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ABSTRACT

Innovation and the Determinants of Firm Survival *

While many firms compete through the development of new technologies and products, it is well known that new-to-the-world innovation is inherently risky and therefore may increase the probability of firm death. However, many existing studies consistently find a negative association between innovative activity and firm death. We argue that this may occur because authors fail to distinguish between innovation investments and innovation capital. Using an unbalanced panel of over 290,000 Australian companies, we estimate a piecewise-constant exponential hazard rate model to examine the relationship between innovation and survival and find that current innovation investments increase the probability of death while innovation capital lowers it.

JEL Classification: O31, O32, C41

Keywords: firm survival, innovation

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I. INTRODUCTION

Much effort has been expended in describing and explaining firm survival and industry dynamics (for a sample, see Agarwal and Gort 2002; Dunne, Roberts and Samuelson 1988; Klepper and Simons 1997; Klepper and Thompson 2006). Although innovation features prominently in case studies of industry evolution, systematic analysis of the issue has typically failed to account for the complexity of the innovation process. In particular, many studies do not account for the fact that while some innovations succeed, most fail. Thus, innovation increases the *ex ante* likelihood of both exceptional performance *and* death. In this article, we attempt to disentangle these two effects.

The typical line of argument adopted in most studies of firm survival is that innovation is the essence of firm survival since only those firms that are able to successfully innovate are able to establish and maintain a competitive advantage in the market (Bruderl, Preisendorfer and Ziegler 1992; Wagner 1999). Although there is an element of truth in this line of argument, it only tells one side of the story since it ignores the fact that innovation, especially new-to-the-world innovation, is subject to fundamental uncertainty. Consequently, studies of firm survival using measures of innovation based on "successful" innovation erroneously infer a positive causal relationship between innovation and firm survival. In doing so, they fail to account for a simple selection bias: firms which successfully commercialise innovations are also more likely to survive.[1] Cefis and Marsili (2005), for example, find evidence of an innovation premium – the increase in survival time due to "successful" innovation – of approximately 11 per cent. In order to understand whether innovation really does improve the likelihood of firm survival, we argue that both upside *and* downside risks associated with innovative activity should be properly accounted for.

Part of the difficulty in understanding the complex relationship between innovation and survival lies in the fact that "unsuccessful" innovative activity is difficult to observe. In this paper, we attempt to do so in two novel ways. In the first place, we differentiate between innovation capital (i.e. stocks) and innovation investment (i.e. flows). While the

[1] The endogeneity problem observed here is not confined to studies of firm survival – it is endemic to all studies of firm performance.

former has already been put through a selection filter (the market), the latter largely consists of unproven ideas and creations. If our contention is correct, innovation investments should have a more ambiguous effect on firm survival than innovation capital. We also differentiate innovations with different risk profiles – that is, whether the innovations are new-to-the-world (e.g. patents) or new-to-the-firm (e.g. trade marks). Since new-to-the-world investments are inherently riskier than investments in new-to-the firm innovations, we would expect them to have differing effects on the rate of firm survival.

To examine the determinants of firm survival, we collated data at the firm-level (e.g. intellectual property [IP] stocks and flows), the industry-level (e.g. gross entry rate) and the economy-level (e.g. change in GDP growth). Firm-level data were collected on an unbalanced panel of approximately 290,000 Australian companies per annum over the period 1997-2003. Using this data, a flexible age-death relation is estimated using a piecewise-constant exponential hazard rate model (Lancaster 1979).

This paper makes a number of contributions to the literature on firm survival. First and foremost, we deepen our understanding of the role innovation plays in determining firm survival by separating innovation investment flows from innovation capital stocks whilst controlling for observable industry and macroeconomic factors. When both the upside and downside risks of innovation are properly accounted for, we are able to show that the previously-observed "innovation premium" effect relates most clearly to capital measures of innovation: the effect is however mixed if we consider current investments in innovative activity. In fact, current investments that represent new-to-the-world innovations actually *decrease* the likelihood of firm survival.

Second, we use a large, representative sample of firms in the Australian economy which enables us to draw out generalisable inter-industry effects. The importance of such generalisable effects has often been overlooked as many studies on this issue focus on specific technologies or innovative product markets which are known to be highly idiosyncratic. Such studies show that technological maturity, time of entry and innovation type are all important determinants of firm survival (see Bayus and Agarwal 2006; Audretsch and Lehmann 2004; Hoetker, Mitchell and Swaminathan 2003; Fontana and

Nesta 2006). Our study on the broader inter-industry effects of innovation on firm survival should be seen as a natural complement to these case studies.

The paper is organised as follows: Part II develops a simple deductive model of firm model survival based on firms' ability to pay their current liabilities. Part III examines the construction of the dataset used to analyse the determinants of firm survival including the linking of firm-level data on registration, IP and accounting variables with other industry-level characteristics. Part IV presents the empirical model and Part V analyses the results of the estimation. Part VI concludes.

