Research Paper

Discrete Choice Panel Data Modelling Using the ABS Business Longitudinal Database

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QUESTIONS FOR THE COMMITTEE

1. What are your views on the usefulness of the approach taken, that is, to investigate a number of modelling options, ranging from simple to complex, for answering policy relevant questions and for checking the robustness of the results?

2. What other discrete choice modelling approaches are suitable for assessing dynamics in a longitudinal (or panel) data?

3. This is the first time ABS has included Average Partial Effects (APEs) in its research publications. In this study, the APEs are attractive in that they provide a more interpretable effect measure, which does not depend on the unobserved firm-specific effects, than simply reporting the probit coefficients. What are the views of the MAC members regarding their inclusion in other ABS studies?

4. In future studies the ABS might be interested in extending these analyses by including survey weights. Given the discrete nature of the dependent variable, the complexity of the models, and the panel nature of the data, how should this be done? In particular, what adjustments are required in terms of modelling, standard errors adjustment, and bootstrapping? Also should the adjustments be made on a per year basis given that the longitudinal data span a few years?

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ABSTRACT

This study explores a number of discrete choice panel data models to analyse the effects of three factors on innovation: flexible working arrangements, information technology, and collaboration, while controlling for the effects of other important variables, such as industry, business size, competition, and market location. The study also examines whether firms that innovated in the past are more likely to innovate in subsequent periods.

The econometric models examined range from the relatively simple pooled model to the more complex dynamic probit model. The aim is to assess both the static and dynamic relationships and to take care of the categorical dependent variable and the longitudinal nature of the dataset.

The analyses undertaken are in the context of the Australian small and medium-sized firms. Three waves of the ABS Business Longitudinal Database (BLD) are used: 2007–2008, 2008–2009, and 2009–2010.

1. INTRODUCTION

In recent times, there has been a considerable increase in the number of longitudinal (or panel) data analyses. One main reason is the greater availability of such data.

The advancement of statistical methodologies and greater computing power have enabled the 'creation' of rich longitudinal datasets, by combining and linking different datasets, where, for example, employees are linked to employers, survey data are combined with administrative datasets, and different waves of the same survey are linked over time. In addition, longitudinal data can now be constructed from existing administrative data collections, in addition to repeatedly collected survey data. As this trend, towards bigger, richer, and more dynamic data, is expected to continue, it is important for statistical agencies to equip themselves with the adequate analytical skills and statistical and computing tools to adequately process and analyse these datasets.

Longitudinal data are attractive in that the data are typically very rich and by blending both time and cross-sectional characteristics, the data provide a lot of opportunities for analysis that are often not available with simple cross-sectional or time-series data.

Longitudinal data allow for changes over time to be analysed at the unit, rather than aggregate, level. This greatly enhances the data available for individual-level modelling. Important advantages include the increased precision and efficiency in estimation, the possibility of controlling for the impact of omitted variables, the analysis of more complex behaviours, and the possibility of incorporating dynamic effects in the model. (See Cameron and Trivedi, 2005 and Hsiao, 2007 for more details.)

However, despite these advantages, extracting valid and meaningful inferences from longitudinal data can prove very challenging. This is especially the case when dealing with non-linear models, which is usually the case if the dependent variable is discrete. In these instances, the models are usually complex, the statistical inferences sophisticated, and the well-established approaches of dealing with the incidental parameters (which are typically implemented in linear models) do not always work. Rather, the analyst often needs to deal with non-additive heterogeneity, make assumptions about the interactions between the observed and unobserved covariates, address difficult asymptotic theory, and implement modern techniques such as bootstrapping to make valid statistical inferences.

Focus of this paper

It is in this context, that this study explores the implementation, estimation, and performance of different discrete choice longitudinal data models using the Main Unit Record File (MURF) of the ABS Business Longitudinal Database (BLD).[1] The empirical analysis is based on modelling the behaviour of innovation using firm-level data comprised of Australian small and medium-sized enterprises (SMEs). Three waves of the BLD are used: 2007–2008, 2008–2009, and 2009–2010.

A range of econometric models are examined that are aimed to assess both the static and dynamic relationships and to take care of the discrete dependent variable and the longitudinal nature of the dataset. 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) to deal with the initial conditions problem.

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1 For more information on the BLD, see ABS (2010).

As both relatively simple as well as complex models are implemented, it is of interest to see how the results differ across models and whether the findings of previous ABS studies that examined the same relationships using cross-sectional data, collected by the same survey, are supported by the models run on the longitudinal data.

The main focus is on analysing the effects of three key factors on innovation: flexible working arrangements, information technology, and collaboration, while controlling for the effects of other important variables, such as industry, business size, competition, and market location. The study also examines whether firms that innovated in the past are more likely to innovate in subsequent periods – i.e. whether there is 'persistence in innovation' (Clausen *et al.*, 2012).

The study uses an output-based measure of innovation and follows the OECD approach in differentiating between four types of innovation: new goods and services, new organisational processes, new operational processes, and new marketing methods. To the best of the author's knowledge, this is the first study that examines the persistence of innovation by distinguishing between the four types of innovation using Australian firm-level survey data.

Apart from the main relationships, the different models are intended to assess the following: (1) the lag effects and the importance of the initial conditions; (2) the importance of controlling for the unobserved firm-specific effects; and (3) the independence assumption between the regressors and firm heterogeneity. Incorporating and testing these model aspects is important in that they give an indication of whether omitting them (as it is done with standard cross-sectional analyses) has any bearing on the results.

From the perspective of the ABS, this study is important for a number of reasons, including capability building in longitudinal analysis, the exploration of the longitudinal aspect of the BLD (this is the first longitudinal study conducted on the BLD MURF), and the extension of the previous ABS cross-sectional analyses to the longitudinal front[2]. Given the categorical nature of some of the data items collected by the ABS and the potential of more panel data work in the future, these methods have the potential of being used in other ABS outputs.

The paper is structured as follows. Section 2 presents a short conceptual background to the empirical application. In Section 3, the theory of the models implemented in the analysis is described. Section 4 applies the models and describes the results. Section 5 concludes.

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2   In particular the extension is for the following ABS studies: Todhunter and Abello (2011), Soames *et al.* (2011), Soriano and Yong (2011), Rotaru *et al.* (2013), and Tiy *et al.* (2013).

2. CONCEPTUAL BACKGROUND AND HYPOTHESES

In a global economy, innovation plays a key role in the success and competitiveness of businesses and corporations. Its benefits are far-reaching and they can extend from the innovating firms to the welfare of the society and to the whole economy (DIISRTE, 2012). Innovation is often regarded as a pivotal engine of output and productivity growth, employment performance, and international competitiveness (Stokey, 1995; Aghion *et al.*, 2013; OECD/Eurostat, 2005) and for some as "the cornerstone of economic growth" (White House, 2011).

Following the writings of Joseph Schumpeter, a prolific amount of research has been undertaken on examining, both empirically and theoretically, the innovation process and the factors that affect innovation. These include information technology, collaboration, competition, labour market flexibility, productivity, as well as others.

