovation* as provided in the Oslo Manual:

> ...the implementation of a new and significantly improved product (good or service); or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations.(OECD 2005a, p. 46)

A business is called 'innovation-active' if it engages in any innovation activities that were implemented, ongoing or abandoned during a period. A business is called an 'innovator' if it successfully developed and implemented an innovation, which may have taken many years to complete (OECD 2005a). The current investigation is conducted for 'innovation-active' businesses.

The study uses an output-based measure of innovation obtained from the ABS BCS data. Four types of innovation are scoped in the analysis: product innovation, organisational or managerial innovation, operational process innovation and marketing innovation (OECD 2005a). Product innovation is any good or service or combination of these which is new (or significantly improved) to a business. New or significantly improved strategies, structures or routines of a business that aim to improve performance belong to organisational or managerial innovations. Operational process innovations refer to new methods of producing or delivering the products including significant changes in techniques, equipment and/or software. And, new design, packaging or sales methods to increase the appeal of goods or services of a business or to enter new markets are classified as marketing innovations. Of course, a business could undertake more than one type of innovation.

The earliest work on innovation came from Schumpeter (1942), who described capitalism as a form or method of economic change which can never be stationary. The fundamental impulse that sets and keeps the capitalist engine in motion comes from new consumer goods, new methods of production or transportation, new markets or new forms of industrial organisations those capitalist enterprises create. Schumpeter developed a theory where an enterprise's ability to innovate was mainly due to its size, stating that large businesses are the main drivers of innovation, being better resourced and having monopolistic power in the market. In this study, we provide supportive evidence that small businesses in the Australian food sector can be strong innovators too.

2.2 Innovation and collaboration

According to the Oslo manual, the innovative activities of a firm partly depend on the variety of linkages to sources of information, knowledge, technologies, practice, and human and financial resources. One of the external links is innovation cooperation, which requires active collaboration with other firms or research institutions on innovation activities (OECD 2005a). The Nelson and Winter (1982) model states that the organised R&D efforts of firms are the sources of innovation. This model views innovation as a path-dependent process where knowledge and technology are established via interaction between various participants (firms, institutions and society) known as the evolutionary approach. Closely intertwining this are the systems of innovation approaches (Nelson 1993 and Lundvall 2010) where external institutions influence the innovation activities of firms through the transfer of ideas, skills, knowledge and information. The above models link collaboration with innovation.

Another model receiving much attention recently that works very well with collaboration is open innovation (OI). Chesbrough (2003) introduced and defined OI as the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation. The OI concept has been applied in several studies. For example, Bigliardi and Galati (2016) indicated that SMEs operating in less innovative industries give emphasis to collaboration as barriers to OI. Henttonen and Lehtimäki (2017) show that technology-intensive SMEs engaged in OI for commercialisation rather than for R&D. Marangos and Warren (2017) examined what strategies the senior managers of R&D-intensive SMEs in the life sciences sector conduct concerning OI. Studies by Bigliardi and Galati (2016), Henttonen and Lehtimäki (2017), and Marangos and Warren (2017) also provide good literature reviews on OI in SMEs. An extensive review of the literature regarding the adoption of OI in the food industry is by Bigliardi and Galati (2013). The adoption of OI practices in the food industry is still emerging, and requires attention and further investigations from academia using firm-level data.

Analysing the relationship between collaboration and innovation in the food industry is not new in the international arena. There is evidence that innovation is influenced when businesses collaborate externally. De Martino and Magnotti (2017) found that partnerships between academia and research institutions were crucial in boosting the innovative capacity of small food firms in Italy. Galati *et al*. (2016) looked at how networking with innovation partners is needed for food firms to perform effective OI. Innovation in Italian food businesses has also been shown to rely on R&D activities and knowledge sourcing with external partners (e.g. universities, customers, suppliers, competitors, public or private institutions) (Maietta 2015; Ciliberti *et al*. 2016a,b). Wixe *et al*. (2017) and Caiazza and Stanton (2016) found that innovation in small food firms had significant association with external collaboration to access knowledge. A study by Grunert *et al*. (1997) in Denmark found that the interaction among R&D, market orientation and collaboration are major determinants of innovation in the food sector. McAdam *et al*. (2014) observed that horizontal collaboration (i.e. between firms in the same industry, not competing directly but selling and marketing to similar customers) among SMEs in the UK agri-food sector also played a significant role. However, in Australia, studies on collaboration and innovation in the food industry are minimal and only focused on the descriptive profiling of industries without quantitative measures with respect to the determinants of innovation (ABS 2015d).

Collaboration is highly valued in Australian innovation systems. It is defined as an interactive process that involves more than two individuals, businesses or organisations working cooperatively towards a common goal, including some sharing of technical and commercial risk (DIIS 2008). Innovation and collaboration are high priorities for the Australian Government because working with researchers can give Australian businesses a competitive edge. The Cooperative Research Centres Program is a good example of the initiative led by the DIIS focusing on collaborative research partnerships between industry entities and research organisations (DIIS 2018b). In relation to the food industry, FIAL recently released Australia's first food, beverage and agribusiness cluster initiative that would benefit farmers, food suppliers and retailers across Australia. This program encourages businesses, researchers and educational institutions to work together to build on their comparative advantage and develop innovations (FIAL 2017). For policymakers like the DIIS, understanding if collaboration enables, or is at least associated with, innovation among small food industry businesses is of great interest.

In this study, collaboration is measured as a binary response when a business is involved in any of the following collaborative arrangements: joint R&D, joint buying, joint production of goods and services, integrated supply chain, joint marketing or distribution, and other collaborative arrangements specified by the business. It can be simple partnerships between suppliers and customers, linked networks on common interests, associations of like industries, industry or business groups, research institutes, joint ventures and entities. It has been established in some ABS and DIIS research studies that collaboration plays a significant role in driving business innovation. It is found to be strongly and positively associated with a higher likelihood of being an innovator (DITR 2006; ABS 2008; Rotaru 2013; Rotaru and Soriano 2013). To provide empirical evidence to support the proposition that this relationship also holds true in the case of the small food businesses in Australia, we seek to test the hypothesis: 'Small food industry firms that collaborate are more likely to innovate' (Hypothesis 1).

2.3 Innovation and skills

Much innovation knowledge is embodied in people and their skills, and appropriate skills are needed to make use of external sources of innovation (i.e. the role of human capital in a firm's engagement in any form of innovation); for example, how well the skills of employees match the needs of innovative firms and collaborators (OECD 2005a). According to OI strategy, firms need smart and technologically capable managers to properly communicate and exchange ideas with external partners (Marangos and Warren 2017). Galati *et al.* (2016) studied how personnel skills were needed for food firms to perform effective OI.

The link between skills and innovation is supported by the human capital theory and resource-based theory. Becker (1994) viewed human capital as directly useful in the production process (and the process connects to innovation). More explicitly, human capital increases the productivity of workers in different tasks. The Australian Workforce and Productivity Agency (2013) compiled international and national literature that establishes skills that play a key role in productivity. The resource-based theory (Grant 1991) established that both resources and capabilities of a firm (hereby human capital) are central in formulating its strategy that provides direction as well as the primary source of profit. Resources include the skills of employees which are inputs in the production process, and capabilities are the capacity of employees to perform tasks.

