THE UNIVERSITY OF MELBOURNE

Melbourne Institute Working Paper Series

Working Paper No. 26/06

Innovation, Technological Conditions and New Firm Survival

Paul H. Jensen, Elizabeth Webster and Hielke Buddelmeyer

MELBOURNE INSTITUTE
of Applied Economic and Social Research

Innovation, Technological Conditions and New Firm Survival*

Paul H. Jensen[†‡§], Elizabeth Webster[†‡§] and Hielke Buddelmeyer[†‡◊]
[†]Melbourne Institute of Applied Economic and Social Research, The University of Melbourne
[‡]Centre for Microeconometrics, The University of Melbourne
[§]Intellectual Property Research Institute of Australia, The University of Melbourne
[◊]IZA Bonn

Melbourne Institute Working Paper No. 26/06

ISSN 1328-4991 (Print)

ISSN 1447-5863 (Online)

ISBN 0 7340 3227 7

November 2006

* Author order is randomised. Thanks are due to John Creedy, Alfons Palangkaraya, Jongsay Yong for comments on this paper. We would like to thank Debbie Cowley, Sean Applegate, Paul Mills and Jason Baker for vital assistance in collating the data. Views expressed represent those of the authors. All errors remain the responsibility of the authors. This paper has been funded through an ARC Linkage Grant (LP0348635) which includes the partners IBISWorld, the Australian Bureau of Statistics, the Productivity Commission, Austrade and the Victorian Department of Treasury and Finance.

Melbourne Institute of Applied Economic and Social Research
The University of Melbourne
Victoria 3010 Australia
***Telephone* (03) 8344 2100**
***Fax* (03) 8344 2111**
***Email* melb-inst@unimelb.edu.au**
***WWW Address* http://www.melbourneinstitute.com**

Abstract

High neo-natal mortality is one of the most salient 'facts' about firm performance in the industrial organization literature. We model firm survival and examine the relative influence of firm, industry and macroeconomic factors on survival for new *vis-à-vis* incumbent firms. In particular, we focus on how the intensity of innovation in each industry affects firm survival. Our results imply that while new firms, compared with incumbent firms, thrive in risky and innovative industries, they are also more susceptible to business cycle effects such as changes in the rate of growth of aggregate demand, interest rates and the availability of equity finance.

"The most palpable consequence of entry is exit"

Paul Geroski (1995, p45).

1. Introduction

High neo-natal mortality is one of the most salient 'facts' about firm performance (Caves 1998; Geroski 1995; Dunne, Roberts and Samuelson 1988; Baldwin and Rafiquzzaman 1995). However, like Thompson (2005), we argue that there is no intrinsic reason why firm survival should be related to age. It is not age *per se* which determines survival, but other factors which may be correlated with age such as managerial experience, ownership structure and capital constraints. In this article, we examine the role that firm, industry and economy-wide factors play in shaping new-firm survival. Contrary to other studies, we find that all three sets of factors have differential impacts on new and incumbent firm survival.

The particular focus of this study is the effect on the relative survival rates for new versus established firms of firm-level innovation and the intensity of innovation in the firm's industry. Our argument is that young firms, being more nimble and flexible, have a comparative advantage when the dominant form of competition in the market is through innovation.[1] Tripsas (1997) coins incumbent disadvantage as a 'core rigidity' which arises from years of low-level innovation and selection-induced inertia. Although the idea of new firm adeptness is not novel – many others, at least since the conception of entrepreneurial/routinised technological regimes by Nelson and Winter (1978), have made this point – the way we measure both firm-level innovation and industry-level innovation is quite different. For firm-level innovation, we create four conceptually distinct time-varying measures: high-risk innovation investments, high-risk innovation capital, low-risk innovation investments and low-risk innovation capital. For the industry-level measure of innovation, we construct a time-varying index of innovation, broadly defined, in each industry using commonly-available data. The new construct is a

[1] Sometimes it is argued that incumbent firms are less inclined to compete than young firm because they have invested more (sunk) costs into the prevailing technologies (Tripsas 1997). However, this should not stop them successfully competing through innovation if and when innovation becomes the prevailing form of competition in the market.

continuous variable rather than the simple binary variables which have typically been used previously, such as whether the industry is low/high tech or whether it is in a formative/mature stage of its life cycle.