One area of interest, which has received limited empirical attention, is on the relationship between flexible working arrangements and innovation. As emphasised in a recent report of the White House Council of Economic Advisors (White House, 2010) the limited empirical research on the effects of these arrangements is mainly due to a lack of appropriate data. Other studies have also highlighted the need for more research in this area, for example Martínez-Sánchez *et al.* (2008) and Zhou *et al.* (2011). One important question is whether, and to what extent, a flexible working environment influences innovative thinking and the likelihood of a firm to innovate.

Information technology and collaboration are two other factors that play key roles in influencing innovation. Similar ABS studies using the ABS Business Characteristics Survey (BCS)[3] found a positive and significant relationship between innovation and information communication technology (Todhunter and Abello, 2011; Rotaru *et al.*, 2013; and Tiy *et al.*, 2013) and between innovation and collaboration (ABS, 2008 and DITR, 2006). One limitation however, is that all these former studies were cross-sectional in nature and therefore were not able to capture the dynamic behaviour of firms. As found in Martínez-Ros and Labeaga (2002), the significance of some determinants of innovation can vanish after controlling for the dynamic effects.

In what follows, this section describes the key variables and relationships examined in this study and summarises the hypotheses to be tested. Given that some of these analyses where conducted previously by the ABS (although, only at a cross-sectional level), the readers are directed to the specific ABS studies for a more thorough coverage.

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3   For more information on the BCS see Selected Characteristics of Australian Business, 2009–2010 (ABS, 2011b).

Four influences to innovation are analysed in this paper, namely:

1.   Innovation persistence;

2.   Flexible working arrangements;

3.   Information technology; and

4.   Collaboration.

2.1 Innovation and its persistence

Innovation has many dimensions and is a complex phenomenon to define and analyse (OECD/Eurostat, 2005). Amongst others, innovation can differ with respect to the degree of novelty (new to the firm, new to the industry, new to the country, or new to the world), type of innovation (new goods or services, new operational processes, new organisational processes, or new marketing methods), and degree of implementation (successfully implemented, ongoing, or abandoned). Part of its complexity stems from its multidimensional nature, continuous process (i.e. innovation keeps on upgrading), dynamic and non-linear behaviour, and complex diffusion process. (See Fagerberg *et al.*, 2010; DIISRTE, 2012; OECD/Eurostat, 2005 for more details.)

In defining innovation, this study uses the internationally recognised definition given in the *Oslo Manual*, where innovation is defined as:

> "… the implementation of a new or 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/Eurostat, 2005, p. 46)

Due to its importance for the success of firms and for the whole economy there has been considerable research done on different fronts of this complex phenomenon. One such front is on understanding the dynamic behaviour of innovation. This area of research aims to assess whether the firms that innovated in the past are more likely to innovate in subsequent periods, or as it is termed in some studies, whether innovation is persistent or path-dependent.

There are different theories to explain why this might be the case. Clausen *et al.* (2012) lists three main lines of reasoning identified in previous research that support the dynamic behaviour of innovation. The first relates to the notion that "success breeds success". The idea is that as firms successfully innovate, they also become more profitable, as innovation generates more profits, which in turn leads to further innovation. The second line of reasoning relates to the idea of learning-by-doing, where firms learn from the innovation process to be more effective in dealing with issues and in solving problems. The theory also rests on the idea that knowledge is cumulative and as such, by innovating, a firm expands its knowledge base, which then

can be used to innovate more successfully in the future. The final theory claims that innovation is persistent because of the absorptive nature of the R&D. The idea is that because knowledge is absorbed by the human capital, it is unlikely that a firm invests in R&D and then pursue a one-off type of innovation.

A number of studies found strong evidence of such persistence, for example Martínez-Ros and Labeaga (2002) and Clausen *et al.* (2012). Note that due to the relatively short panel, the focus is only on the one-period lag effects. The first hypothesis to be tested is thus:

> *H1:* Firms that innovated in period $t-1$ are more likely to innovate in period t.

Note that as different types of innovation may have different behaviours, the study distinguishes between the four types of innovation mentioned above. Note however that the study does not disseminate the results with respect to the different degrees of novelty or the degree of implementation.

2.2 Innovation and flexible working arrangements

To gain and maintain a competitive edge in the global and the ever increasing competitive environment, firms often need to quickly and adequately adapt to the fast-paced labour market changes. Labour market flexibility plays an important role in addressing this challenge (European Commission, 2007; OECD, 1994).

Although there are different views regarding what constitutes labour market flexibility, one widely-used categorisation of the concept is given by Atkinson (1984) and Atkinson and Meager (1986). These studies categorise labour market flexibility into four types:

- external numerical (i.e. flexibility in adjusting the labour intake from the external market),

- internal numerical (i.e. flexibility in adjusting the working hours or schedules of employees, such as flexible working hours or shifts, part-time, or leave flexibility),

- functional (i.e. flexibility in transferring employees to different tasks and activities), and

- financial or wage flexibility (i.e. flexibility in deciding wage levels).

In addition to these, there are other types of flexibility, one of which is the location flexibility or flexibility of place (e.g. home-based work) (Reilly, 2001; Wallace, 2003).

Most of the studies that examined labour market flexibility have concentrated on the strategies employed by businesses to deal with and adapt to the changes in the labour market. The idea is that by quickly adapting to the fluctuations in the labour market,

businesses are more competitive and more likely to innovate. (See Martínez-Sánchez *et al.*, 2008; Zhou *et al.*, 2011 and Chung, 2009 for a theoretical and a literature review.)

On the other hand, flexibility can also refer to the business strategies to meet the needs of its employees. The idea is that by creating an appropriate environment, where key capabilities are promoted and nurtured, employees are more committed and more likely to innovate. (See Storey *et al.*, 2002 and Chung, 2009 for more details.)

Although the two views seem to be mutually exclusive, that need not be the case. As stated in a recent European Commission report (European Commission, 2007), labour market flexibility can be used by businesses to address both the business need for adapting to the fast changes in the market, as well as the employees' needs of working in a productive and secure environment.

This study looks at four types of flexible working arrangements: flexible working hours, flexible leave, job sharing, and working from home. To the best of the author's knowledge this is the first study to examine the relationship between flexible working arrangements and innovation using Australian longitudinal business survey data at the micro-firm level.

The hypothesis is thus:

> *H2:* Firms that have flexible working arrangements are more likely to innovate.

2.3 Innovation and information technology

Information technology is often regarded as a major driver of innovation (White House, 2011; Atkinson and Andes, 2009). This is particularly true in the current environment where businesses are faced with fast-paced technological advancements and tough global competition. Although the role of ICT as a source of business innovation is not explained in this report, the readers interested are directed to the study of Todhunter and Ruel (2011).

This study examines whether having intensive information technology systems, summarised by an information technology index, improves the likelihood to innovate. It is of interest to observe whether the positive link between innovation and information technology found by previous studies using the ABS BCS (i.e. Todhunter and Abello, 2011; Rotaru *et al.*, 2013; Tiy *et al.*, 2013) is maintained when using longitudinal data. The hypothesis to be tested is thus:

> *H3:* Firms that have higher information technology intensity are more likely to innovate.

2.4 Innovation and collaboration

The relationship between collaboration and innovation is another aspect that this study looks at. As it has been pointed in numerous studies, collaboration plays a key role in affecting innovation (see ABS, 2008 and DITR, 2006 for more details). The hypothesis to be tested is thus:

H4: Firms that collaborate are more likely to innovate.