II. A MODEL OF FIRM EXIT

While companies may deregister for many reasons, this article is only interested in the economic factors that determine firm survival. The main systematic economic reason firms cease to operate is their inability to pay their accounts payable.[2] In this respect, it is their efficiency in production relative to their market position – both of which are determined by past investments into technology, market penetration and current prices (outputs relative to inputs) – that systematically governs the probability of survival. We model these revenues relative to costs as:

$$\pi = p_o f(z)k - c(l,k) \qquad (1)$$

where π is the level of profits[3]; p_o represents current prices of output; $f(.)$ is the current output-capital ratio which is a function of the technical efficiency, z; and c represents current costs as a function of intermediate inputs (i.e. some types of labour) l and investment goods (tangible and intangible capital) k. We specify $c(l,k) = wl + rp_k k$ where w is the current price of intermediate inputs, r is the current rate of interest on borrowed funds (being the risk-free rate of interest plus the premia for risk applicable to the firm's activities), and p_k represents the costs of capital goods at the time of purchase. The rate of profit is accordingly:

[2] For a comparable model which considers firm exit from the position of default on debt, see Schary (1991).
[3] Net of deprecation.

$$\frac{\pi}{p_k k} = \frac{p_o}{p_k} f(z) - \frac{wl}{p_k k} - r. \quad (2)$$

The probability of firm death is a decreasing function of the rate of profit: if the rate of profit is negative the firm will struggle to continue operations unless it has access to a source of short-term finance, *s*.[4] To model the forces affecting business closure, we define hazard (i.e. firm exit/death), *H*, to occur (i.e. *H=1*) when the rate of profit is less than the opportunity cost of funds, such that:

$$H = \begin{cases} 1 \text{ if } \frac{\pi}{p_k k} + s < 0 \\ 0 \text{ if } \frac{\pi}{p_k k} + s \geq 0 \end{cases} \quad (3)$$

Substituting Equation 2 into Equation 3 gives:

$$H = \begin{cases} 1 \text{ if } \frac{p_o}{p_k} f(z) - \frac{wl}{p_k k} - r + s < 0 \\ 0 \text{ if } \frac{p_o}{p_k} f(z) - \frac{wl}{p_k k} - r + s \geq 0 \end{cases} \quad (4)$$

Firm size influences survival only in so much as it is associated with economies of scale, which will affect efficiency (*z*) relative to the inputs (*l, k*) or short-term finance (*s*).

There has been considerable empirical research on the determinants of firm survival. Learning-by-doing and capabilities – as proxied in different studies by firm age (Agarwal and Gort 2002), initial endowments (Dunne et *al*. 1988; Agarwal and Gort 2002), prior experience (Bruderl, Preisendorfer and Ziegler 1992; Klepper 2002; Klepper and Simons 2000; Thompson 2005), the parent company (Caroll *et al.* 1996), and firm-level heterogeneity (Audretsch 1995b; Caves 1998) – have been found to have a positive effect on survival. More specifically, employees' skills and capabilities at the time of market entry have also been shown to have lasting effects on survival (Bruderl, Preisendorfer and Ziegler 1992; Baldwin and Rafiquzzaman 1995; Thompson 2005). In some cases, first-

[4] This variable is included since firms which have a low ratio of liabilities to assets, or access to a pool of short-term finance (for example, from a parent company), have the option to continue trading if they believe their current set back is temporary.

mover advantages in a new technological area have been profound (Klepper and Simons 1997) but survival rates has also been shown to vary according to pre-entry experience and entry time (Bayus and Agarwal 2006).

Further studies have focused on the effects of innovation on firm survival. As previously mentioned, one obstacle to analysing this issue relates to the measurement of innovation. Any observed correlation between innovation and survival which relies on measures of 'successful' innovation – such as new products and innovation sales – may suffer from a selection bias. Given the lack of distinction in the literature to these differences, we are not surprised to find mixed empirical findings. On the positive side, Cockburn and Wagner (2006) find that recent internet-related IPO-firms were more likely to survive if they held registered patents, after controlling for age, venture-capital backing, financial characteristics and stock market conditions. Perez and Castillejo (2004) found a positive relation between R&D spending and survival but only for firms in highly innovative industries, while Ortega-Argiles and Moreno (2005) used the same dataset and found that it held only for small firms.[5] Ortega-Argiles and Moreno (2005) also found that dichotomous product and process innovation had positive effects on small-firm survival.

Other studies were more ambiguous, finding either no relationship, a negative one or a mixture (see Wagner 1999; Audretsch and Mahmood 1995; Audretsch and Lehmann 2004; Segarra and Callejon 2002). More interesting findings include Bayus and Agarwal (2006) who found that it is only once the technological trajectory is established that being an innovative start-up firm confers a higher probability of survival. In earlier stages of development when the trajectory is less clear, it can be a disadvantage to be an independent start-up firm. Audretsch (1995) found that survival rates for small firms vary inversely with the level of innovation in their industry: more innovative industries have higher neo-natal death rates than less innovative industries, *ceteris paribus*. However, for those that survive beyond the first few years, survival is positively associated with the innovative intensity of the industry.

[5] However, both studies controlled for indicators of firm performance such as the firm's price-cost margin and export intensity which we expect to be endogenous, so it is unclear how to interpret the results. There were no lagged explanatory variables in the data.