Through this new approach, we are able to shed light on the following important questions about industry dynamics: Are newborn firms more likely to survive in industries characterised by rapid technological change? To answer this question, we model firm survival and compare the effect of innovative activity on newborn firms vis-à-vis incumbent firms. We use a flexible age-death relation which is estimated through a piecewise-constant exponential hazard rate model. A comprehensive dataset including firm, industry and economy-level characteristics is used to estimate the model. The data are drawn from an unbalanced panel of approximately 260,000 Australian companies which were alive at some stage during the period 1997-2003. Thus, we have numerous cohorts of newborn firms which enables us to disentangle the influence of aggregate macroeconomic fluctuations from other firm and industry-specific effects.

In the next section of this paper, we present the empirical model of firm survival. In Section 3, we describe the construction of the dataset used to analyze the determinants of firm survival including the linking of firm-level data on registration, intellectual property (IP) and accounting variables with other industry- and economy-level characteristics. Section 4 then contrasts the estimations for new and incumbent firms and Section 5 concludes.

2. Empirical Model

We model the probability of firm death using a hazard rate model. 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:

$$h_i(t \mid \mathbf{x}) = h_0(t)\exp(\mathbf{x}_i'\boldsymbol{\beta}) \tag{1}$$

where $h_0(t)$ is the baseline-hazard function 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 piecewise-constant specification for our baseline hazard since it is a flexible specification which avoids potential mis-specification bias resulting from choosing an inappropriate parametric specification for the baseline hazard. Company age (in years) is the unit of time-analysis.

We estimate the empirical model specified in Equation (1) for two different types of firms: NEWBORN and INCUMBENT firms. We define NEWBORN firms to be any firm who was first registered as a company on or after the first date of our period of analysis, 1 January 1997, and before the last date of our analysis, 31 December 2003. INCUMBENT firms are defined as any firm whose date of registration as a company precedes 1 January 1990 and for whom we observe information during the period 1997-2003.[2] The seven year window is to ensure that, conditional on company age, we consistently classify a firm as either NEWBORN or INCUMBENT.

2.1 Dependent Variable

Our dependent variable is firm exit, which equals 1 if this is the last year the company is either registered with the official Government agency or appears in the Yellow Pages telephone book (under its current company name), 0 if it's not the last year and missing if dead.

2.2 Firm-Level Explanatory Variables

The empirical literature identifies a number of factors affecting firm survival which we classify as firm-level, industry-specific or macroeconomic factors. These form the basis of our explanatory variables which are described below. The first firm-level variables included in the empirical model relate to innovation. We use for each firm in each year, patent applications as a measure of high-risk (or new-to-the-world) investment and trademark applications as a measure of low-risk (new-to-the-firm) investments. These we denote PATENTAPPS and TMAPPS respectively. As these variables are measured as applications (rather than grants), they include market uncertainty. These are innovations

---

[2] Thus, there is left censoring (or truncation) issue in our dataset - companies that were born and died before our period of study are not observed. However, our empirical technique accounts for this truncation.

that may or may not be granted by the patent and trade mark office, and may or may not turn out to fill a niche in the market.

Hall (1987) found evidence that the survival is affected by the stock of knowledge and other intangible assets that are proxied by accumulated R&D expenditures. We extend this idea and derive innovation capital measures from past patent and trademark grants that are still in-force. These PATENTSTOCK and TMSTOCK variables are calculated using renewal data and, therefore, capture more economically-valuable innovations since IP owners must outlay monies in order to renew IP rights.[3]

We experimented with several ways to represent both IP flow and stock variables involving dummy and continuous variables. Since, the specific form did not substantially alter the results, we only present one form which is log of the number of applications or years in-force (plus one to account for the numerous observations that have no applications of stocks).[4]

The fact that we measure innovative activity using IP data introduces a possible endogeneity issue into our model when firms realise they are about to die and lower innovative activity. This is the so-called "shadow of death" (Griliches and Ragev 1995; Almus 2004). To the extent that this is true, we may under-estimate the true effect of innovation on the likelihood of firm survival. To attenuate this effect we use lagged measures of both patent and trade mark applications (but not stock since these predominantly reflect historic decisions).