3. MODELS

This section highlights the theoretical underpinnings of the models used in analysis. In this general setting let subscript i index firm i (referring to the cross sectional aspect of the data) and t the time period. For firm i at time t let $\boldsymbol{x}_{it}$ be the vector of (observed) explanatory variables, y_{it} the (observed) dichotomous outcome variable, and ε_{it} the residual term. The general model (assuming a balanced panel) can be represented as

$$P\left(y_{it}=1\mid \boldsymbol{x}_i\right) = F\left(\boldsymbol{x}_{it}'\boldsymbol{\beta}\right), \text{ where } i = 1,2,\ldots,n; \ t = 1,2,\ldots,T \qquad (3.1)$$

and $F(\cdot)$ is an appropriate cumulative density function for a dichotomous response variable, which in this study is a probit distribution function, and

$$y_{it} = \mathbf{1}\left(\boldsymbol{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it} > 0\right), \qquad (3.2)$$

$\mathbf{1}(\cdot)$ denoting the 0–1 indicator function.

Note that the model described by equation (3.1) only specifies the marginal distribution of y_{it} and therefore leaves the joint distribution $P\left(y_{i1},\ldots,y_{iT}\right)$ unspecified. There are two important reasons why $P\left(y_{it},y_{i,t-1}\right) \neq P\left(y_{it}\right)P\left(y_{i,t-1}\right)$. The first is due to the unobserved firm specific effects (i.e. unobserved heterogeneity), which have the potential to affect the outcome of interest. The second type is due to lag effects of the dependent variable, i.e. true state dependence. (See Amemiya, 1985, chapter 9 for more details.)

Both types of dependence can be observed in equation (3.3), where c_i captures the unobserved heterogeneity corresponding to firm i and the coefficient ρ whether there is state dependence or not.

$$P\left(y_{it} = 1 \mid y_{i,t-1},\ldots,y_{i0},\boldsymbol{x}_i,c_i\right) = F\left(\rho y_{i,t-1} + \boldsymbol{x}_{it}'\boldsymbol{\beta} + c_i\right) \qquad (3.3)$$

A few considerations are worth noting about the specifications of model (3.3). First, the dynamics have a relative simple structure, representing a first-order Markov process in that only the first lag is included. Second, the heterogeneity in the model is additive, in a functional form. Third, only $\boldsymbol{x}_{it}$ appears in the model, although $\boldsymbol{x}_i = \left(\boldsymbol{x}_{i1},\ldots,\boldsymbol{x}_{it}\right)$ is in the conditioning set.

In what follows, this section briefly presents the five models that were used in the analysis. The models are classified according to the way they deal with the two types of dependence aforementioned and the specification of the joint probability.

Model 1: The Pooled Model

One simple way of specifying the joint probability is by assuming some form of independence, in the sense that

$$P\left(y_{it}\mid y_{i,t-1},\ldots,y_{i0},\boldsymbol{x}_i\right) = P\left(y_{it}\mid \boldsymbol{x}_{it}\right) \tag{3.4}$$

In this case the joint probability follows directly from the marginal probability by simply multiplying the individual marginal probabilities. Mathematically this can be written as

$$P\left(y_{i1},\ldots,y_{iT}\mid \boldsymbol{x}_i\right) = \prod_t P\left(y_{it}\mid \boldsymbol{x}_{it}\right).$$

Although the model does not directly deal with either the unobserved firm specific effects or the state dependence of the outcome variable, one can make adjustments for these by computing panel-robust standard errors. The 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 been widely used and provides a good reference for the other models considered.

Model 2: The Standard Random Effects (RE) Model

A different approach, which has become very popular, is to incorporate the unobserved heterogeneity directly in the model. The model assumes that

$$P\left(y_{it}\mid y_{i,t-1},\ldots,y_{i0},\boldsymbol{x}_i,c_i\right) = P\left(y_{it}\mid \boldsymbol{x}_{it},c_i\right). \tag{3.5}$$

From (3.5), it immediately follows that

$$P\left(y_{i1},\ldots,y_{iT}\mid \boldsymbol{x}_i,c_i\right) = \prod_t P\left(y_{it}\mid \boldsymbol{x}_{it},c_i\right).$$

One problem with the conditional probability above is that although it is conditioned on c_i, one does not observe the firm specific effects. This raises the important consideration of how to treat the unobserved effects. Two important aspects that need to be considered include the distribution of the unobserved effects and the way the unobserved heterogeneity enters into the joint probability, i.e. the relationship with the other variables in $\left(y_{it},\boldsymbol{x}_{it}\right)$.

With regards to its relationship with y_{it} most applications consider an additive functional form, where the relationship between y_{it} and c_i is linear and additive, in a functional form, similar to the relationship described by equation (3.3). With regards to $\boldsymbol{x}_{it}$ the traditional random effects model assumes independence between c_i and $\boldsymbol{x}_{it}$. An alternative is to assume some form of dependence in the form of a specified relationship as shown in the next model.

Finally, for the distribution, most applications assume a normal distribution. In notational form the conditional distribution of c_i is given by

$$c_i \mid \boldsymbol{x}_i \sim \mathrm{N}\!\left(0, \sigma_c^2\right).$$

To obtain the joint probability $P\!\left(y_{i1}, \ldots, y_{iT} \mid \boldsymbol{x}_{it}\right)$ one can integrate out the firm specific effects.

This model although widely used in practice, rests on a strong independence assumption between the regressors and the unobserved heterogeneity. It also does not include lag effects. The model is nonetheless attractive in that it controls for the unobserved firm specific effects in a simple and intuitive way, treating the unobserved effects as a random variable with a definite distribution.

Model 3: The Mundlak/Chamberlain Random Effects Model

The previous model is restrictive in that it does not allow for any correlation between c_i and $\boldsymbol{x}_{it}$. To relax this assumption, one can follow the approaches of Mundlak (1978) and Chamberlain (1984) and allow for a specific type of dependence between firm-specific effects and the explanatory variables, namely, one that is linear and that has a normally distributed functional form. Using notation, the relationship can be expressed as

$$c_i = c + \boldsymbol{z}_i' \boldsymbol{\gamma} + u_i$$

where
$$c_i \mid \boldsymbol{z}_i \sim \mathrm{N}\!\left(c + \boldsymbol{z}_i' \boldsymbol{\gamma}, \sigma_u^2\right)$$

and where $\boldsymbol{z}_i$ refers to the group/cluster means of the time-varying variables in $\boldsymbol{x}_{it}$ (i.e. $\bar{\boldsymbol{x}}_i$), in the case of the Mundlak (1978), or to the vector of time-varying $\boldsymbol{x}_{it}$ across all time periods, i.e. $\boldsymbol{z}_i := \boldsymbol{x}_i := \left(\boldsymbol{x}_{i1}, \ldots, \boldsymbol{x}_{iT}\right)'$, in the case of the Chamberlain (1984) specification, and σ_u^2 is the conditional variance of $c_i \mid \boldsymbol{x}_i$. It follows that

$$P\!\left(y_{it} \mid y_{i,t-1}, \ldots, y_{i0}, \boldsymbol{z}_i, c_i\right) = P\!\left(y_{it} \mid \boldsymbol{z}_i, c_i\right) = F\!\left(\boldsymbol{x}_{it}' \boldsymbol{\beta} + c + \boldsymbol{z}_i' \boldsymbol{\gamma} + u_i\right) \qquad (3.6)$$

The estimation of the model is very similar to that of the traditional random effects probit model. This immediately follows since $\boldsymbol{x}_{it}$ and $\boldsymbol{z}_i$ are observed and since it is assumed that $u_i \mid \boldsymbol{z}_i \sim \mathrm{N}\!\left(0, \sigma_u^2\right)$.