Toner (2011) reviewed the literature on the role of workforce skills in the innovation process (to incremental innovation, in particular) in developed economies. It draws from the innovation studies discipline, neoclassical human capital theory, institutionalist labour market studies and the work organisation discipline. It showed that the quantity and quality of workforce skills are a major factor in determining the observed patterns of innovation and are key aspects of economic performance. The quality of human capital, as an important driver of process and product innovation, has also been seen in the works of Capitanio *et al.* (2009, 2010). In the food sector, Huiban and Bouhsina (1998), Avermaete *et al.* (2004), Smit *et al.* (2015), Vancauteren (2016), and Brown and Roper (2017) showed that skills of the workforce play a key role in business innovation.

A recent ABS study by Soriano and Abello (2015) found that the probability of innovation is higher for a business that uses employees with science, technology, engineering and mathematics (STEM) skills than for a business that does not use these skills. The impact of the use of STEM skills on the probability of having 'new-to-the-world' type of innovation is also found to be strong and positive. Following the work of Soriano and Abello (2015), skills in this study are assessed using the STEM qualifications of employees used by the firm. STEM skills are defined to be present in a firm, according to the Australian Standard Classification of Education (ABS 2001), if employees have qualifications of one or more of the following:

postgraduate degree, master degree, graduate diploma, graduate certificate, bachelor degree, advanced diploma and Certificates II and IV, in any of the fields of the natural and physical sciences (including mathematical sciences); information technology (IT); engineering and related technologies; and agricultural, environmental and related studies. The STEM skill variables are constructed based on the type of skills used by a business, as reported in the ABS BCS. A business is considered to have used STEM skills if it reported using any of the following skills: engineering, scientific research, IT professionals and IT support technicians. These are based on subjective responses by businesses to the BCS question about the types of skills used in undertaking core business activities. It is worth noting that a particular business may use any of the above STEM skills in combination with other non-STEM skills such as trade, transport, and plant and machinery operation. To determine whether skills of employees drive the small food businesses in Australia to innovate, we want to test the hypothesis 'Small food industry firms that use STEM skills are more likely to innovate' (Hypothesis 2).

2.4 Innovation and ICT

A conceptual link between the adoption of information and communication technology (ICT) and innovation was established by Köllinger (2005) who argued that ICT has strategic relevance for firms because it is a valuable source of business innovation providing substantial efficiency gains. ICT technologies that create automated system links lead to more streamlined businesses processes and enable employees to develop closer links between businesses, their suppliers, customers, competitors and collaborative partners, allowing the business to be more responsive to innovation opportunities (Todhunter and Abello 2011; Domenech *et al.* 2014; Salim *et al.* 2015; Galati *et al.* 2016). The same arguments were discussed and analysed by Gretton *et al.* (2003) and Tiy *et al.* (2013) using Australian data, indicating that ICT plays an important role in business innovation. Gago and Rubalcaba (2007) found that businesses that invest in ICT, particularly those that regard their investment as strategically important, are significantly more likely to engage in services innovation. In regard to the food industry, Galati *et al.* (2016) revealed that ICT was needed for Italian food firms to perform effective OI.

OECD (2003, pp. 3–4) defined *ICT* as 'goods ... that are either intended to fulfil the function of information processing and communication by electronic means, including transmission and display, or which use electronic processing to detect, measure and/or record physical phenomena, or to control a physical process'. In this study, we combine broadband Internet connection, business Web presence and use of e-commerce into an *ICT intensity index* to develop a convenient and meaningful measure of ICT sophistication (i.e. business not having broadband connection (low ICT intensity) to having the three components of innovation (most intense ICT). This index was also applied by Todhunter and Abello (2011) and Tiy *et al*. (2013). Using the same index, econometric analyses at ABS have shown that there is a positive and significant association between business innovation and the use of ICT (Todhunter and Abello 2011; Rotaru 2013; Rotaru and Soriano 2013; Rotaru *et al*. 2013; Tiy *et al*. 2013). These studies reveal that more intense ICT users are likely to undertake more types of innovation. The same hypothesis is tested here for small food businesses in Australia, stated as 'Small food industry firms that have higher ICT intensity are more likely to innovate' (Hypothesis 3).

2.5 Innovation and flexible working arrangements

Is labour market flexibility good for innovation? Can businesses gain and maintain a competitive edge in the global and ever-changing and uncertain environment if they allow this flexibility? Labour market flexibility, being a dynamic concept, has received considerable and growing attention in recent years (Beatson 1995), in which 'flexibility' was defined as the ability of markets (and the agents that operate in them) to respond to changing economic conditions. There are different forms of labour market flexibility and, following Atkinson (1984), Beatson (1995), Michie and Sheehan-Quinn (2001), Reilly (2001) and Kleinknecht *et al*. (2006), labour market flexibility can be categorised into five types:

- *Numerical flexibility* is the ability of firms to allow variation in the number of employees or workers used. Examples are temporary, seasonal, casual, outsourcing and fixed-term workers.
- *Temporal flexibility* is the ability of firms to allow variability of working hours. Examples are part-time, shift, reduced hours, overtime and leave flexibility.
- *Functional flexibility* is the ability of firms to allocate their labour force to carry out a wide range of task and activities. Examples are multiskilling, task flexibility and cross-functional working.
- *Locational flexibility* is the ability of firms to use employees outside the normal workplace. Examples are home-based work, use of mobile phones and tele/outworkers.
- *Financial or wage flexibility* is the ability of firms to decide wage levels in line with corporate performance. Examples are gain or profit sharing, wage-cutting deals and pay increases based on performance.

Studies that examined labour market flexibility (following any of the above types) and innovation have been increasing (Michie and Sheehan-Quinn 2001; Storey *et al*. 2002; Michie and Sheehan 2003; Kleinknecht *et al*. 2006, 2014; Zhou *et al*. 2011). Kleinknecht *et al*. (2006) followed Schmooklerian demand-pull theory (see Schmookler 1966) where higher effective demand increases innovative activity and labour productivity. In relation to labour market flexibility, they found that wage restraint or downward wage flexibility impedes innovation. In terms of numerical flexibility, the study noted that a large inflow of new people (skilled and productive) enriched the pool of innovative ideas within firms and led to new collaborations. Zhou *et al*. (2011) found that firms with high shares of workers on fixed-term contracts tend to have fewer sales of innovative new products, while high functional flexibility enhances firm's new products sales. Chung (2009) observed that temporal flexibility had an effect on innovation, whereas Martinez-Sanchez *et al*. (2008) revealed that innovation performance was positively associated with internal functional flexibility and negatively associated with numerical flexibility and outsourcing, but the relationships between them were moderated by interorganisational cooperation.

Rotaru (2013) and Rotaru and Soriano (2013) were the first to examine the relationships between four types of flexible working arrangements (flexible working hours, flexible leave, job sharing and working from home) and innovation using Australian business survey data at the firm level. Both studies found that all these four factors played important roles in influencing innovation. The degree of relationship varied but was mostly positive and significant. We know of no study on labour market flexibility and innovation in the food industry; hence, this paper is a pioneering work that establishes the role of work flexibility on innovation for small food businesses in Australia. Thus, we hypothesise that 'Small food industry firms that have flexible working arrangements are more likely to innovate' (Hypothesis 4).