We also included a number of firm-level dummy control variables in the model. The first is LARGE which is included here to indicate the size of the company, since firm size (or start-up size) has consistently been shown to be an important determinant of survival (Dunne and Hughes 1994; Audretsch et al. 2000; Segarra and Callejon 2002). One plausible explanation for this result is that liquidity constraints decrease with firm size. This seems plausible in Australia since there is evidence suggesting that the vast majority (approximately 75 per cent) of all business expenditure on innovation is financed by internal resources (see Australian Bureau of Statistics 2003) and newborn firms are less

[3] Alternatively, the patent stock variable could be measured using patent citations as weights. However, we don't have citation data so we use renewals to construct the capital stock.

[4] All of the IP variables have been aggregated to the ultimate-parent company level and then matched to each company. Accordingly, a parent company and a subsidiary will have the same IP values for each year.

likely to have such financial reserves. Most studies use employment (normalized by the minimum efficient scale) to measure firm size, but these data are not available to us here, so we simply use a dummy variable to differentiate large firms from other firms. LARGE takes the value 1 if the firm has 200 or more employees or assets worth more than AU$200m.

Ownership structure of the firm has also been shown to play an important role in shaping firm survival (see, for example, Heiss and Koke 2004). To account for this, we include the following dummy variables. PRIVATE is a dummy variable which indicates whether the company is privately-owned. Two further dummies indicate whether the company is part of a family as either a subsidiary (SUBSIDIARY) or a parent of subsidiaries (PARENT). The missing category is independent firms. These variables are included as Audretsch and Mahmood (1995) and Audretsch (1995a) have previously argued that the hazard rate should be systematically lower for firms which are subsidiaries of incumbent firms presumably because the parent's managerial experience (and other tacit knowledge) can be transferred to its subsidiary.

2.3 Industry-Level Explanatory Variables

While the main industry-level variable is the intensity of innovation, we also include two other variables which describe the competitive environment. We deal with these first. The first is GROSSENTRY, which is the annual gross entry rate in the company's 2-digit ANZSIC industry, that is, the number of entrants divided by the number of incumbents. This variable is included in the model on the basis that the number of new entrants in an industry exerts direct competitive pressure on incumbents and therefore affects survival.5 It is also well-known that industries with high levels of entry are also associated with high levels of exit (see Geroski 1995, for example), so it is important to control for the level of gross entry in the industry when estimating the likelihood of exit.

The second competitive environment variable is a measure of industry uncertainty. Industries also vary according to their inherent uncertainty that may affect the risk premium firms desire in order to remain in business. In order to capture the inter-industry

[5] It has also been argued that high levels of entry could reflect low barriers to entry in an industry (Segarra and Callejon 2002).

variation in risk, we included an explanatory variable, RISK[6], which is the profit margin in each industry divided by the tangible capital-output ratio to adjust for capital intensity. Numerous other studies have included measures of risk in their analysis, although the construction of the proxy varies substantially (see Tveteras and Eide 2000 for example). Importantly, we allow for industry heterogeneity by measuring the riskiness of an industry in terms of profit margin for a given level of capital intensity.

Our main focus for this study is a composite measure of the innovativeness of the industry, INDINNOV. This annual index is based on a set of common, and often publicly-available data, comprising R&D expenditure, R&D employment, labour productivity and patent, trade mark and design applications in each 1-digit ANZSIC industry[7]. We weight each component by the relevant contribution of each dimension to the performance of the industry. This weighting process is described in the appendix. The construction of the variable is designed to capture a broad cross-section of innovative activities including all types of process, product and organisational innovations.[8] This variable is lagged one year to avoid any influence of firm survival on industry measures of innovativeness in the estimation.

Many other studies have attempted to capture the effects of technological conditions (or variants on this such as technological regimes, technological activity and technological intensity) including Agarwal (1998), Agarwal and Audretsch (2001), Audretsch and Mahmood (1995) and Sarkar et *al*. (2006). Each study has had to deal with limited data available for constructing a plausible measure of industry innovation. Previous attempts, such as Audretsch and Mahmood (1995), used a simple cross-section calculation of the number of innovations by total employment in one year to proxy industry innovativeness. Other empirical approaches have used simple dichotomous variables such as whether the industry is low/high tech or whether the industry is in a formative/mature stage of its life-cycle. For instance, Audretsch and Agarwal (2001) use the net entry of firms in an industry to determine whether an industry is in a mature stage of its development (which is reflected by negative net entry). This is combined with a proxy for whether the firm is

[6] We use the terms ‘risk’ and ‘uncertainty’ synonymously to mean fundamental, or non-actuarial, uncertainty.
[7] The innovation index excludes activity from non-trading government organisations.
[8] Although we don’t directly measure process innovations, labour productivity has been included in the INDINNOV index to proxy their effects.

in a hi/low tech industry based on the level of R&D employment in the industry. More recent studies, such as Sarkar et *al*. (2006), use a similar approach to capture the effects of the "innovative environment" (as defined) on firm survival.