Although somehow restrictive in the sense that one needs to specify the dependence between the unobserved effects and the regressors, the model is attractive in that it does not impose the strong independence assumption of the standard RE model.

Model 4: The Standard Dynamic Model

The previous models deal with the dependence that comes from the firm specific effects and do not make direct allowance for the lag terms (although, some adjustments are usually made in computing standard errors that are robust to serial correlation). In some cases, modelling this dynamic relationship is important for analysis. This and the next model are aimed to address this.

In terms of the general model described by equation (3.3), the standard dynamic model assumes that

$$P\left(y_{it} = 1 \middle| y_{i,t-1}, \ldots, y_{i0}, \boldsymbol{x}_i\right) = F\left(\rho y_{i,t-1} + \boldsymbol{x}'_{it}\boldsymbol{\beta}\right)$$

Similar to model 1, some corrections are usually required in the form of computing panel-robust standard errors. Once again, given its simplicity, the model is a good reference for other more complex dynamic models.

Model 5: The Wooldridge Dynamic Model

This model aims to model both types of dependence, i.e., that coming from the unobserved firm specific effects as well as the persistence of the outcomes. In general, the model is described by (3.3), which is also included below:

$$P\left(y_{it} = 1 \middle| y_{i,t-1}, \ldots, y_{i0}, \boldsymbol{x}_i, c_i\right) = F\left(\rho y_{i,t-1} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + c_i\right)$$

One additional challenge in this case is that the unobserved firm effects, captured by c_i, are likely to be correlated with $y_{i,t-1}$. With a relatively short panel the initial conditions, y_{i0}, are likely to play an important role and ignoring this correlation might not be sensible. One relatively simple solution is the approach suggested by Wooldridge (2005), where the idea is to model the conditional joint distribution

$$P\left(y_{i1}, y_{i2}, \ldots, y_{iT} \middle| y_{i0}, \boldsymbol{x}_i, c_i\right)$$

rather than $\qquad P\left(y_{i0}, y_{i1}, y_{i2}, \ldots, y_{iT} \middle| \boldsymbol{x}_i, c_i\right)$

Similar to the Mundlak/Chamberlain specification, the approach specifies c_i in the same way with the difference that now it also includes the initial conditions. This can be expressed as

$$c_i \middle| \boldsymbol{z}_i, y_{i0} = \psi + \boldsymbol{z}'_i\boldsymbol{\gamma} + \xi_0 y_{i0} + a_i$$

where $a_i \sim \mathrm{N}\left(0, \sigma_a^2\right)$ and where a_i is independent of y_{i0} and $\boldsymbol{z}_i$.

It immediately follows that

$$y_{it} = \mathbf{1}\left(\psi + \xi_0 y_{i0} + \mathbf{z}_i'\boldsymbol{\gamma} + \rho y_{i,t-1} + \mathbf{x}_{it}'\boldsymbol{\beta} + a_i + \varepsilon_{it} > 0\right) \tag{3.7}$$

where $\varepsilon_{it} \sim N(0,1)$.

As y_{it} conditional on $\left(y_{i0},\ldots,y_{i,t-1},\mathbf{x}_i,a_i\right)$ follows a probit distribution and as a_i are normally distributed, the model is similar to the previous Chamberlain/Mundlak Random Effects Model. The difference here is that the conditioning set also includes y_{i0} and that the lag effects are also included.

The table below briefly summarises the five models discussed. Note that the summary is not exhaustive.

3.1 Summary of the five models[4]

	Model 1	Model 2	Model 3	Model 4	Model 5
Treatment of unobserved heterogeneity (α_i)	Ignored; panel-robust standard errors are computed instead.	Treated as a random variable with a specified distribution.	Treated as a random variable with a specified distribution.	Ignored; panel-robust standard errors are computed instead.	Treated as a random variable with a specified distribution.
Inclusion of lag effects	Not included.	Not included.	Not included.	Included (first lag).	Included (first lag).
Allowance for correlation between α_i and covariates	Not applicable.	Assumes independence.	Allows for correlation between α_i and the covariates.	Not applicable.	Similar to model 3 but it also includes the correlation between α_i and the initial conditions.
Disadvantage	The estimated coefficients can be inconsistent if the true model has individual-specific random effects. Also the estimators can be inefficient.	The estimated coefficients can be inconsistent if the individual-specific effects are correlated with regressors. The model requires distributional assumptions for firm-specific effects.	The estimation and implementation of the model are more complex. The model requires distributional assumptions for firm-specific effects.	Same as model 1.	The estimation and implementation of the model are much more complex. The model requires distributional assumptions for firm-specific effects.
Advantage	The model is relatively simple to use and implement. No need for distributional assumptions of the firm-specific effects.	The model is relatively simple and it makes direct allowance for individual-specific effects.	Similar to model 2. The model also allows for correlation between α_i and the regressors.	Similar to model 1 but it also includes lag effects.	Similar to model 3 but it also includes lag effects.
Complexity (implementation and interpretation)*	1	3	4	2	5

* = Relative complexity across the five models, with ranking of 1 standing for the least complex model, while 5 for the most complex.

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4   See Baltagi (2008), Green (2012), Wooldridge (2010), and Cameron and Trivedi (2005) for more details regarding the technical details of the models.

4. MODEL APPLICATION

This section has three parts. The first discusses the methodological findings of the five models implemented. These are based on the results for overall innovation (i.e. any type of innovation) and the average partial effects (APEs).[5] The second part focuses on the empirical application and discusses the effects of the key variables on innovation. The results are compared to those of other ABS studies that used cross-sectional data collected by the same survey. The final part gets a closer look at the relationships by disaggregating innovation into four categories: new goods and services, new operational processes, new organisational processes, and new marketing methods. For brevity, only the Wooldridge Dynamic Probit model results are reported in this final part.

In all models the reference firm belongs to the Manufacturing industry, is very small, does not have any type of flexible working arrangements, faces no competition, has most intense ICT, operates only locally, and does not collaborate. The reference year is 2007–2008. In choosing the variables to be included in the models the study followed the aforementioned similar cross-sectional ABS studies. The interested readers are referred to these studies for more details.

4.1 Methodological findings

Building on the theory presented in Section 3, five models were adopted, three non-dynamic: the Pooled model (model 1), the standard Random Effects (RE) model (model 2), and the Chamberlain/Mundlak RE (model 3); and two dynamic: the Standard Dynamic Probit model (model 4) and the Wooldridge Probit model (model 5).

To control for the presence of heterogeneity and/or serial correlation, panel-robust standard errors were computed for all models either by clustering (when this option was available in the software package) or by bootstrapping for panel data. For models 3 and 5 both the Chamberlain and the Mundlak specifications were investigated, where apart from some minor differences the results were similar. Due to their similarities, only the Mundlak results are reported. Table 4.1 presents the APEs for the five models considered, whereas table 4.2 the results for overall innovation.