The variable for flexible working arrangements in this paper is limited to a business offering their employees any of the above four arrangements, as in Rotaru (2013) and Rotaru and Soriano (2013).

2.6 Innovation and competition

Studying the relationship between market competition and innovation has long been of interest to economic researchers and policy analysts. Schumpeterian theory states that greater levels of market competition faced by businesses lead to declining innovation, but most empirical works have found the opposite result. There is a wealth of theoretical literature on the connection between competition and innovation, but a more recent theory by Aghion *et al*. (2005) suggests that the relationship between the two has an inverted-U shape. This framework is an attractive one because it reconciles the Schumpeterian and non-Schumpeterian results (i.e. increased competition is associated with more innovation). In addition, the industrial organisation theory of Tirole (1988) also emphasised the importance of competitive positioning – that businesses innovate to remain in their competitive position and avoid losing (see Correa (2012) for a similar framework to Aghion *et al.* (2005)).

There is a wealth of international empirical literature that has examined the link between competition and innovation using firm-level data, but examples are few in Australia (Bhattacharya and Bloch 2004; Rogers 2004; Wong *et al.* 2007; ABS 2008; Griffiths and Webster 2009; Soames *et al.* 2011; Rotaru and Soriano 2013; Rotaru *et al.* 2013; Soriano and Abello 2015; Palangkaraya *et al.* 2016). Soames *et al.* (2011) obtained empirical results that supported the Aghion *et al.* hypothesis. Similar results were reported by Rotaru *et al.* (2013), Rotaru and Soriano (2013), and Soriano and Abello (2015) using the ABS BCS data.

In this paper, the degree of market competition is divided into four categories: no effective competition (no competitors); minimal competition (1–2 competitors); moderate competition (3–4 competitors) and strong competition (five or more competitors). We are interested to test whether the theory of Aghion *et al.* (2005) holds in the case of small food businesses in Australia. This will add to the empirical literature on the link between competition and innovation in the food industry, which is minimal at the moment. The specific hypothesis is 'Small food industry firms that face moderate-to-strong competition are more likely to innovate' (Hypothesis 5).

2.7 Other drivers of innovation from food industry studies

Empirical studies using firm-level data in the food industry have also observed some other important determinants of innovation, one being exporting behaviour of firms. The modern trade and growth theories by Grossman and Helpman (1991), and Aghion and Howitt (2009) suggest that access to export markets affects innovation. The recent work of Aghion *et al.* (2018) provides evidence where a simple model of trade and innovation predicts that a positive export shock increases market size and, therefore, innovation incentives for more productive businesses. A study on the food industry by Domenech *et al.* (2014) indicated that the adoption of ICT technologies was a key factor for innovation in agri-food industries in Spain, and it was highly influenced by firm size and export orientation. Another study of Spanish agri-food firms showed that export was positively associated with the four types of innovation (Zouaghi and Sanchez 2016). Providing evidence on the relationship between export and innovation in small businesses in the food industry has received little attention, although there is evidence showing that Australian businesses engaging in any export activity are more likely to innovate (Soames *et al.* 2011; Rotaru 2013; Tuhin 2016; Tuhin and Swanepoel 2017).

Another important driver of innovation is having good financial support, either internally or externally, to fund innovations. Getting access to finance is of crucial importance for investing in innovations (Sauer 2017). In Australia, lack of access to additional funds was the most commonly reported barrier (17 per cent) to undertaking innovation (ABS 2017). Rotaru *et al.* (2013) applied propensity score matching in the context of causal modelling, using the ABS BCS data, and found a statistically significant association between government assistance and innovation. De Martino and Magnotti (2017) also concluded that public funding is crucial in boosting the innovative capacity of small food firms in Italy.

Other food industry studies like that by Avermaete *et al.* (2003) found that innovation depends on business age and regional economic performance. Zouaghi and Sanchez (2016) found a significant impact of the global financial crisis (GFC) on the innovative performance of agri-food firms. The year effects were considered in this current study to capture the impact of GFC. The authors also found a local study that examined the important role of intellectual property (IP) in the food innovation process. IP Australia (2014) used patent analysis to assess the scope, quality and impact of innovative activity in the food sector and showed that Australia exhibits a positive technological specialisation in the food industry and collaboration is prevalent among universities and research institutes.

From the above food industry studies on innovation, it can be gleaned that other factors such as export, finance, age of firms, patents and an external factor like the GFC may be associated with firms' propensity to innovate. Smith and Hendrickson (2016) also verified the importance of a firm's age in their analysis of Australian SMEs. Unfortunately, patents and age information are not currently available in our data set.

2.8 The conceptual framework

In view of the above literature and hypotheses, the conceptual framework employed in this study is presented in Figure 1.

The above framework shows the key determinants for business innovation that are expected to play an important role in small businesses in the Australian food industry. The determinants (i.e. collaboration, the use of resources with STEM skills, ICT, flexible working arrangements, competitiveness, export capability, access to finance and business size) were selected or have been limited by the availability of data on small food businesses in the ABS BCS. These drivers are believed to push businesses in the small food industry in Australia to engage in forms of innovation, thereby providing empirical evidence that will support the Australian Government's Industry Innovation and Competitiveness Agenda. Establishing the connections between collaboration, the use of STEM skills, ICT and innovation among small businesses in the Australian food industry are also very important for the National Innovation and Science Agenda (Australian Government 2017). Such evidence serves as an input for the DIIS policy evaluation regarding innovation and productivity growth in the food industry. The directions of the arrows in Figure 1 show their interdependency relationships. The general focus of the analyses is for one aspect of innovation – the propensity of businesses to innovate (i.e. overall innovation). However, additional analysis incorporating the four types of innovation using multivariate modelling is undertaken to complement the main findings. The study also examines the