Although much progress has been made in measuring technological conditions, we believe there is still some way to go. One of the problems with the existing measurement of the phenomenon is that it often forces firms (or products) to be in either one state of development (formative) or another (mature). In doing so, they grossly simplify the complexity of industry evolution – industries don't really move from one discrete stage of their life cycle to another; rather, they are in a constant state of flux. If nothing else, the detailed case-study work exemplified by Klepper and Simons (1997) has shown us that, indeed, there are powerful evolutionary forces at work in industries and there are certain stages of development that are analogous to a life cycle.[9] What is really needed to capture these effects is one time-varying continuous variable. That is exactly what we have done in this study. The INDINNOV variable captures the underlying technological conditions in the industry *as they change over time*: industries with higher levels of innovativeness are associated with higher levels of (broadly-defined) technological change. Allowing technological conditions to change over time is an important facet of this variable since other studies purporting to explain evolution include time-invariant constructs.

One of the costs of focusing on systematic inter-industry effects is that it becomes difficult to capture rich firm-level characteristics which have previously been shown to shape survival: factors such as start-up size (Mata and Portugal 1994; Mata, Portugal and Guimaraes 1995; Geroski 1995; Caves 1998), and minimum-efficient scale (Dunne, Roberts and Samuelson 1988). We use dummy variables at the 1-digit industry level to control for these missing variables.

2.4 Macroeconomic Explanatory Variables

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

[9] An important difference is that unlike animals, firms and industries may be infinitely lived. While products may come and go, most industries (and some firms) may be with us forever. So, it is important not to take the analogy too far.

(see Boeri and Bellman 1995). To capture this effect, we include three different variables in the model in order to understand the importance of each of them for new and incumbent firm survival. First, we include a measure of the macroeconomic strength of the economy – MACRO – in the model. This variable was constructed by using factor analysis to obtain a single measure of macro effects which included the change in annual GDP and the change in the change in annual GDP. Secondly, we capture the effects of interest rates on firm survival by the 90-day bank-bill rate, which we call INTEREST RATE. Thirdly, we include an index of the Australian stock market, STOCKMKT, to reflect ease of access to external equity.

3. Data and Descriptive Statistics

Our dataset is an unbalanced panel of 261,262 companies (observed over the period 1997-2003) which was created by linking firm-level registrations/de-registrations from the Australian Securities and Investment Commission (ASIC)[10] with data on intellectual property from IP Australia and accounting data from a proprietary dataset, IBISWorld.[11] In order to determine each company's industrial classification, the data were then matched (by company name) to a listing of all companies in the Yellow Pages. Our unit of analysis was the Australian Company Number (ACN) and we define a death of a firm as the disappearance or de-registration of an ACN from one year to the next.[12] We define a new company as an entity registered after 1997. 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. Since we observe the population of companies in Australia, the age profile is diverse: companies range in age from newborn to 124 years old.

[10] This is an independent Australian government organisation which maintains a complete record of all company registrations and de-registrations in Australia.
[11] The match was done on company name.
[12] Since we do not observe the reason for de-registration, we cannot differentiate de-registrations that occur as a result of business failure from those that occur for personal reasons or as a result of a merger. Other Australian data suggests that business exits occurring as a result of takeover/merger or sale may account for about 21 per cent of all exits (Bickerdyke et al. 2000). However, anecdotal evidence suggests that companies that acquire a new firm through takeover often *do not* deregister the purchased firm. To the extent this is true, the fact that we don't directly account for mergers will not bias our estimates.

We were able to match approximately 67.0 per cent of the population of companies across to the Yellow Pages. Non-matches are partly due to the fact that the Yellow Pages lists *trading* names while ASIC lists *company* names. Thus, any non-matched bias is most likely to affect industries where company names differ from trading names (such as retail shops and restaurants). However, there is no reason to believe that our matched sample varies systematically from the population. We then merged 2-digit industry-level data such as profit margins and value-added from the Australian Bureau of Statistics (ABS).[13] Finally, we also linked the dataset across to macroeconomic variables on the change in GDP, interest rates and stock market prices.[14] Thus, the final complete linked dataset provides firm-level, industry-level and economy-level characteristics.