Average partial effects

A number of points are worth noting on the APEs results. These results have the advantage of being comparable across models, an advantage which is often not preserved with the regression coefficients (see Wooldridge, 2010, chapter 15 for more details). It is interesting to note that with a few exceptions, the results are not too

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5   See Appendix B for a brief theoretical exposition of the APEs and Wooldridge (2010) for more details.

different across the five models. In particular, the sign and the significance are all the same. The biggest difference in the magnitude of the coefficients is that between the lagged innovation of model 4 and that of model 5. This difference can be attributed to two factors. The first being the initial conditions which are directly incorporated in model 5, but not in model 4. This is reflected in the results presented in table 4.2, where the coefficient for initial conditions, is highly significant and is even higher than that of lagged innovation. The second reason is due to the different treatment of the unobserved heterogeneity: model 5 incorporating the firm-specific effects directly in the model, whereas model 4 adjusting the standard errors.

4.1 Average Partial Effects (APEs)

Variables*	Model 1 Pooled		Model 2 Standard RE		Model 3 Mundlak		Model 4 Dynamic		Model 5 Dynamic RE	
Innovation (t–1)	...	...	...	...	...	...	0.380	(0.015)	0.113	(0.025)
Collaboration	0.138	(0.020)	0.119	(0.018)	0.165	(0.028)	0.104	(0.016)	0.126	(0.025)
Flexible working arrangements										
Flexible work hours	0.085	(0.017)	0.079	(0.016)	0.091	(0.027)	0.068	(0.014)	0.071	(0.023)
Flexible leave	0.066	(0.017)	0.048	(0.016)	0.096	(0.025)	0.041	(0.014)	0.071	(0.024)
Job sharing	0.064	(0.022)	0.045	(0.020)	0.080	(0.034)	0.053	(0.018)	0.066	(0.029)
Working from home	0.030	(0.019)	0.029	(0.017)	0.033	(0.026)	0.020	(0.014)	0.032	(0.022)
ICT intensity**										
Low	–0.204	(0.040)	–0.170	(0.036)	–0.250	(0.074)	–0.116	(0.033)	–0.156	(0.064)
Moderate	–0.191	(0.020)	–0.157	(0.019)	–0.229	(0.025)	–0.110	(0.016)	–0.144	(0.022)
High	–0.126	(0.025)	–0.095	(0.023)	–0.177	(0.038)	–0.070	(0.020)	–0.118	(0.033)

* = Overall Innovation being the dependent variable
** = Comparative to the most intense ICT intensity
Standard Errors included in brackets (computed using bootstrapping with 200 replications)

Regression results

Next consider the results presented in table 4.2. One important consideration is the proportion of the combined variance that is attributed to the panel-level variance component. With the current data, the unobserved effects for both model 2 and 3, are significantly different from zero (on the basis of the likelihood-ratio test results) and account for more than 56% of the variance of the composite error, whereas for model 5, this proportion is around 37%. These results indicate that controlling for unobserved effects is important in the current analysis.

4.2 Regression results for the five models for (overall) innovation

	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pooled	Standard RE	Mundlak	Dynamic	Dynamic RE
Innovation (t–1)				1.076 ***	0.423 ***
Innovation (t=0)					0.746 ***
Industry *(Manufacturing)*					
Mining	–0.058	–0.095	–0.066	–0.034	–0.028
Construction	–0.316 ***	–0.529 ***	–0.487 ***	–0.199 **	–0.272 *
Wholesale	–0.121	–0.168	–0.204	–0.062	–0.103
Retail	–0.042	–0.066	–0.103	0.008	–0.022
Accommodation	–0.243 **	–0.406 **	–0.403 **	–0.155 *	–0.209
Transport	–0.278 ***	–0.459 ***	–0.417 ***	–0.215 ***	–0.311 **
Telecommunications	–0.052	–0.082	–0.117	–0.053	–0.103
Real Estate	–0.175	–0.251 *	–0.347 **	–0.137	–0.221 *
Professional	–0.122	–0.172	–0.212	–0.091	–0.136
Administrative	–0.312 ***	–0.484 **	–0.485 ***	–0.218 **	–0.354 **
Recreation	–0.243 **	–0.380 **	–0.372 **	–0.130	–0.180
Other Services	0.026	–0.035	0.038	0.048	0.074
Size *(Very small)*					
Small	0.052	0.135	0.036	0.040	0.052
Average	0.140 **	0.323 ***	0.124	0.104 **	0.092
Flexible work hours	0.239 ***	0.326 ***	0.259 ***	0.218 ***	0.249 ***
Flexible leave	0.186 ***	0.201 ***	0.025	0.131 ***	0.015
Job sharing	0.184 ***	0.189 **	0.099	0.174 ***	0.108
Working from home	0.085	0.119 *	0.032	0.066	0.025
Competition *(No competition)*					
Minimal	0.142	0.183	–0.015	0.121	0.016
Moderate or Strong	0.270 ***	0.276 **	–0.073	0.188 **	–0.040
ICT intensity *(Most intense)*					
Low	–0.556 ***	–0.689 ***	–0.170	–0.364 ***	–0.128
Moderate	–0.522 ***	–0.638 ***	–0.043	–0.344 ***	–0.038
High	–0.344 ***	–0.390 ***	–0.140	–0.221 ***	–0.094
Market location *(Only local)*					
Only overseas	–0.456 **	–0.779 **	–0.823 **	–0.420 **	–0.594 **
Both local and overseas	0.232 ***	0.328 ***	0.240 **	0.176 ***	0.172 **
Financial year *(2007–2008)*					
2008–2009	–0.232 ***	–0.340 ***	–0.313 ***	–0.359 ***	–0.333 ***
2009–2010	–0.167 ***	–0.241 ***	–0.216 ***	–0.193 ***	–0.205 ***
Collaboration	0.394 ***	0.502 ***	0.339 ***	0.337 ***	0.324 ***
Intercept	–0.063	–0.019	–0.164	–0.554 ***	–0.672 ***
Group Means					
Flexible hours			0.132		0.027
Flexible leave			0.389 ***		0.262 **
Job sharing			0.254		0.153
Working from home			0.111		0.103
Competition *(No competition)*					
Minimal			0.217		0.109
Moderate or Strong			0.598 **		0.359 *
ICT intensity *(Most intense)*					
Low			–0.880 **		–0.461
Moderate			–0.915 ***		–0.506 ***
High			–0.603 ***		–0.352 **
Collaboration			0.391 **		0.172

4.2 Regression results for the five models for (overall) innovation (continued)[6]

Variables	Model 1 Pooled	Model 2 Standard RE	Model 3 Mundlak	Model 4 Dynamic	Model 5 Dynamic RE
Log Likelihood	–3,370.4	–3,078.8	–3,029.8	–2,971.4	–2,898.3
AIC	6,798.9	6,217.6	6,139.6	6,002.9	5,880.7
BIC	6,990.5	6,415.8	6,404.0	6,201.1	6,158.2
Sigma		1.135	1.154		0.768
rho		0.563 ***	0.571 ***		0.371 ***
Observations (n)	5,481	5,481	5,481	5,481	5,481

*** = significant at the 0.01 level; ** = significant at the 0.05 level ; * = Significant at the 0.10 level;
Reference category included in brackets.