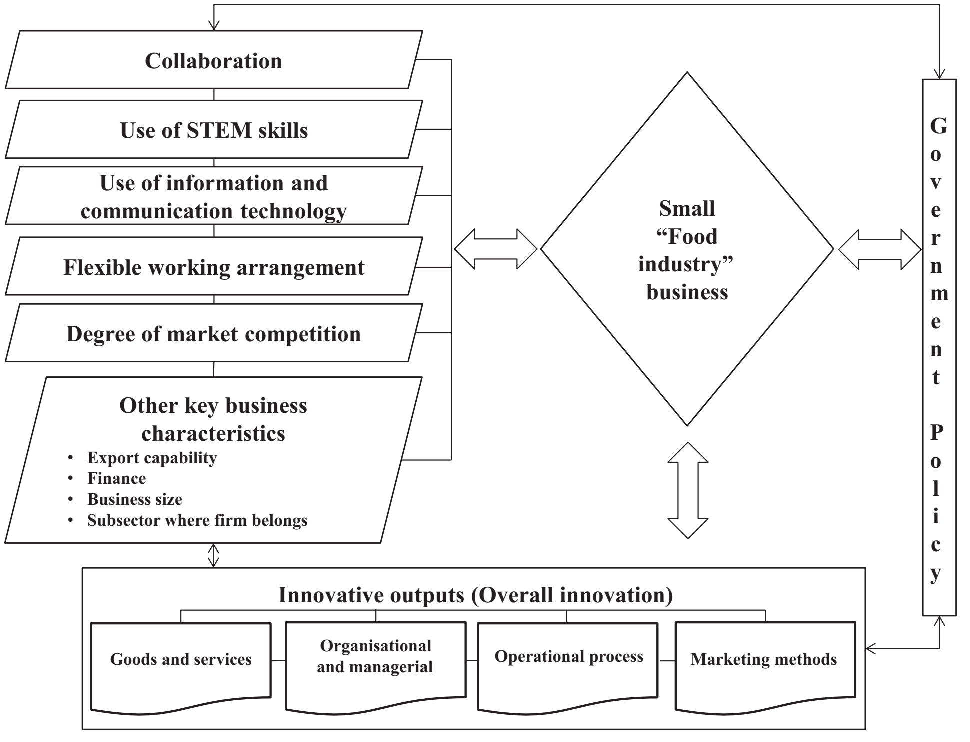

Figure 1 Conceptual framework for the study.

effects of the above determinants on the food industry subsectors – the small food businesses belonging to the agriculture, forestry and fishing industry, and manufacturing and wholesale trade industries.[4]

3. Data and methods

3.1 Data source

This study uses firm-level data from the ABS BLD contained in the ABS Business Longitudinal Analysis Data Environment (ABS BLADE).[5] The BLD contains longitudinal data from small and medium businesses that are designed to allow analysis of micro drivers of business innovation and performance over time. The BLD is specifically designed for longitudinal analyses and not to produce reliable aggregated/population information/

[4] These are the only Australian and New Zealand Standard Industrial Classification (ANZSIC) division 1 industries covered in the ABS Business Longitudinal Data (BLD) used in this study. Businesses sampled are predominantly associated with food for human consumption in the above three industry divisions (ABS 2013).

[5] Formerly known as the ABS Expanded Analytical Business Longitudinal Database (ABS EABLD) (ABS 2015e).

estimates. Successive panels are followed for five years, with collected characteristics data using the BCS linked to a small number of financial data items sourced from the Business Activity Statement (BAS) data provided to the ABS by the Australian Taxation Office. The BCS collects data on key indicators of business performance, use of ICT and innovation in Australian businesses (ABS 2015a,c). The BLD is made available to researchers via a confidentialised unit record file (CURF) that is accessible through the ABS Data Laboratory.[6]

The empirical analysis specifically utilises the third panel of the ABS BLD CURF (ABS 2013). This BLD CURF comprises one sample (referred to as a panel) that is drawn from the in-scope Australian business population at 30 June 2007. This panel contains data from this one sample over five reference periods (2006–2007, 2007–2008, 2008–2009, 2009–2010 and 2010–2011). The total sample size is 3,075. The BLD sample design is based on the panel that represents the Australian business population when the panel is introduced in the BLD. The scope of the BLD is actively trading businesses with a simple structure in the Australian economy.

The requirement to include the food industry component in the first three panels of the ABS BLD arose in 2003 following the commissioned project of the Department of Agriculture, Fisheries and Forestry to analyse the business performance of small and medium businesses in the Australian food industry. This component was developed by including an additional sample in the three relevant industry divisions: agriculture, forestry and fishing (AgriFF); manufacturing (MFG); and wholesale trade (WT) (non-AgriFF = MFG and WT). It is defined by the 2006 Australian and New Zealand Standard Industrial Classification (ANZSIC06) classes predominantly associated with food for human consumption in the above three industry divisions (ABS 2006). The third BLD CURF panel is the last panel to include the food industry component (ABS 2013).

Of the 3,075 businesses sampled for the third BLD Panel, 984 businesses are flagged belonging to the food industry. Table 1 presents the distribution of the sampled units by business size. The volume of data included in the BLD is substantial, and users should take into consideration cleaning and quality checking them before using them in any analysis. Data may be missing in the BLD CURF due to changes in the survey questions, sampled businesses ceasing operation (either temporary or permanent death), sampled businesses undergoing structural change, survey nonresponse and other reasons. After cleaning and quality checking the food industry sample, particularly the data items required for the panel modelling, the current study ended up with a balanced panel of 417 small businesses, 237 belonging to AgriFF and 180 coming from the combined manufacturing and wholesale

[6] For more information on the ABS Data Laboratory, see Parker (2017).

trade divisions. Although part of the original BLD, the medium-sized food businesses are not included in our study.

The panel analysis discussed in Section 4 has been shortened to four years (i.e. 2007–2008 to 2010–2011) because the questions on business use of STEM skills and flexible working arrangements were not available in the 2006–2007 BCS questionnaire.

3.2 Methods

This subsection presents the methodological framework employed to address the objectives stated in Section 1 and in testing the five hypotheses outlined in Section 2. We follow Wooldridge (2010) to provide the theoretical underpinnings for the various empirical models.

The main panel modelling approach utilised in our study mostly follows that of Rotaru (2013), and Rotaru and Soriano (2013). These studies are the first ABS methodological papers that explore the implementation, estimation and performance of different discrete choice longitudinal data models using the Main Unit Record File of the ABS BLD. The models include the following: the pooled model; the standard random-effects model; the correlated random-effects model, using the specifications of Mundlak (1978) and Chamberlain (1984); a standard dynamic model; and a dynamic random-effects probit model that follows Wooldridge (2005).

The standard random-effects probit model is employed. It is one of the most popular and widely used nonlinear models for binary outcomes with panel data (Wooldridge 2005, 2010, 2013; Greene 2012; Hensher *et al*. 2015). It has been applied also to model innovation propensity in the food industry (Triguero *et al*. 2013; Vancauteren 2016). A key assumption for this model is that the observed covariates are strictly exogenous, conditional on the unobserved effect.

Table 1 Food industry panel sample size in the ABS BLD CURF panel three, 2006–2007 to 2010–2011

	Nonemploying businesses no.	Micro (1–4 persons) no.	Small (5–19 persons) no.	Medium (20–199 persons) no.	All business size groups No.
BLD sample					
AgriFF	144	144	132	129	549
Non-AgriFF	135	111	96	93	435
Total	279	255	228	222	984
Sample used in the modelling					
AgriFF	64	88	85		237
Non-AgriFF	59	56	65		180
Total	123	144	150		417

For firm i at time t, let x_{it} be a vector of (observed) explanatory variables. The explanatory variables include the following business characteristics: business size; subsector where the business belongs; collaboration status; business use of STEM skills; business use of ICT (or ICT intensity); degree of market competition; business export capability[7] ; flexible working arrangements; business finance (i.e. business seeks debt and/or equity); time period (year effects); and a constant term. The construction of the variables included in the model follows the ABS studies mentioned in Section 2 (ABS 2008; Todhunter and Abello 2011; Rotaru 2013; Rotaru and Soriano 2013; Rotaru *et al.* 2013; Tiy *et al.* 2013; Soriano and Abello 2015). Interested readers are referred to these studies for more details.