To understand the pattern of entry and exit over the period, we took the stock of matched companies registered in ASIC in 1997 and, for each subsequent year, we tracked incumbents, newborn firms and deaths. Table 1 presents a summary of the stock of companies in each year and the relevant birth and death rates. Our data indicates that the death rate ranged from 1.6 to 4.2 per cent, with some evidence of an upward trend. Birth rates ranged from 5.7 to 12.1 per cent, with strong signs of a downward trend.

Table 1: Company Birth and Death Rates, by Year

Year	Stock (number)	Birth Rate (% of stock)	Death Rate (% of stock)
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
Total	**1,786,168**	**8.1**	**3.3**

Table 2 presents descriptive statistics on firm-level (such as size, ownership structure, and IP stocks/flows), industry-level (e.g. gross entry rate and technological conditions) and macroeconomic variables. Broadly, we find that new firms are slightly less likely to

[13] 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.
[14] ABS Cat. rbabf01.xls; rbabf07.xls; 8140.0.55.002.

be LARGE (i.e. slightly more likely to be an SME) but are more likely to be a parent and less likely to be a subsidiary firm compared with established firms. As expected, new firms have considerably lower application rates and IP stocks. The distribution of entrants across industries is not dissimilar from the distribution of incumbent firms.

Table 2: Descriptive Statistics for New and Incumbent Firms

	New firms	Incumbent firms	Total
Patent applications	0.007	0.019	0.016
Trade mark applications	0.065	0.137	0.119
Patent stock (days)	35.0	222.1	174.9
Trade mark stock (days)	566.8	3222.4	2551.6
SMEs	0.997	0.988	0.990
Subsidiary	0.022	0.040	0.036
Parent	0.023	0.014	0.016
Gross entry rate	6.5	7.3	7.1
Industry innovativeness	126.0	127.6	127.2
Interest rate	5.1	5.2	5.2
Macro conditions	-0.084	0.018	-0.004
Stock market index	31.2	29.8	30.1
Industry distribution			
Agriculture, Forestry	3.6	3.1	3.5
Mining	0.8	0.4	0.7
Manufacturing	31.5	27.2	30.6
Electricity, Gas and Water	0.0	0.0	0.0
Construction	12.0	12.7	12.1
Wholesale Trade	3.4	2.7	3.2
Retail Trade	7.8	7.4	7.7
Transport and Storage	4.2	4.1	4.2
Communication Services	0.7	2.0	1.0
Finance and Insurance Services	3.5	3.8	3.5
Property and Business Services	19.7	21.9	20.1
Government Administration	1.3	1.8	1.4
Health and Community Service	6.3	7.8	6.7
Cultural and Recreation Services	2.8	2.4	2.7
Personal and Other Services	2.5	2.8	2.6
TOTAL	**100.0**	**100.0**	**100.0**

Sources: ABS, IP Australia, IBISWorld data.

4. Results and Analysis

The results from the estimated hazard functions are presented in Table 3. We present three different models: Models 1 and 2 are constrained models with a restricted set of explanatory variables, while Model 3 is an unconstrained model with the full set of explanatory variables. The rationale for presenting the results in this stepwise manner is to highlight the explanatory information contained in our main variables of interest: PATENTSTOCK, TMSTOCK and INDINNOV.

All three Models were estimated using the piece-wise exponential hazard function.[15] For each Model, we present the results from two estimations: one where the dependent variable is the probability of new firm death and the other where the dependent variable is the probability of incumbent firm death. Each explanatory variable is presented in the first column; the 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 firm death (i.e. de-registration from ASIC or disappearance from the Yellow Pages).

The analysis of our results focuses on the relative importance of the explanatory variables in determining the rate of survival for new firms *vis-à-vis* incumbent firms. The results are intuitively appealing: although there is no formal deductive model presented here, the empirical model was constructed inductively so we have strong *a priori* beliefs about the sign and significance of each explanatory variable. In general, we would expect, for example, that aggregate economic fluctuations affect firm survival. And this is exactly what we find – increases in the stock market index or the growth of the GDP generally increase the likelihood of firm survival, while an increase in the interest rate lowers firm survival rates. We also find that industry turbulence exists. In those industries characterised by high levels of gross entry, there is also a lot of firm exit and the effect is particularly pronounced for new entrants. Geroski's opening statement therefore needs to be qualified somewhat: for entrants, entry begets exit.