Ideally, we want a measure of innovation that sums all *ex ante* expenditures on the full spectrum of activities (new products, processes, forms of work organisation and marketing). Unfortunately, this was not possible given the size and scope of our data set and we are limited to those activities that leave an administrative trail through IP applications. While this excludes all activities that failed to result in a patent, trade mark or design application – and were thus unsuccessful – by separating current IP applications from the stock of IP registered titles in-force, we are able to separate activities that are technically feasible but not market tested from those that have shown to have enough value to the company that the company has renewed the title. In addition, patents and designs are only granted to creations that are new-to-the-world while trade marks need only be new to the local market. Hence we have in our dataset a natural distinction between innovation that is aligned with higher risk new-to-the-world activities and innovation that is aligned with lower risk new-to-the-firm activities.

III. Data and Descriptive Statistics

Our data was drawn from a seven-year unbalanced panel of 292,080 companies (over the period 1997-2003) which matched firm-level registrations/de-registrations from the Australian Securities and Investment Commission (ASIC)[6] with data on IP applications (i.e. IP flows) and renewals (i.e. IP stocks) from IP Australia, accounting data from a proprietary source, IBISWorld, and industry classification data from the Yellow Pages.[7] [8] Our unit of analysis was the Australian Company Number (ACN) and we defined death of a firm as the de-registration of an ACN on the ASIC database.[9] We validated this by cross-checking with Yellow Pages data, from which we determined that no ASIC de-

[6] The Australian Securities and Investment Commission (ASIC) is an independent Australian government body which enforces and regulates company laws to protect consumers, investors and creditors. As part of its charter, ASIC maintains a complete record of all company registrations and de-registrations in Australia. Note that the ASIC registry does not include data on sole proprietors or partnerships.

[7] The match was done on company name.

[8] The Australian Bureau of Statistics (ABS) has such data, but it is confidential.

[9] Similar to many other empirical studies, we do not observe the specific reason for de-registration. Thus, we are unable to differentiate between de-registrations that occur as a result of genuine business failure and de-registrations that occur for health/personal reasons. Moreover, we are unable to identify deaths that may occur as a result of a merger or takeover. However, anecdotal market information suggests that companies' registration is generally maintained after merger or acquisition as it provides the new parent with the flexibility to transfer profits and assets, minimise taxation and offer more diverse ownership structures.

registered companies were listed in the Yellow Pages. Thus, de-registration implies that the company has ceased to operate, in the economists' sense of the word. Company age (in years) was the unit of time-analysis. Companies that changed names or addresses were treated as continuing entities. A parent-subsidiary concordance for each year was determined using ASIC share ownership files.

The industry classifications from the Yellow Pages enabled us to add 2-digit industry-level data (such as profit margins and value-added) from the Australian Bureau of Statistics (ABS) to our firm-level data.[10] Note that one anomaly of this matching process is that ABS industry data is collated on a financial year (July-June) basis and therefore lags 6 months behind our other data. Finally, we also matched the data across to macroeconomic variables on the change in GDP, interest rates and stock market prices.[11] Thus, the final complete linked dataset provides firm-level, industry-level and economy-level characteristics that mimic variables in equation (4).

Table 1 provides an overview of our sample relative to the population of Australian companies. Specifically, it provides information on the population of companies according to ABS data relative to the sample of companies we were able to match across from ASIC data to the Yellow Pages. In 2004, the only year for which comparative data is available, the ABS reported that the population of companies in Australia was 799,333. However, many of these companies are holding companies and other non-employing entities. Since we are interested here in operating entities (as these are the companies whose deaths have important economic consequences), we excluded non-employing companies from the comparison, which leaves a population of 423,080 companies.[12]

If we then compare our sample to the population of companies in 2004, we can see that 67.0% of the population was successfully matched across to the Yellow Pages. Since our match was made on company name, we were not able to match companies whose trading

[10] ABS Cat. No. 8140.0.55.002 Summary of Industry Performance, Australia, Final 2000-01 -- Data Report, Electronic Delivery, cat no. 8160.0.55.001 - Experimental Estimates, Entries and Exits of Business Entities, Australia, Cat No. 8155.0 Australian Industry Experimental Estimates Industry Performance by ANZSIC Class, Australia, 2002-03.

[11] ABS Cat. rbabf01.xls; rbabf07.xls; 8140.0.55.002.

[12] In 2002-03, non-employing businesses accounted for 63.6 per cent of all businesses but only 6.3 per cent of all sales, see Cat No. 8155.0.55.002. Employing businesses excludes sole proprietors since they do not employ anyone.

name (as listed in the Yellow Pages) is different from the company name (as listed in ASIC). These non-matches cause a systematic under-representation in industries such as wholesale and retail trade and accommodation, cafés and restaurants where company names commonly differ from trading names (see Table A1 in the appendix). Note that due to imperfections in the matching process, we over-sample the population of public, employing-only companies.[13] Aside from these cases, there are no major reasons to believe that our matched sample varies systematically from the population.[14]

Table 1: Population and Sample of Australian Companies, 2004[(a)]

Type of entity	Population		Sample	
	ABS[(b)]	ABS[(b)]	ASIC data matched to Yellow Pages	
	Employing & non-Employing	***Employing only***	***Mainly employing***	
Private company	785,727	414,660	273,607	66.0%
Public company	13,606	8,420	9,848	117.0%
Total	799,333	423,080	283,455	67.0%

Notes: (a) ABS data in this format prior to 2004 was not available. (b) Cat. no. 8161.0.55.001 Australian Bureau of Statistics Business Register, Counts of Businesses.