We consider the dependent variable, y_{it}, as a binary response variable taking the value 1 if the i-th business innovated in the t-th year, and 0 otherwise. Assume that the values taken by y_{it} are determined by a latent variable, y_{it}^*, given by

$$y_{it}^* = x_{it}'\beta + \alpha_i + \varepsilon_{it}, \text{where } i = 1, k, n; t = 1, 2, 3, 4, \tag{1}$$

where y_{it}^* is the unobserved binary variable which corresponds to y_{it}, the observed dichotomous variable for firm i at time t. The relationship between y_{it} and y_{it}^* is defined by

$$y_{it} = \begin{cases} 1 \text{ if } y_{it}^* > 0 \\ 0 \text{ if } y_{it}^* \leq 0 \end{cases} \tag{2}$$

x_{it} is a vector of observed covariates including a constant term, as defined earlier; β is a vector of fixed, yet unknown, population parameters; α_i stands for the random component (unobserved heterogeneity); and ε_{it} is the error term, and $\varepsilon_{it}|x_{it} \sim N(0,1)$.

For a balanced panel, the random-effects probit model has the form:

$$\begin{aligned} P(y_{it} = 1|x_i, \alpha_i) &= P(y_{it}^* > 0|x_{it}, \alpha_i) \\ &= P(x_{it}'\beta + \alpha_i + \varepsilon_{it} > 0|x_{it}, \alpha_i) \\ &= \Phi(x_{it}'\beta + \alpha_i) \end{aligned} \tag{3}$$

Note that x_{it} appears in the model, although $x_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$ is in the conditioning set and where $\Phi(\cdot)$ is the normal cumulative distribution function for ε_{it} conditional on x_i and α_i.

[7] In this analysis, the export capability variable is defined as business selling products to local and/or overseas markets. Following the ABS BCS, local (geographic) market includes the immediate area, town or city in which the business is located as well as outside this area but within Australia.

It follows that the joint probability function is as follows:

$$P(y_{i1}, \ldots, y_{i4} | x_i, \alpha_i) = \prod_{t=1}^{4} P(y_{it} | x_{it}, \alpha_i). \quad (4)$$

The relationship between y_{it} and α_i above is linear and additive in functional form, and we assume independence between regressors and the unobserved heterogeneity.

The conditional distribution of α_i (assuming the normal distribution) is given by

$$\alpha_i | x_i \sim N(0, \sigma_\alpha^2), \quad (5)$$

and α_i is independent of the error term ε_{it}. The standard random-effects probit model is estimated using the method of maximum likelihood. To measure the relative importance of the unobserved effect, the correlation between the composite latent errors, say, $\alpha_i + \varepsilon_{it}$, across any two time periods (t and s), is estimated as

$$Cov(v_{it}, v_{is}) = rho(\rho) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\varepsilon^2} \text{ where } v_{it} = \alpha_i + \varepsilon_{it}, t \neq s. \quad (6)$$

In this case, σ_α^2 is the variance of the unobserved effects, σ_ε^2 is the variance of the idiosyncratic component and $\sigma_\alpha^2 + \sigma_\varepsilon^2$ is the composite error. The significance of the estimate for *rho* is tested using a likelihood ratio test. If the estimate for *rho* is not significantly different from zero, then the random-effects probit estimator is favoured over the pooled probit estimator.

The bootstrap technique was implemented for robust statistical inferences in the standard random-effects probit model. All statistical computing was executed using Stata 15 MP software.

To check the sensitivity of the standard random-effects probit model results, we also estimated the pooled probit model which does not directly deal with the unobserved firm-specific effects. Because this model ignores the unobserved heterogeneity, one can make adjustments in the estimation by computing panel-robust standard errors. This model is attractive in that it is simple to implement and interpret and because robust standard errors can be obtained without imposing specific functional forms. The model has also been widely used and provides a good reference for the standard random-effects probit model (Wooldridge 2005, 2010, 2013; Greene 2012; Hensher *et al*. 2015).

To complement the sensitivity analysis, a standard multivariate panel probit model is also estimated using simulated maximum likelihood (see Cappellari and Jenkins 2003; Wooldridge 2010, 2013; Greene 2012). The same technique was employed by Soames *et al*. (2011) and Srholec (2016) in their research work on innovation. This is undertaken to further investigate the correlation structure between the four types of innovation and to estimate simultaneously the effect of the drivers for all innovation outcomes. For this, we considered the four-equation multivariate latent process given by

$$\begin{aligned} y^*_{it(1)} &= x'_{it(1)}\beta_{(1)} + \varepsilon_{it(1)}, \text{ where } i = 1, k, n; t = 1,2,3,4 \\ y^*_{it(2)} &= x'_{it(2)}\beta_{(2)} + \varepsilon_{it(2)} \\ y^*_{it(3)} &= x'_{it(3)}\beta_{(3)} + \varepsilon_{it(3)} \\ y^*_{it(4)} &= x'_{it(4)}\beta_{(4)} + \varepsilon_{it(4)} \end{aligned} \tag{7}$$

where

$$y_{it(m)} = \begin{cases} 1 \text{ if } y^*_{it(m)} > 0 \\ 0 \text{ if } y^*_{it(m)} \leq 0 \end{cases}, m = 1,2,3,4, \tag{8}$$

and ε_{itm}, m = 1,2,3,4, are error terms distributed as multivariate normal, each with a mean zero and variance-covariance matrix V, where V has values 1 on diagonal and correlations $\rho_{kl} = \rho_{lk}, \neq k, l, k = 1,2,3,4$ as off-diagonal elements. Note that the above model is a simultaneous system of four binary probit equations, where the dependent variable, $y_{it}(m)$, is a binary response variable taking the value 1 if the *i*-th business innovated a particular type of innovation (i.e. product innovation (m = 1); organisational or managerial innovation (m = 2); operational process innovation (m = 3); marketing innovation (m = 4)) in the *t*-th year, and 0 otherwise.

The modelling conducted here is static in relation to the response variable, and, as such, it is not possible to establish the existence or direction of causality between the various conditioning (business characteristics) variables and the propensity to innovate. The average partial effects (APEs) are then computed to summarise the marginal effects across the distribution of all observable covariates in the balanced sample. The APEs have the advantage of being comparable across the models investigated in this study, an advantage which is not often preserved with the estimated regression coefficients. The APEs are an alternative way to summarise marginal effects. In our study, the APE of any discrete variable (as are most of our covariates) can be thought of as measuring the discrete increment in probability of the small food business to innovate, averaged over the distribution of the unobserved variable(s), usually done by conditioning on a set of values.

The APE for a binary variable, x_h, is given by

$$A\hat{P}E_{x_h} = \frac{1}{n}\left[\sum_{i=1}^{n}\left[\Phi\left(x'_{it}\hat{\beta} + \hat{\alpha}_i | x_h = 1\right) - \Phi\left(x'_{it}\hat{\beta} + \hat{\alpha}_i | x_h = 0\right)\right]\right]. \tag{9}$$

The statistic in Equation (9) is simply the average of the discrete differences in the predicted probabilities. Again, robust standard errors for the APEs are calculated by the bootstrapping method. The same technique has been thoroughly explored in Rotaru (2013). To complement each of the estimated APEs, we also examined its distribution focusing on the quantiles (particularly the 25th and 75th percentiles, largest and smallest values), variance, skewness and kurtosis.