In addition, the results for models 3 and 5 indicate that the allowance for correlation between the firm-specific effects and the regressors is important for the current data. In particular, the group means for flexible leave, all ICT intensities, and one category for competition are all significant. As model 2 is a specific type of model 3, i.e. the case where the heterogeneity vector is perpendicular on the vector of regressors, the Wald and the log likelihood tests were conducted to test the null hypothesis that assumes that all the coefficients for the group means are equal to zero, case when the Mundlak model becomes the Standard RE model. Both tests strongly rejected the null hypothesis at the 5% significance level. This indicates that some allowance for the correlation between the firm heterogeneity and regressors is favourable by the current data.

For the dynamic models (models 4 and 5), the first order lag terms are significant and positive. For the Wooldridge model, the initial conditions (innovation at t=0), as well as some of the group means are also positive and significant. These results indicate that the persistence of innovation hypothesis is supported, i.e., a firm that innovated in the previous period has a higher likelihood to innovate, and that it is important to control for the firm-specific effects. To confirm the results, tests were conducted on the joint significance of the extra variables added in model 5 (i.e. comparing model 5 to model 4 and model 3, respectively). In all cases, the tests rejected the null hypotheses, giving support to model 5.

Finally, based on the AIC and BIC results, model 5 is most favoured, followed by model 4, model 3, model 2, and finally model 1. (See Appendix C for the definition of these criteria.)

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6   The author also examined the potential for endogeneity between organisational innovation and flexible working arrangements, however, the investigations on the sample did not support such a claim. The models were also run excluding organisational innovation from overall innovation; the results were similar.

4.2 Overall innovation results

The overall innovation results for the five models are presented in table 4.2. Across all models, the three key variables of this study (collaboration, flexible working arrangements, and ICT) play an important role in explaining the innovation behaviour. Collaboration is significant at the highest level and positive. This supports the findings of previous ABS-related studies that used cross-sectional data (ABS, 2008; Rotaru *et al.*, 2013; and DITR, 2006).

For the flexible working arrangements indicators, providing flexible work hours and flexible leave are both significant and positive.[7] Job sharing is also positive and is significant for some of the models. Working from home, although positive, is not significant for any of the models. These findings are in line with those of Rotaru et al., 2013 (the only other ABS study that included flexible working arrangements in the innovation model), with the exception of the working from home variable which was found to be significant in the former study.

The ICT intensity categories are also significant and they indicate that all other things being held constant, moving up to a more intense ICT improves the likelihood of innovation. Todhunter and Abello (2011), Rotaru *et al.* (2013), and Tiy *et al.* (2013) also found these results.

The results for the other control variables indicate the following. First, market location plays an important role. Compared to a firm that operates only locally, expanding the business operation of local firms to overseas markets positively and significantly affects the likelihood of the firm to innovate. Competition has a positive effect on innovation, but the results are only significant for the Moderate or Strong category. Size is only significant for some of the models. For the dynamic models, the coefficients for lagged innovation and initial innovation are both positive and highly significant.

To complement the results and in order to get a better indication of the effects of the main variables on innovation, consider also the APEs included in table 4.1. The results show that after averaging across all firms and all time periods, having innovated in the previous period is associated with an increase of more than eleven percent in the propensity to innovate. This indicates that even after controlling for unobserved heterogeneity and the other covariates, state dependence plays an important role for the likelihood of a firm to innovate.

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7   Note: for models 3 and 5, significance refers to either the significance of the individual coefficients, those of the group means, or both.

The results also show that with the exception of the *Working from Home* indicator, all the key variables across all models are highly significant. The coefficients for collaboration, as well as three of the four flexible working arrangements, are all positive. The results also support the importance of ICT intensity. Relative to a most intense ICT firm, having any lower ICT intensity significantly decreases the likelihood to innovate. In the case of model 5 this is by at least eleven percent.

4.3 Different types of innovation results

In this subsection, the study expands the previous results of the dynamic model by considering each type of innovation separately. The results are presented in table 4.3.

As expected, the magnitude and sign of the coefficients differ across the different types of innovation. The significance of the coefficients also differs, but there are regressors which remain significant across most models. Collaboration is such an example, where for all types of innovation the effect is positive and significant, mostly at the highest level.

Amongst the flexible working arrangements indicators there is more variation with regards to their significance. The effect of flexible work hours is positive and significant for new goods and services, new operational services, and new marketing methods. For flexible leave the effect is positive and significant for new operational and organisational services. Job sharing also plays an important role in influencing the new organisational and operational services, as well as new marketing innovation.

Similar to the previous results, overall, having a more intense ICT is associated with an increase in the likelihood to innovate. Likewise, operating both locally and overseas has a positive and mostly significant effect on the propensity to innovate.

In all cases, initial innovation and innovation lagged are highly significant and positive. These findings give support to the hypothesis that innovation is persistent and that the initial innovation plays an important role in the analysis, which is in line with what one would expect given the short time-frame.

4.3 Results for the different types of innovation (Model 5)

Variables	Goods & Services	Organisational	Operational	Marketing
Innovation (t–1)	0.371 ***	0.482 ***	0.541 ***	0.447 ***
Innovation (t=0)	0.961 ***	0.637 ***	0.672 ***	0.528 ***
Industry *(Manufacturing)*				
Mining	–0.306 *	0.060	0.030	–0.260
Construction	–0.238 *	–0.048	–0.402 ***	–0.260 **
Wholesale	–0.008	–0.045	–0.216 **	–0.067
Retail	–0.004	–0.055	–0.420 ***	–0.004
Accommodation	–0.188	0.060	–0.321 ***	0.061
Transport	–0.273 **	–0.098	–0.294 **	–0.249 *
Telecommunications	0.032	–0.030	–0.262 *	–0.020
Real Estate	–0.457 ***	0.035	–0.476 ***	0.178
Professional	–0.252 *	–0.128	–0.310 ***	–0.191
Administrative	–0.376	–0.163	–0.366 **	–0.221
Recreation	–0.295 *	–0.180	–0.512 ***	–0.114
Other Services	–0.062	0.082	–0.198	0.205
Size *(Very small)*				
Small	–0.083	0.103	0.148	0.041
Average	–0.182 **	0.147 **	0.139 *	–0.012
Flexible work hours	0.164 **	0.110	0.252 ***	0.142 *
Flexible leave	0.036	0.092	0.036	0.068
Job sharing	0.130	0.245 ***	0.169 *	0.246 ***
Working from home	0.134	0.068	–0.006	0.001
Competition *(No competition)*				
Minimal	–0.121	0.047	0.034	0.185
Moderate or Strong	–0.007	0.064	0.021	0.163
ICT Intensity *(Most intense)*				
Low	0.058	–0.247	–0.054	0.155
Moderate	0.030	0.001	–0.050	–0.181
High	–0.123	–0.038	–0.133	–0.177 *
Market Location *(Only local)*				
Only overseas	–0.597 **	–0.450 *	–0.458 *	–0.240
Both local and overseas	0.304 ***	0.036	0.124 *	0.157 **
Financial year *(2007–2008)*				
2008–2009	–0.227 ***	–0.130 ***	–0.161 ***	–0.085
2009–2010	–0.191 ***	–0.077	–0.185 ***	0.007
Collaboration	0.283 ***	0.294 ***	0.279 ***	0.168 **
Intercept	–1.202 ***	–1.348 ***	–1.431 ***	–1.442 ***
Group Means				
Flexible hours	0.009	0.131	–0.059	0.088
Flexible leave	0.046	0.276 ***	0.330 ***	–0.001
Job sharing	0.029	–0.094	0.103	0.002
Working from home	–0.014	0.101	0.066	0.099
Competition *(No competition)*				
Minimal	0.329	–0.222	0.244	–0.119
Moderate or Strong	0.351	0.011	0.277	0.274
ICT intensity *(Most intense)*				
Low	–0.332	–0.284	–0.353	–0.985 ***
Moderate	–0.511 ***	–0.352 ***	–0.288 **	–0.529 ***
High	–0.187	–0.130	–0.269 *	–0.083
Collaboration	0.225 *	0.048	0.311 ***	0.333 ***