To understand the pattern of entry and exit over the period 1997-2003, we took the stock of companies registered in ASIC in 1997 for which we were able to match across to IBISWorld, IP Australia and the Yellow Pages. For each year of analysis, we then tracked incumbents, new-born firms and those that died. Table 2 presents a summary of the stock of companies in each year and the relevant birth and death rates. Among most developed counties, the average firm death rate varies from 3.3 to 8.2% of firms in a given market over a single year (Cable and Schwalbach 1991; Agarwal and Gort 2002). Our data indicates a similar, albeit slightly lower, pattern in Australia – the observed death rate ranged from 1.6% to 4.2%, with some evidence of an upward trend. On the other hand, birth rates ranged from 5.7% to 12.1%, with a downward trend.

Table 2: Stocks, Birth and Death Rates of Companies, by Year

Year	Stock (number)	Birth Rate (% of stock)	Death Rate (% of stock)

[13] Some non-employing companies are parent companies of subsidiaries that employ many people.
[14] Table A1 in the Appendix compares the industry distribution from the ABS with our matched sample and finds that our sample is broadly representative of the population.

1997	219,318	12.1	1.6
1998	236,958	10.4	2.5
1999	250,911	9.5	3.0
2000	264,680	8.0	3.2
2001	269,864	5.7	4.2
2002	271,861	5.9	4.2
2003	272,576	6.1	4.1
Average		8.1	3.3

In total, there are 2,010,800 observations in the dataset which relate to 292,080 individual companies. In

Table 3, we present a summary of the characteristics of the companies in our dataset by 2-digit industrial classification. Almost half of the firms are in two industries – Manufacturing (84,529) and Property and business services (60,090). Other industries such as Construction (35,852) and Retail trade (23,440) are also well-represented in our sample. The vast majority (99.1%) of companies are small-medium sized, the main exception being the Mining industry which is characterised by high minimum efficient scale. Most of the companies are also privately-owned.

Table 3 also suggests substantial variation in both profit margins and entry rates. Profit margin – which is operating profit before tax as a percentage of operating income – ranges from 0.99 in Wholesale trade to 6.22 in Communication services. Gross entry rate – which is the number of firms entering an industry divided by the number of incumbents – provides an indication of competition in the industry. Industries such as Mining are characterised by low gross entry rates (4.63) while others such as Communication Services (12.34) are much higher. The innovation measures also demonstrate widespread inter-industry variation. Mining engages in a lot of innovative activity while Manufacturing is the only other industry which has a substantial patent stock.

Table 3: Average Firm Characteristics, by Industry, 1997-2003

Industry	Companies (number)	SME (%)	Private company (%)	Profit margin	Gross entry rate	Patent applications (number)	Trade mark applications (number)	Design applications (number)	Patent stock (years)	Trade mark stock (years)	Design stock (years)
Agriculture, Forestry and Fishing	8,327	99.3	97.9	1.57	7.50	0.009	0.087	0.009	0.249	4.574	0.662
Mining	1,950	90.2	74.3	2.25	4.63	0.166	0.565	0.063	5.034	30.233	7.462
Manufacturing	84,529	98.9	98.6	2.29	6.76	0.016	0.126	0.015	0.562	10.529	1.701
Construction	35,852	99.5	99.5	5.32	7.71	0.003	0.028	0.003	0.140	1.804	0.284
Wholesale Trade	9,678	97.6	98.0	0.99	6.33	0.017	0.147	0.014	0.556	12.573	1.730
Retail Trade	23,440	98.9	99.0	1.70	7.06	0.005	0.093	0.006	0.180	7.676	0.776
Transport and Storage	12,227	99.0	96.8	2.35	7.15	0.008	0.059	0.002	0.260	4.379	0.431
Communication Services	3,603	98.6	96.7	6.22	12.34	0.007	0.127	0.003	0.311	4.608	0.737
Finance and Insurance	5,323	99.0	91.5	1.48	9.18	0.012	0.169	0.011	0.349	9.047	1.076
Property and Business Services	60,090	99.5	97.9	2.80	7.79	0.005	0.050	0.003	0.139	2.808	0.274
Health and Community Services	20,047	99.6	93.1	5.36	8.83	0.004	0.052	0.003	0.104	3.006	0.402
Cultural and Recreational Services	7,871	99.4	78.0	3.16	6.75	0.004	0.098	0.004	0.149	7.900	0.615
Personal and Other Services	7,666	99.6	79.0	5.56	8.21	0.002	0.063	0.002	0.070	4.298	0.245
TOTAL	**292,080**	**99.1**	**96.6**	**3.04**	**7.44**	**0.010**	**0.087**	**0.008**	**0.331**	**6.410**	**0.908**

Sources: ABS, IP Australia, IBISWorld data.