4. Findings

This section presents the empirical results of the econometric models. The standard random-effects probit model is applied to the food industry using the balanced panel sample described in Section 3.1. The same modelling procedure is also applied to the balanced panel samples created for businesses belonging to the AgriFF and non-AgriFF subsectors. The model estimates presented here are for overall innovation (i.e. business engaged in any type of innovation). To complement the empirical results and to get a better indication of the effects of the main drivers on overall innovation, the average partial effects (APEs) are included.

In all models, the reference firm belonging to the AgriFF subsector (for the food industry sample only) is small, does not collaborate, has low ICT intensity, has no effective competition, does not use STEM skills, with no debt or equity finance, has export capability and does not have any flexible working arrangements. The reference year is 2007–2008. The pooled probit panel model was also estimated to check the sensitivity of the random-effects probit results. The pooled probit model and multivariate probit model estimates are contained in the Appendix S1, together with the summary statistics for the distributions of the APEs.

The empirical results are compared with those of other ABS and DIIS studies that used cross-sectional modelling and employed data collected in the same survey (i.e. BCS) as well as with the findings coming from previous international food industry studies.

4.1 Findings for the food industry

Table 2 presents the estimated coefficients and their bootstrapped standard errors (SEs) for the standard random-effects probit model of overall innovation propensity. The estimated coefficients for the dummy variables for industry and business size are not significant, contrary to the results of Zouaghi and Sanchez (2016), although the latter covered all Spanish firms in the food sectors. Despite these results, it is important that these two covariates remain in the model because this information is used in the BCS survey design to generate the randomly sampled businesses in the food industry, and the current modelling did not apply any weights. The estimated proportion of the total variance contributed by the panel-level variance component (rho) is significantly different from zero (using the likelihood ratio test) and indicates that this component accounts for more than 44 per cent of the variance of the composite error. These results are consistent with the

Table 2 Standard random-effects probit regression results for (overall) innovation and average partial effects for selected key drivers of innovation

Variable	Coefficient	Bootstrap SE	APE†	SE‡
Innovation (response variable)				
Subindustry (non-AgriFF)	0.14	0.13		
Business size (nonemploying)	0.22	0.14		
With collaboration	0.68***	0.12	0.172***	0.029
Market competition				
Minimal	0.50***	0.18	0.114***	0.041
Moderate	0.87***	0.16	0.207***	0.035
Strong	0.67***	0.15	0.156***	0.033
ICT intensity				
Moderate	0.25**	0.12	0.061**	0.029
High	0.73***	0.24	0.183***	0.057
Most intense	0.71***	0.20	0.177***	0.048
Used STEM skills	0.58***	0.13	0.144***	0.033
Export capability (Local only)	−0.33**	0.16		
With flexible working arrangements	0.68***	0.11	0.171***	0.028
Sought debt and/or equity finance	0.23**	0.11		
Financial year				
2008–2009	−0.45***	0.13		
2009–2010	−0.50***	0.12		
2010–2011	−0.52***	0.13		
Intercept	−1.33***	0.23		
Log likelihood	−844.89			
AIC	1725.77			
BIC	1823.32			
Sigma	0.894	0.085		
rho	0.444***	0.047		
Number of observations (*n*)	1668			

Note: The asterisks, ***, ** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two significant digits, and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs. †Average partial effects for selected key drivers of innovation. ‡SEs for APEs are computed using bootstrapping.

findings of Triguero *et al.* (2013) and Vancauteren (2016), indicating that controlling for unobserved effects is important in the current analysis. The log likelihood, AIC and BIC results also confirm the goodness of fit of the model compared with the pooled probit model, as exhibited in Table A1 in the Appendix S1.

Overall, there is statistical significance at the 5 per cent level for all three key business characteristics (i.e. collaboration, use of STEM skills and ICT intensity). All play an important role in explaining the innovation behaviour of small businesses in the food industry. All of the APEs are found highly significant except for the APE of moderate ICT intensity which is small compared with the rest, but still significant at the 5 per cent level. The distributions of the estimated APEs are presented in Table C1 in the Appendix S1. We note that all of the distributions are skewed to the left, which implies that there were a significant number of firms where the effects of the drivers were positive, but relatively small in magnitude. Therefore, the results suggest that there are potential avenues to intensify the effects of the key drivers on the propensity to innovate among firms.

Collaboration is positive and highly significant, implying that food businesses reporting involvement in any collaborative arrangement are more likely to innovate. This conforms to the findings in ABS (2008), Rotaru (2013), Rotaru *et al*. (2013), Rotaru and Soriano (2013) and DITR (2006) where collaboration was found to strongly drive overall innovation among Australian businesses. The corresponding APE result shows that after averaging across all small food businesses and time periods, assuming all other variables constant, having some form of collaboration is associated with an increase of more than 17 per cent in the propensity to innovate. The APEs for collaboration at the 25th and 75th percentiles are 15.9 and 19.6 per cent, respectively. This indicates that even after accounting for unobserved heterogeneity, engaging in collaborative arrangements plays an important role for the likelihood of a firm to innovate. This result provides evidence that joint R&D collaboration between small food firms and universities, private and public organisations and other firms plays a key role on business innovation (Grunert *et al*. 1997; Maietta 2015; Caiazza and Stanton 2016; Ciliberti *et al*. 2016a,b; De Martino and Magnotti 2017; Sauer 2017; Wixe *et al*. 2017). This result also implies that small businesses in the Australian food industry can gain external knowledge, acquire technology and improve their technical capability to boost their innovation performance through collaboration. Access to external knowledge through collaborations is an important factor that drives the survival and growth of local food producers (Wixe *et al*. 2017). Businesses require resources with a broad range of technical and nontechnical skills and capabilities working together to foster innovation (Cunningham *et al*. 2016). Small food firms usually lack skills and resources; hence, they need external partners/networks to realise innovations (Caiazza and Stanton 2016; Galati *et al*. 2016). Even horizontal collaboration between firms in the Australian food industry should be encouraged (McAdam *et al*. 2014). The above results also support the Nelson and Winter (1982) model and the systems of innovation approaches by Nelson (1993) and Lundvall (2010). It is interesting that the results are supportive of the OI models and with the results in Bigliardi and Galati (2013).

The use of STEM skills is positively associated with the likelihood of innovation. Small food businesses that use STEM skills in their production are significantly more likely to engage in any one of the four broad types of innovation than other businesses. These results are consistent with Soriano and Abello (2015), for all business sizes in all industries. Its impact is around 14 per cent with the 25th and 75th percentiles at 13.1 and 16.6 per cent, respectively. The results are consistent with Palangkaraya *et al*. (2016) on science and research core skills, having significant positive association with any types of innovation in Australian businesses. The significant relationship between employee skills and innovation has also been observed in Huiban and Bouhsina (1998), Avermaete *et al*. (2004), Capitanio *et al*. (2009), Smit *et al.* (2015), Vancauteren (2016) and Brown and Roper (2017). This implies that the quality of the human capital in the small food businesses has strong influence on the innovation propensity. A recent Australian farm study exemplified a very strong link between skills and training, innovation and productivity (Xayavong *et al.* 2015).