4.3 Results for the different types of innovation (Model 5) (continued)

Variables	Goods & Services	Organisational	Operational	Marketing
Log Likelihood	−2,640.8	−2,707.6	−2,594.4	−2,562.9
AIC	5,365.5	5,499.1	5,272.8	5,209.8
BIC	5,643.1	5,776.7	5,550.4	5,487.4
Sigma	0.868	0.616	0.688	0.688
rho	0.430 ***	0.275 ***	0.321 ***	0.321 ***
Observations (n)	5,481	5,481	5,481	5,481

*** = significant at the 0.01 level; ** = significant at the 0.05 level; * = Significant at the 0.10 level;
Reference category is in brackets.

5. CONCLUDING REMARKS

This is the first longitudinal analysis study conducted on the Main Unit Record File of the ABS Business Longitudinal Database. The investigation explores the implementation, estimation, and performance of five popular discrete choice longitudinal data models. In doing so the analysis extends some of the previous BLD-based cross-sectional analyses conducted by the ABS to the longitudinal analysis front.

Given that a lot of the micro data collected by the ABS is categorical in nature and considering the current trend towards the collection and "creation" of richer datasets, desirably with both cross-sectional and time dimensions, the methodology developed in this study plays and important role and has the potential of being used in other ABS outputs.

The empirical stage is set on the analysis of the effects of four key factors on innovation, namely collaboration, flexible working arrangements, information technology, and innovation's own history.

From an empirical perspective, the study found that all four factors play important roles in influencing innovation. Across all models, collaboration was highly significant and positive. Flexible working arrangements were also positive and significant (with the exception of working from home). However, the results differed depending on the type of innovation considered. The results for ICT indicate that all other things being held constant, the more technological intense a firm is, the higher its propensity to innovate. The coefficient for lagged innovation was highly significant and positive.

Another finding, which showed up across most of the models, indicates that by operating locally as well as globally a firm increases its probability of innovation relative to the firms that operate only locally or only overseas. Overall, the results support the previous findings of related ABS studies that have examined the same relationships using cross-sectional data. Innovation was also found to be persistent.

On the technicalities of the models, the following can be summarised: (1) the lag effects and the initial conditions played key roles in the analysis; (2) controlling for the unobserved firm-specific effects was important in the analysis; and (3) allowing for some correlation between the firm specific-effects and the regressors was favourable.

From a methodological perspective, a few things are worth noting. The richness of longitudinal data provides great opportunities for analysis and opens the door to a lot of analyses that cannot be done on pure cross-sectional or time-series data. However, these benefits come at a cost, as the analyst is faced with one major task: extracting meaningful and valid inferences from these highly dependent data.

With non-linear models this undertaking is usually challenging. The non-additive heterogeneity and the serial dependence of the standard errors make the empirical analysis difficult and laborious. In these instances, it is often the case that the analyst cannot rely on the default standard errors computed by software packages, as they are not robust to serial correlation or heterogeneity. Rather, one needs to implement alternative methods, such as allowing for clusters in the estimation of the standard errors or simulating them via bootstrapping for panel data. This however, requires a lot of computation power, as evidence by some of the models in this study where the estimation time was in excess of five hours.

Singer and Willet (2003, Preamble, p. vii) summarises these points well:

> These methods are complex, their statistical models sophisticated, their assumptions subtle. The default options in most computer packages do not automatically generate the statistical models you need. Thoughtful data analysis requires diligence. But make no mistake; hard work has a payoff.

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APPENDIXES

A. DATA COMPILATION

The study utilises firm level data for Australian small- and medium-sized businesses covered by the 2007–2008, 2008–2009, and 2009–2010 waves of the BLD.[8] With a few exceptions, the compilation of the variables followed that described in Rotaru *et al.* (2013).

This section describes the compilation of the variables, beginning with the three main variables and then including the other control variables used in the model.

Innovation

The different types of innovation were based on the categories included in the Oslo Manual (OECD/Eurostat, 2005). Four types of innovation were identified:

- *New goods or services* – These include any good or service or combination of these which is new to the business (or significantly improved). Its characteristics or intended uses differ significantly from those previously produced/offered.

- *New operational processes* – These include any new or significantly improved methods of producing or delivering goods or services of a business (including significant change in techniques, equipment and/or software).

- *New organisational / managerial processes* – This includes new or significantly improved strategies, structures or routines of a business which aim to improve performance.

- *New marketing methods* – This includes new or significantly improved designs, packaging or selling methods aimed to increase the appeal of goods or services or to enter new markets.

In addition to the four types of innovation, an overall measure of innovation was constructed. The overall measure indicates whether a business engaged in any of the four types of innovation activity.

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8   Note that the information from all three waves was used in the analysis. For the dynamic models the innovation for 2006–2007, which was available from the BCS, was retrieved and used.

Flexible working arrangements

In the context of this paper, 'flexible working arrangements' refer to the working arrangements offered by businesses to their employees. The different arrangements were grouped into four indicators:

- Flexible working hours – which includes the availability of the employees to deal with non-work issues and the selection of own shifts and rosters;

- Flexible leave– which includes paid parental leave, flexible use of leave (personal sick, unpaid or compassionate leave), ability to buy extra annual leave, cash out annual leave or take leave without pay;

- Job sharing – which refers to the availability of job sharing; and

- Working from home – which refers to the availability of working from home.

ICT intensity:

For information technology, an indicator was constructed following Rotaru *et al.* (2013) and Todhunter and Abello (2011). Some slight changes were made to the groupings:

- *Most intense* – the business has broadband connection, web presence, and places or receives orders via the internet;

- *High* – the business has broadband connection, web presence, but does not place or receive orders via the internet;

- *Moderate* – the business has broadband connection but no web presence; and

- *Low* – the business does not use broadband connection

Collaboration:

The collaboration indicator indicates the presence of the following collaborative arrangements: joint research and development, joint buying, joint production of goods and services, integrated supply chain, joint marketing or distribution, and other collaborative arrangements specified by the business.

Other variables:

The selected business characteristics employed in the models are described below.