IV. EMPIRICAL MODEL

We use a piecewise-constant exponential hazard rate model with proportional unobserved heterogeneity[15] to examine the relationship between innovation and survival depicted in equation 4. The hazard, or the probability of death, for firm *i* in period *t* conditional on having survived up to that point, is denoted as $h_i(t \mid \mathbf{x})$, and can be written as:

$$h_i(t \mid \mathbf{x}) = h_0(t)\alpha_i \exp(\mathbf{x}_i'\boldsymbol{\beta}) \qquad (5)$$

where $h_0(t)$ is the baseline-hazard function, α_i is the firm-specific effect (i.e. proportional unobserved heterogeneity), and $\mathbf{x}_i$ is a vector of explanatory variables which impose a proportional characteristic-specific shift on the baseline hazard. Since the mortality rate is defined with respect to time, h_0 is written as an unspecified function of time. We choose a flexible specification for our baseline hazard in order to avoid potential mis-specification bias resulting from choosing an inappropriate parametric specification for the baseline hazard. The proportional unobserved heterogeneity α_i is assumed to be gamma distributed.[16]

The vector **x** in our empirical model includes a range of explanatory variables relating to the factors affecting firm survival presented in equation (4). In particular, for the technical efficiency (*z*) variable we use the IP application and stock variables. **x** also includes control measures relating to: market conditions (p_o); the cost of capital goods (p_k); the interest rate (*r*); industry risk (μ); short-term finance (*s*); and the ratio of variable to fixed costs ($wl/p_k k$). Each of these factors (and the proxies used in the estimation) – which may be measured at the firm-, industry- or economy-level – are explained in more detail below.

Technical Efficiency and the Cost of Capital Goods. Firm-level technical efficiency affects firm survival since firms with higher productive efficiency (better products and more cost-effective processes) are more likely to survive. Although we don't observe

[15] This model is also known as the Mixed Proportional Hazard (MPH) model. See Van den Berg (2001).
[16] This choice is not only made for computational reasons. See Abbring and Van den Berg (2001) for a rationalisation for choosing the gamma distribution.

technical efficiency directly, this effect is captured in the estimation by two sets of innovation variables; current innovative activity and past 'successful' innovation. As mentioned above, we observe each variable with regard to three types of innovation output – patents, trade marks and designs. Thus, there are three variables reflecting current innovative activity – *Patent applications*, *Trade mark applications* and *Design applications*. Patents and designs only apply to ideas or creations that are new-to-the-world, while trade marks are associated with products launches that may be either new-new-to-the-firm or new-to-the-world. We modelled these variables as the natural log of the number of current applications plus one.[17]

There are also three innovation capital variables included – *Patent stock*, *Trade mark stock* and *Design stock* – to reflect past partially successful innovation, that is, innovation capital. To test the sensitivity of our method of aggregating IP stocks to our results we entered stocks as a series of dummy variables.[18] The resulting coefficients suggested that there are diminishing returns to IP stocks, measured in total years in-force. Accordingly, we chose to measure IP stocks by the log of the number of years in-force plus one.[19]

One of the major drawbacks of using IP applications in a model of firm survival is that it may be endogenous to the decision to de-register the company since firms that know they are about to "die" may be less likely to apply for a patent. To the extent this occurs, any observed positive relationship between patent applications and death would *underestimate* the true size of the effect and a negative relationship would *overestimate* the true effect. To partly account for this problem, we use 1- or 2-year lags of our measures of innovative activity. It is also important to note that the endogeneity problem is only an issue for IP applications since IP stocks are accumulations of decisions made many years ago, and are slow to react to current conditions.

While the IP variables represent activities that may increase the technical efficiency of the firm, they impose a cost on the firm which developed the idea. As such, the same IP

[17] We add one since many firms have no IP applications or stocks.
[18] There was a series of dummies for zero, 1-1000, 1001-5000 and 5000 days for each of patents, trade marks and designs.
[19] Since all of the IP variables were computer matched to ACNs using company name, we were not in many cases able to distinguish between parents and their subsidiaries that have similar names. Accordingly, we thought it was more accurate to aggregate IP variable to the ultimate-parent company level. Each company is then assigned the same level of IP applications and stock as all firms in their family.

variables that are expected to enhance the revenue-side of the firm, will also contribute to costs. The net effect can go either way.

Market Conditions. The likelihood of firm survival is also affected by conditions in the market place – for instance, business cycle effects and the buoyancy of demand at the macroeconomic level and competitive pressure at the microeconomic level can strongly influence a firm's chances of survival. To capture the first effect, we included a measure of the macroeconomic strength of the economy – *Macro conditions* – in the model. This variable was constructed by using the scored factors from three components: the change in annual GDP, the change in the change in annual GDP and the stock market index. The second effect was proxied by the gross-entry rate on the assumption that gross entry exerts direct competitive pressure on incumbents. Our variable – *Gross entry* – is the annual gross-entry rate in the company's 2-digit industry over the period 1997 to 2003. This *Gross entry* variable – which is the number of firms entering an industry divided by the number of incumbents – is lagged 6 months.