There is a strong relationship between ICT intensity and the likelihood that a small food business will undertake innovative activity. The empirical results indicate that, all other things being held constant, moving from moderate to high and more intense ICT increases the likelihood of innovation. They imply that small businesses in the food industry that engage in more sophisticated forms of ICT are significantly more likely to innovate. Averaging across all small food businesses and time periods, assuming all other variables constant, small food businesses using high ICT intensity are 18.3 per cent more likely to innovate than businesses using low ICT intensity. The APEs for high ICT intensity at the 25th and 75th percentiles are 16.6 and 21.0 per cent, respectively. Todhunter and Abello (2011), Rotaru *et al.* (2013), Tiy *et al.* (2013) and Soriano and Abello (2015) found similar results in their cross-sectional analyses. The results support the findings of Galati *et al.* (2016) that ICT plays a crucial role for effective OI performance for food firms as well as the work of Domenech *et al.* (2014) on the adoption of ICT innovations in the agri-food sector. ICTs have been transforming economic activities in all sectors, particularly farming (including the food industry) for technological innovation and improvement in agricultural output (World Bank 2011; Lamb 2013; Salim *et al.* 2015).

Having flexible working arrangements was found to be significant and had a strongly positive effect on a firm's propensity to innovate. This means that a small food business is more likely to innovate if it offers flexible working arrangements for employees. Rotaru (2013) and Palangkaraya *et al.* (2016) obtained similar results for Australian businesses. The findings also conform with Storey *et al.* (2002), Michie and Sheehan (2003), Kleinknecht *et al.* (2006), Martinez-Sanchez *et al.* (2008), Chung (2009), Zhou *et al.* (2011) and Kleinknecht *et al.* (2014).

Market competition had a positive and significant association with the propensity to innovate, indicating that the more competitors that small businesses face, the more likely they are to innovate. This supports the anti-Schumpeterian frameworks. The strongest effect was felt when small food businesses have three to four competitors in the market, which is a similar finding to that of Soames *et al.* (2011). This highest impact is reflected in the estimated ATE, which is an increase of more than 20 per cent in the probability for small businesses to innovate. The APEs at the 25th and 75th percentiles were also higher at 17.2 and 24.4 per cent, respectively. This complements the result of Smit *et al.* (2015) where weak association was found between competition and innovation but aligns with the theoretical works of Aghion *et al.* (2005) and Correa (2012).

The following results were obtained for other business characteristics:

- The geographic market for the food industry from which the small businesses sell their goods or services played an important role in propensity to innovate. Compared with a firm that operates only locally, expanding the business operation of small firms to overseas markets positively and significantly affected the likelihood to perform any form of innovation. In fact, the recent work of Tuhin (2016) indicated that innovation and export behaviour of Australian small and medium businesses were interrelated and that exporters were 7 per cent to 10 per cent more likely to be innovators, which shows some consistency with the findings of Domenech *et al*. (2014) and Zouaghi and Sanchez (2016).
- Access to finance is of crucial importance for investing in innovations (Sauer 2017). In this study, small businesses that sought debt and/or equity finance were found significantly more likely to innovate. The lack of financial resources suffered by small agri-food firms influenced innovation, but public funding can boost their innovation capacity (Caiazza and Stanton 2016; and De Martino and Magnotti 2017). This result shows the need of small food businesses in Australia for continued government assistance to help sustain their innovation activities.

Inclusion of year effects in a short balanced panel is important because it controls for the unexpected variation or special events that may affect the response variable. In terms of the year effects, the results indicate that, all other things being held constant, the association is negative and significant moving onwards from 2007 to 2008. This perhaps reflects the effect on a firm's likelihood to engage in any form of innovation of the global financial crisis that occurred in 2008. A similar negative impact was also evident from the work of Zouaghi and Sanchez (2016).

Table B1 in the Appendix S1 presents the results for the multivariate probit modelling. The estimated coefficients for collaboration, the use of resources with STEM skills, ICT, flexible working arrangements, competitiveness and business size for each of the types of innovation are in line with our expectations (i.e. positive and significant). Export capability was found significant in marketing method innovation, whereas access to finance through debt and equity was only significant for operational process innovation. Another key result of the multivariate probit model is in the lower part of the same table where correlations between the residuals in the four equations (Eqn 7) are reported. All of the estimated correlations are significantly positive, which indicates that small food industry businesses combine different types of innovation. The significance might be associated with possible omitted variables (e.g. R&D intensity; firm age).

4.2 Findings for food industry subsectors

In this subsection, we expand the food industry model by dividing the food industry balanced sample into two subsamples, the AgriFF panel (948

Table 3 Standard random-effects probit regression results for (overall) innovation and average partial effects for selected key business characteristics, by food industry subsector

Variables	AgriFF				Non-AgriFF			
	Coefficient	Bootstrap SE	APE†	SE‡	Coefficient	Bootstrap SE	APE†	SE‡
Innovation (response variable)								
Business size (nonemploying)	0.09	0.22			0.32	0.22		
With collaboration	0.71***	0.16	0.179***	0.044	0.70***	0.23	0.177***	0.053
Market competition								
Minimal	0.30*	0.18	0.063	0.045	0.71**	0.35	0.17*	0.10
Moderate	0.89***	0.14	0.211***	0.046	0.85***	0.30	0.210***	0.083
Strong	0.72***	0.17	0.165***	0.038	0.61**	0.31	0.150*	0.086
ICT intensity (high to most intense)	0.50**	0.24	0.123**	0.052	0.62***	0.16	0.161***	0.050
Used STEM skills	0.63***	0.15	0.157***	0.040	0.51***	0.15	0.127***	0.046
Export capability (Local only)	−0.30	0.20			−0.32	0.20		
With flexible working arrangements	0.71***	0.20	0.174***	0.037	0.63***	0.11	0.163***	0.039
Sought debt and/or equity finance	0.19	0.20			0.27	0.21		
Financial year								
2008–2009	−0.33*	0.18			−0.52***	0.15		
2009–2010	−0.44**	0.22			−0.52***	0.18		
2010–2011	−0.40***	0.14			−0.58**	0.23		
Intercept	−1.22***	0.33			−1.02***	0.28		
Log likelihood	−465.18				−378.14			
AIC	948.35				774.27			
BIC	992.04				815.49			
Sigma	0.853	0.058			0.94	0.16		
Rho	0.421***	0.033			0.469***	0.085		
Number of observations (*n*)	948				720			

Note: The asterisks, ***, ** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two significant digits, and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs. †Average partial effects for selected key drivers of innovation. ‡SEs for APEs are computed using bootstrapping.

observations) and the non-Agriff panel (720 observations). In the subsector models, the categories in the ICT intensity variable are combined to form two binary dummy variables because of the presence of high correlations between the original four categories in the subsector samples. This is brought about by the reduced number of observations in the subsector samples. The results using the standard random-effects probit modelling are presented in Table 3.