Industry Division:

- Mining
- Manufacturing
- Construction
- Wholesale
- Retail trade
- Accommodation and food service
- Transport, postal and warehousing
- Information, media and telecommunications
- Rental, hiring and real estate services
- Professional, scientific and technical services
- Administrative and support services
- Arts and recreation services
- Other services

Number of employees:

- Very Small: 0–4 employees[9]
- Small: 5–19 employees
- Average: 20–199 employees

Degree of competition:

- No competition: 0 competitors
- Minimal: 1–2 competitors
- Moderate or Strong: 3 or more competitors

Financial year:

- 2007–2008
- 2008–2009
- 2009–2010

Market location:

- Only local
- Both local and overseas
- Only overseas

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9   Note that the number of businesses with zero employees is very small, around 1%.

B. AVERAGE PARTIAL EFFECTS (APES)

This section briefly describes the derivation of the average partial effects (APEs) in the context of the Wooldridge Dynamic Model (model 5 in Section 3).[10] The methodology can be easily modified to derive the APEs for the other models.

The typical interest is on estimating

$$\mu_0\left(\boldsymbol{x}_t^*, y_{t-1}^*, c^*; \boldsymbol{\theta}\right) = E\left(y_{it} \mid \boldsymbol{x}_{it} = \boldsymbol{x}_t^*, y_{t-1} = y_{t-1}^*, c_i = c^*\right) \tag{B.1}$$

where $\boldsymbol{\theta}$ is a vector of parameters, y_{it}, in the context of this study, is a binary variable, and $\boldsymbol{x}_t^*, y_{t-1}^*, c^*$ are values of interest to the researcher.

As it is usually unclear which value(s) should be selected for c^*, rather than selecting c^*, one can proceed with the estimation of (B.1) by averaging across the distribution of c_i. This is indicated below:

$$\mu_1\left(\boldsymbol{x}_t^*, y_{t-1}^*; \boldsymbol{\theta}\right) = E_{c_i}\left[\mu_0\left(\boldsymbol{x}_t^*, y_{t-1}^*, c_i; \boldsymbol{\theta}\right)\right] \tag{B.2}$$

where the expectation is with respect to the unobserved effects.

From the model specified in (3.3),

$$P\left(y_{it} = 1 \mid \boldsymbol{x}_t^*, y_{t-1}^*, c_i\right) = F\left(\rho y_{t-1}^* + \boldsymbol{x}_t^{*\prime}\boldsymbol{\beta} + c_i\right)$$

and from

$$c_i \mid \boldsymbol{z}_i, y_{i0} = \psi + \boldsymbol{z}_i'\boldsymbol{\gamma} + \xi_0 y_{i0} + a_i$$

it follows that

$$\mu_1\left(\boldsymbol{x}_t^*, y_{t-1}^*; \boldsymbol{\theta}\right) = E_{c_i}\left[F\left(\psi + \boldsymbol{z}_i'\boldsymbol{\gamma} + \xi_0 y_{i0} + \rho y_{t-1}^* + \boldsymbol{x}_t^{*\prime}\boldsymbol{\beta} + a_i\right)\right] \tag{B.3}$$

Recall that $a_i \sim \mathrm{N}\left(0, \sigma_a^2\right)$.

As only the conditional distribution of c_i is assumed in the model, leaving the unconditional distribution unspecified, one cannot directly estimate (B.3). Instead the law of iterated expectations is used and the left-hand side of expression (B.3) becomes

$$\mu_1\left(\boldsymbol{x}_t^*, y_{t-1}^*; \boldsymbol{\theta}\right) = E_{\boldsymbol{z}_i, y_{i0}}\left\{E_{c_i \mid \boldsymbol{z}_i, y_{i0}}\left[F\left(\psi + \boldsymbol{z}_i'\boldsymbol{\gamma} + \xi_0 y_{i0} + \rho y_{t-1}^* + \boldsymbol{x}_t^{*\prime}\boldsymbol{\beta} + a_i\right) \mid \boldsymbol{z}_i, y_{i0}\right]\right\} \tag{B.4}$$

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10 For more details see Wooldridge (2010) and Wooldridge (2005).

Using the fact that the dependent variable is dichotomous, which implies that the expectation is simply the propensity, after some simple mathematics it follows that $E_{c_i|z_i,y_{i0}}[\cdot]$ is equal to

$$F\left(\psi_a + \mathbf{z}_i'\boldsymbol{\gamma}_a + \xi_{a0}y_{i0} + \rho_a y_{t-1}^* + \mathbf{x}_t^{*'}\boldsymbol{\beta}_a\right) \tag{B.5}$$

where

$$\begin{bmatrix} \psi_a \\ \boldsymbol{\gamma}_a \\ \xi_{a0} \\ \rho_a \\ \boldsymbol{\beta}_a \end{bmatrix} = \left(1 + \sigma_a^2\right)^{-0.5} \begin{bmatrix} \psi \\ \boldsymbol{\gamma} \\ \xi_0 \\ \rho \\ \boldsymbol{\beta} \end{bmatrix}$$

Substituting this expression into (B.4) all that is left is to find a good estimator for the outside expected value, i.e. $E_{z_i,y_{i0}}\{\cdot\}$.

The following sample counterpart estimates this consistently:

$$\hat{\mu}_1\left(\mathbf{x}_t^*, y_{t-1}^*; \hat{\boldsymbol{\theta}}\right) = \frac{1}{N}\sum_{i=1}^{N} F\left(\hat{\psi}_a + \mathbf{z}_i'\hat{\boldsymbol{\gamma}}_a + \hat{\xi}_{a0}y_{i0} + \hat{\rho}_a y_{t-1}^* + \mathbf{x}_t^{*'}\hat{\boldsymbol{\beta}}_a\right) \tag{B.6}$$

where the coefficients are the maximum likelihood estimates.

Using (B.6) one can easily estimate the desired APEs. For instance, the APE for a binary variable, w, is given by:

$$\widehat{APE}_w = \hat{\mu}_1\left(\mathbf{x}_t^*, y_{t-1}^*; \hat{\boldsymbol{\theta}}\,\middle|\,w = 1\right) - \hat{\mu}_1\left(\mathbf{x}_t^*, y_{t-1}^*; \hat{\boldsymbol{\theta}}\,\middle|\,w = 0\right)$$

In summary, the average partial effect of a discrete variable can be thought of as measuring the discrete change in probability averaged over the distribution of the unobserved variable(s). Usually this is done by conditioning on a set of values that are of interest to the researcher.

To compute standard errors for the APEs, one can use the delta or the bootstrapping method. In this study, panel-robust standard errors were calculated via the bootstrapping method. Note however, that due to the nonlinearity and complexity of the dynamic random effects model, the bootstrapping simulation had to be done manually.

C. MODEL MEASURES

In computing the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) the following usual formulae were used:

$$AIC = 2k - 2\ln(L) \tag{C.1}$$

$$BIC = k\ln(n) - 2\ln(L) \tag{C.2}$$

where k stands for the number of parameters in the statistical model, n is the sample size, and L is the maximised value of the model likelihood.

For the estimation of rho, which measures the relative importance of the unobserved effects, the following formula was used:

$$rho = \frac{\sigma_c^2}{\sigma_c^2 + \sigma_\varepsilon^2} \tag{C.3}$$

In this case, σ_c^2 is the variance of the unobserved effects, σ_ε^2 is the variance of the idiosyncratic component, and $\sigma_c^2 + \sigma_\varepsilon^2$ is the composite error.

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