Rate of Interest. This comprises the *Default-free rate*, represented here by the 90-day bank-bill rate, and the risk premia which we call *Industry risk.* In order to capture the latter we use a measure of inter-industry variation in risk, being the profit margin, (as defined in the previous section) divided by the (tangible) capital-output ratio in the company's industry. Industry dummies are also included to control for inter-industry variation in risk (and other factors). *Industry risk* is lagged 6 months.

Short-term finance. To represent firm's potential to access external finance we included four explanatory variables in the model: a dummy variable – *Large company* – to indicate the size of the company (Large or SME)[20], a dummy variable – *Private company* – to indicate whether the company is privately-owned and two further dummy variables –

[20] An SME is a company with less than 200 employees or assets worth less than AU$200m. We have no measure of the actual size of the company. To the extent economies of scale exist, they will be reflected in higher survival rates for large companies (captured by the *Large company* dummy variable) and higher survival rates for companies with very high capital stocks.

Subsidiary and Ultimate parent of subsidiaries – to indicate whether the company was a subsidiary, ultimate parent or stand-alone company.

Variable Costs. According to equation (4), the higher the ratio of variable to capital costs, given the rate of interest, the lower the rate of profit. Ideally, we should measure this using firm-level data, however, we do not have this data and rely instead upon an industry-level measure of variable costs – wages divided by total assets. This is called *Variable cost* and is lagged 6 months.

V. RESULTS AND ANALYSIS

We first estimated the model in (4) using a piecewise-constant exponential hazard approach without controls for unobserved heterogeneity; the results of which are presented in Table 4. The explanatory variables are presented in the second column; along with information on whether the variable was measured at the firm-level (f), industry-level (i) or the economy-level (e). Since this is a hazard function, a positive (negative) coefficient implies a positive (negative) effect on the probability of company exit (i.e. de-registration or disappearance). In order to interpret the coefficients of the variables in Table 4, we also present the marginal effects of changing each of the covariates on the average median life span of the company, *ceteris paribus*, in Table 5.

Our main result is that innovation matters, but not in the way other studies have argued. Specifically, our results show that with respect to new-to-the-world innovation, higher capital stocks reduce the probability of death, but higher innovation investment increase death rates. For example, the marginal effects show that companies that increase their annual patent applications from zero to one have a lower average median life span of 4.2 years. However, the marginal effect of increasing the patent stock for a further five years *increases* the average median life span by 9.2 years. These results for patent stocks are consistent with findings from Fontana and Nesta (2006), but not Audretsch and Lehmann (2004).

The pattern for trade marks was however different from patents, most likely because trade marks incorporate elements of both new-to-the-world and new-to-the-firm

innovation. We found that companies with more of both trademark applications and stocks have a lower hazard rate: one additional trademark application is associated with a median life which is longer by 2.2 years and five additional trademark stock years is associated with a median life which is longer by 3.6 years. This concurs with the findings from Ortega-Argiles and Moreno (2005). Neither design applications nor design stock variables were statistically or economically significant.

Table 4: Exit Hazard Function Estimates

	Independent variables	**Model 1: IP applications lagged one year**		**Model 2: IP applications lagged two years**	
Model-Link		***Coef.***			***z***
z, p_k	Lagged patent applications *(f)*	0.25***	3.46	0.29***	3.84
z, p_k	Lagged trade mark applications *(f)*	-0.12***	-3.98	-0.16***	-5.27
z, p_k	Lagged design applications *(f)*	-0.014	-0.16	0.043	0.52
z, p_k	Patent stock *(f)*	-0.037***	-4.53	-0.038***	-4.61
z, p_k	Trade mark stock *(f)*	-0.018***	-7.60	-0.017***	-7.12
z, p_k	Design stock *(f)*	0.004	0.72	0.003	0.600
p_o	Gross entry rate *(i)*	0.03***	7.65	0.03***	7.65
p_o	Macro conditions *(e)*	-0.39***	-32.25	-0.39***	-32.24
r	Default-free rate *(e)*	0.19***	20.68	0.19***	20.66
r	Industry risk *(i)*	0.02***	5.47	0.02***	5.46
r	Industry dummies *(i)*	yes		yes	
s	Large company *(f)*	-0.51***	-7.77	-0.50***	-7.73
s	Private company *(f)*	0.04	1.63	0.04	1.60
s	Subsidiary *(f)*	0.22***	8.93	0.22***	9.04
s	Ultimate parent of subsidiaries *(f)*	-0.42***	-7.26	-0.42***	-7.25
wl/p_kk	Variable costs *(i)*	-0.18***	-3.72	-0.18***	-3.72
	No. of subjects	292,080		292,080	
	No. of failures	49,520		49,520	
	Time at risk	1,535,010		1,535,010	
	Log likelihood	-112,400.61		-112,393.53	
	Number of obs	2,010,800		2,010,800	

Notes:

(1) Piecewise-constant exponential hazard
(2) *(f), (i)* and *(e)* indicate whether the variables are measured at the firm-, industry- or economy-level respectively.
(3) Time of analysis is time since company birth.