The results of the random-effects models are consistent with our expectations. The direction and sign of the estimated coefficients for both dummy variables for AgriFF and non-AgriFF are consistent with the food industry results. However, the coefficients of a few explanatory variables are not statistically significant, as for the food industry results. Coefficients of the export capability and finance variables are not significant in both samples. In addition, the estimated coefficients in the AgriFF for minimal market competition and the year 2008–2009 are significant at the 10 per cent level. The coefficient of the business size variable is not significant at the 10 per cent level, as in the case for the food industry.

The estimated proportions of the total variance contributed by the panel-level variance component (rho) are found significantly different from zero (using the likelihood ratio test). The models for AgriFF and for non-AgriFF account for more than 42 per cent of the variance of the composite error, the percentage for the latter subsector being somewhat larger (47 per cent).These results indicate that accounting for unobserved effects is important in the subsector analyses. The log likelihood, AIC and BIC results also confirm the goodness of fit of the subsector models compared with the pooled probit models, as exhibited in Table A2 in the Appendix S1.

The five key factors (collaboration, ICT intensity, flexible working arrangements, facing market competition and use of STEM skills) again were highly significant in contributing to increase innovation among small food businesses in both subsectors. Year effects, in general, remained negative and statistically significant. The global financial crisis had greater effect on the likelihood to innovate for small food businesses in the non-AgriFF model than for small food businesses in the AgriFF model.

The overall results of the multivariate probit modelling for the two subsectors are consistent with the above results. Correlations between the disturbances for all the innovation outcomes were also positive and significant implying that small food firms even at the subsector level do combine different types of innovation when innovating.

All APEs in the AgriFF model were found to be statistically significant except for the case of minimal market competition, which is smaller in magnitude than the rest. Two of the APEs (minimal and strong market competition) in the non-AgriFF model are significant at the 5 per cent level, whereas the rest are found highly statistically significant (at the 1 per cent level). After averaging across all small food businesses in each subsector and time periods and assuming all other variables constant, the degree of association between having intense ICT and innovation is stronger in the non-AgriFF subsector, whereas the effect on innovation propensity is stronger in the AgriFF subsector when small food businesses use STEM skills and provide flexible working arrangements for employees. The impact of collaboration is similar in both subsectors which is approximately 18 per cent. The distributions of the APEs for the subsector modelling are presented in Tables C2 and C3 in the Appendix S1.

5. Conclusions

This study investigates the key drivers of innovation among small businesses in the Australian food industry, which is an important part of the country's regional economies. While the modelling technique used to identify the factors that play important roles in influencing the innovation behaviour of small food businesses and their strength of association is well established in the literature (see Wooldridge 2005, 2010, 2013 and Greene 2012), estimating robust standard errors for impact summary measures called 'average partial effects' simulation using modern bootstrapping procedures is a novelty in this work. The empirical work utilises firm-level information collected through the ABS BCS (2006–2007 to 2010–2011 ABS BLD CURF) and accessed via the ABS Data Laboratory.

In this paper, we observed the connection between collaboration, the use of STEM skills, the use of ICT, having flexible working arrangements, degree of market competition and innovation among small businesses in the Australian food industry. The analyses focused on one aspect of innovation – the propensity of the businesses to innovate. Other possible drivers of innovation, such as business size, export capability and finance sought, were also examined. Overall, we found that innovation is an essential element in small food businesses primary activities; also in Avermaete *et al*. (2003), Baregheh *et al*. (2012), Caiazza and Stanton (2016), De Martino and Magnotti (2017), and Wixe *et al*. (2017), and the results around associations between the above drivers and innovation propensity were similar with most of the ABS cross-sectional studies on innovation.

One of the highlights in the analyses was the significant and positive association between collaboration and business innovation among small food businesses, where we found that businesses engaging in any form of collaborative arrangements were more likely to innovate. This is similar to the results of most of the previous international studies. The adoption of OI practices in the small food industry in Australia should be supported and encouraged by the DIIS. The work of Huiban and Bouhsina (1998), Avermaete *et al*. (2004), Capitanio *et al*. (2009), Smit *et al*. (2015), Vancauteren (2016), and Brown and Roper (2017) has shown that business innovation is influenced by the workforce's skills and the quality of human capital in the food industry. In this paper, our empirical results also indicate that small food businesses using STEM skills are significantly more likely to innovate. The above findings are currently backing the mission of the Food and Agribusiness Growth Centre – the FIAL – to build capability and encourage collaboration and innovation in the Australian food sector (FIAL 2017).

The findings in our paper also raise important policy implications for growing the food industry in Australia. It is supporting the Industry Innovation and Competitiveness Agenda for small businesses to grow and become competitive both nationally and internationally. The Australian Government appears on the right track in its commitment to create favourable conditions and an environment in small food businesses to utilise the emerging ICT technologies in their business activities; offer flexible working arrangements to their employees; support access to new international markets and increase industry competitiveness.

Moreover, the unique sample data for the Australian food industry have enabled us to undertake separate analyses for businesses belonging to the AgriFF and the non-AgriFF subsectors of the food industry. Additional findings, obtained in these subsector analyses, indicate that the degree of association between having intense ICT and innovation is stronger in the non-AgriFF subsector. On the other hand, the impact on innovation is stronger in the AgriFF subsector when small businesses use STEM skills and provide flexible working arrangements to employees. The impact of collaboration is positive and statistically significant and is similar in magnitude in both subsectors. Further, OI has shown its importance at the subindustry level.

The main output-based measure of innovation used in this paper was overall innovation. However, we also found positive and significant correlation structures between the four types of innovation: new goods and services, new organisational processes, new operational processes and new marketing methods using multivariate probit. Future work could expand the analyses in the small food businesses by considering each type of innovation separately and examining how sensitive the impacts of the drivers are to the different types of innovation, as has been done in the recent work of Smit *et al*. (2015), Zouaghi and Sanchez (2016) and Wixe *et al*. (2017). In addition, there is strong evidence suggesting that persistence of innovation is an important characteristic of successful firms (Rotaru 2013; Rotaru and Soriano 2013; Triguero *et al*. 2013; Tavassoli and Karlsson 2015), and this suggests that the causes of persistence in innovation in the small food businesses are worthy of further investigation. From the modelling perspective of innovation persistence, it is desirable to account for correlation between the firm-specific effects and the regressors, because there may exist time-varying regressors across the periods.

Now that we have established what drives small food businesses to innovate, a next step would be to determine whether these innovating businesses are becoming more productive over time. A recent study by Palangkaraya *et al*. (2015) showed that Australian SMEs that previously introduced innovations had an annual productivity increase of around 2.7 per cent higher than noninnovating SMEs and could further raise their productivity by 4.4 per cent if they were to collaborate. The recent work of Khan *et al.* (2017) in Australia's broadacre agriculture revealed strong link between R&D and productivity. Whether this is so for small food businesses in Australia is worth investigating to provide additional evidence to support the government's policies and investments in growing Australian food businesses.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article

Appendix S1. (A) Pooled probit model results (sensitivity analysis), (B) Multivariate probit model results, (C) Selected summary statistics for the distribution of the APE estimates (random effects probit model).