Nearly all our control variables were statistically and economically significant. More competitive industries, as measured by a high rate of gross entry, were also characterised by high rates of exit. The results also confirm the conventional wisdom that when the economy is growing (GDP per capita is strong and the stock market is increasing), firms are less likely to die. The average expected median life span is 10.8 years longer when the economic activity is one standard deviation above the mean compared with one standard deviation below the mean, *ceteris paribus*. An increase in the interest rate negatively affects firm survival; when the rate of interest rises from one standard deviation below the mean to one standard deviation above the mean, the expected median survival time falls by 4.7 years.

Table 5: Marginal Effects of Explanatory Variables on Average Median Survival

Independent variable	Change in the independent variable	Difference in median survival time (years)
Large	[no : yes]	17.0
Private company	[no : yes]	-1.2
Subsidiary	[no : yes]	-5.2
Ultimate parent of subsidiaries	[no : yes]	13.5
Lagged patent applications	[None : one]	-4.2
Lagged patent applications	[None : five]	-9.5
Lagged trade mark applications	[None : one]	2.2
Lagged trade mark applications	[None : five]	6.2
Lagged design applications	[None : one]	0.3
Lagged design applications	[None : five]	0.7
Patent stock	[None : 5-year]	8.3
Patent stock	[None : 10-years]	9.2
Trade mark stock	[None : 5-year]	3.6
Trade mark stock	[None : 10-years]	4.0
Design stock	[None : 5-year]	-0.7
Design stock	[None : 10-years]	-0.8
Default-free rate	[μ-σ : μ+σ]	-4.7
Industry risk	[μ-σ : μ+σ]	-2.0
Gross entry rate	[μ-σ : μ+σ]	-4.5
Macro conditions	[μ-σ : μ+σ]	10.8

Source: Table 4. Marginal effects for Variable cost have not been included because the coefficient was incorrectly signed.

Our results also confirm the common-sense view that industries which are uncertain are more likely to have higher death rates. The results also indicate that being large and being a parent of subsidiary companies enhances your chances of survival. However, contrary to expectations and the findings of Disney, Haskel and Heden (2003), Heiss and Koke (2004) and Audretsch (1995a), being a subsidiary lowered the probability of survival compared with being a stand-alone company. Common to most other studies in our genre, large firms have considerably greater chances of survival than SMEs. The incorrect sign on variable costs may be a function of the fact that we are using industry-averaged data rather than company-level data.

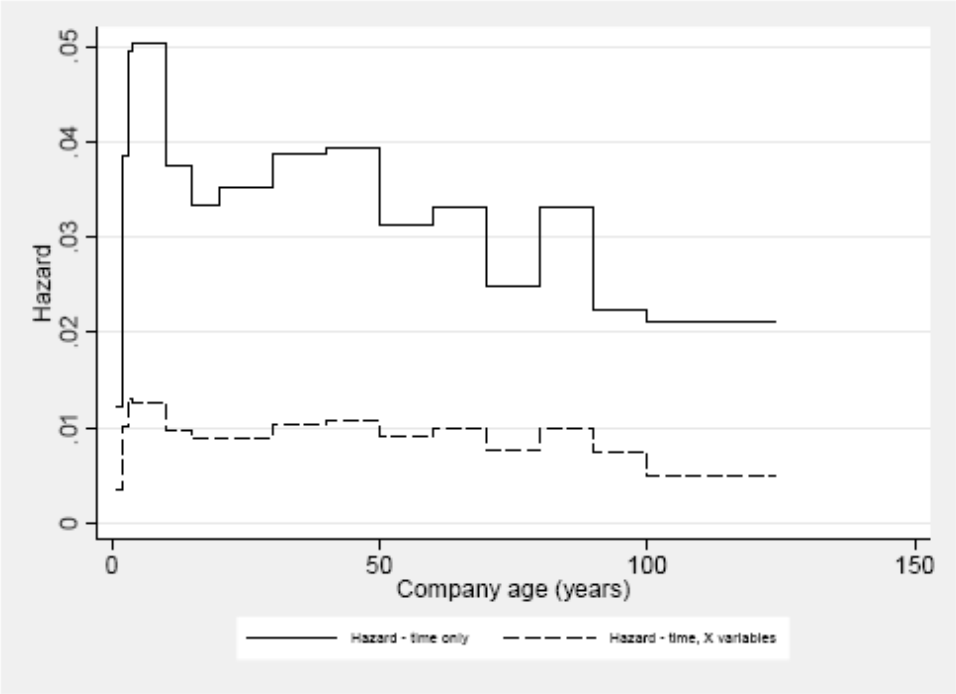
One robust stylised fact from the literature on firm survival is a strong negative bi-variate relation between company age and death.[21] We know however, that age *per se* does not cause death but is merely a proxy for not properly controlling for time-varying factors.[22] These have variously been credited to the prior experience of the founding manager(s) (Thompson, 2005), learning (Disney, Haskel and Heden 2003; Perez, Llopis and Llopis 2004; Segarra and Callejon 2002), organisational networks and capabilities (Perez, Llopis and Llopis 2004). One advantage of using a flexible-baseline hazard model is that we do not impose a prior view on whether firms are more or less likely to exit as the firm ages.

Figure 1 presents two versions of the hazard function depending on the number and variety of covariates. Since we reduce the 124 potential life years (and over 45,000 days) to 15 time periods, all lines appear as step functions. This was necessary for computational purposes. The first solid line, which was estimated using only the time periods, shows the standard negative relation between company age and the probability of firm exit. The second dashed line, shows the hazard once the co-variates listed above are included. Interestingly, it reveals that once account is taken of the firm-efficiency (as defined), market-conditions, interest-rates, financial-constraints, industry-risk and variable-cost effects; age effects disappear up to the age of about 80 years.

[21] However, some empirical studies reveal that the hazard rises after a certain age, see for example Perez, Llopis and Llopis (2004).

[22] Cleves, Gould and Gutierrez (2004) argue that a significant age or time co-variate essentially derives from a mis-specification of the model. Even for humans, death arises from the deterioration in bodily functions rather than age *per se* and this holds *a fortiori* for companies.

Figure 1 Firm Exit Hazard rate by company age, with and without explanatory variables



To check for robustness of our estimates, we experimented with other model specifications. Specifically, we estimated a standard Cox model, which does not parameterise or estimate a baseline hazard. The piecewise-constant baseline specification and the Cox specification produced near identical results, which is a manifestation of the flexibility of the piecewise-constant form. We also experimented with other popular parametric specifications – e.g. Weibull, Gompertz and exponential – for the baseline hazard. These results were overall qualitatively in line with the results in Table 4. However, the time pattern of the baseline hazard implied by these alternative parametric baseline specifications varied and was not necessarily in accordance with the piece-wise constant model.

We also experimented with up to three lagged periods for the IP variables. All estimations produced very similar results. While the three-year lagged variables had the largest effects, we only present 1- and 2-year lags to clearly distinguish the measures for current innovative activities versus past innovative activity.

Recent studies on firm survival have attempted to test for and remove the effects of unobservable heterogeneity (Bayus and Agarwal 2006; Ortega-Argiles and Moreno 2005; Perez and Castillejo 2004; Fontana and Nesta 2006; Nkurunziza 2005; Hoetker, Mitchell and Swaminathan 2003; Audretsch and Lehmann 2004). We experimented extensively with the model specification and similarly found no evidence of unobserved heterogeneity. This is despite compelling evidence from case studies highlighting the importance of founder skills and managerial competence for firm survival (Bruderl, Preisendorfer and Ziegler 1992; Klepper 2002; Klepper and Simons 2000; Thompson 2005).[23]

VI. CONCLUSIONS

According to our results, new-to-the-world innovation investments and innovation capital have disparate effects of a firm's chances of survival once other factors such as market conditions, the cost and access to finance, and the industry risk profile have been taken into account. The explanation for this result is that investment into innovation – as depicted by the company's current applications for patents – is a risky activity which lowers the likelihood of survival. However, this does not mean that average returns from innovation are negative, only that current innovative activity has a negative effect on the median firm, *ceteris paribus*. Conversely, past successful innovations have a clear positive effect on survival: firms that have patents which are worth renewing also possess the bundle of financial, management and economic capabilities that raises their chances of survival.

The result for trade marks was quite different, possibly because the presence of trade marks reflects the occurrence of imitation or new-to-the-firm innovations. Our finding that trade mark applications were associated with a higher survival rate may indicate that the innovative activity associated with the launch of a trade mark is a less risky form of innovation than patent related innovations. Aside from the role of innovation on firm

[23] While Jenkins (2005) has noted that use of flexible base-line hazard specifications alleviates the need to use frailty corrections to ensure the robustness of estimates, this does not satisfactorily explain why unobserved heterogeneity is not found when we have good economic and management literature priors for believing that it exists.

survival, another noteworthy finding from a policy perspective is the large effects of macroeconomic conditions and interest rates on survival. Accordingly, policies designed to curb inflation through artificially depressing the macro-economy, have clear adverse effects on firm survival. Finally, it is noteworthy that once we include firm-specific variables in our estimations, the classic relation between firm age and survival largely disappears.

APPENDIX

Table A1: The number of firms by industry, ABS compared with ASIC matched to Yellow Pages

Major Industry	ABS 1999-2000	ASIC_Yellow Pages 2000
	%	%
Agriculture, forestry and fishing	3.2	2.9
Mining	0.4	0.9
Manufacturing	10.2	40.5
Electricity, gas and water	0.0	0.0
Construction	16.9	16.4
Retailing and wholesaling	32.4	14.5
Accommodation, cafes & restaurants	6.8	0.0
Transport and storage	6.3	5.7
Communication services	0.9	1.6
Private community services	12.0	10.0
Cultural and recreational services; personal and other services	11.0	7.4
TOTAL	100.0	100.0

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