[15] As a robustness check, we also estimated all three Models using a standard Cox hazard function. As the signs and statistical significance of the explanatory variables were consistent across all three Models, we only present the piecewise exponential hazard function results here.

Table 3: Hazard Function Estimates, New and Incumbent Firms

Dep. Var: Probability of Firm Death	**MODEL 1**		**MODEL 2**		**MODEL 3**	
Explanatory Variables	*New Firms*	*Incumbent Firms*	*New Firms*	*Incumbent Firms*	*New Firms*	*Incumbent Firms*
PATENTAPPS (f)	-0.359	0.102	-0.065	0.219**	-0.088	0.257**
	(1.54)	(1.50)	(0.26)	(2.91)	(0.30)	(3.03)
TMAPPS (f)	-0.223**	-0.212**	0.101	-0.087**	-0.034	-0.082*
	(3.19)	(6.86)	(1.35)	(2.64)	(0.35)	(2.14)
PATENTSTOCK (f)			-0.053+	-0.023**	-0.026	-0.024**
			(1.77)	(2.99)	(0.82)	(2.72)
TMSTOCK (f)			-0.073**	-0.026**	-0.059**	-0.029**
			(9.27)	(10.08)	(6.47)	(9.67)
LARGE (f)	-0.302	-0.542**	-0.211	-0.478**	-0.451+	-0.450**
	(1.50)	(8.06)	(1.03)	(7.09)	(1.70)	(6.09)
PRIVATE (f)	-0.286**	0.111**	-0.332**	0.099**	-0.297**	0.097*
	(4.76)	(3.78)	(5.52)	(3.35)	(3.73)	(2.49)
SUBSIDIARY (f)	0.348**	0.185**	0.459**	0.246**	0.440**	0.263**
	(5.83)	(7.16)	(7.60)	(9.35)	(5.89)	(8.38)
PARENT (f)	0.085	-0.454**	0.088	-0.414**	0.044	-0.387**
	(0.94)	(7.85)	(0.97)	(7.14)	(0.37)	(5.42)
RISK (i)	-0.001	0.025**	-0.001	0.025**	-0.008	0.025**
	(0.22)	(7.04)	(0.24)	(6.88)	(1.11)	(6.29)
GROSSENTRY (i)	0.052**	0.003	0.050**	0.002	0.046**	0.015*
	(5.83)	(0.54)	(5.62)	(0.44)	(4.47)	(2.39)
INDINNOV (i)					-0.341**	0.014
					(4.18)	(0.31)
INTEREST RATE (e)	0.667**	0.107**	0.669**	0.107**	0.697**	0.119**
	(24.88)	(8.82)	(24.94)	(8.79)	(21.14)	(8.13)
MACRO (e)	-1.191**	-0.484**	-1.190**	-0.484**	-1.223**	-0.495**
	(48.82)	(56.13)	(48.75)	(56.08)	(40.23)	(47.28)
STOCKMKT (e)	-0.321**	-0.026**	-0.322**	-0.026**	-0.331**	-0.016**
	(31.87)	(7.20)	(31.98)	(7.18)	(26.95)	(3.83)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	445,399	1,387,391	445,399	1,387,391	322,798	1,043,432

Note: Absolute value of z statistics in brackets. + significant at the 10% level; * significant at the 5% level; ** significant at the 1% level.

(1) *(f)*, *(i)* and *(e)* indicate whether the variables are firm, industry or economy-level. Apart from the *LARGE* and *PRIVATE* dummy variables, all co-variates are time-varying.
(2) Time of analysis is time since company birth (in years).

Our main findings can be grouped into three areas. First, we examine the affect of firm innovative behaviour on firm survival. Specifically, do the four firm-level measures of high-risk innovation investments, high-risk innovation capital, low-risk innovation investments and low-risk innovation capital have different impacts on new and incumbent firm survival rates? From Model 1, it is clear that trade mark applications (which reflect current investments in brand and marketing capital) strongly increase the likelihood of survival for both new and incumbent firms. Patent applications, however, have no discernible effect on survival which confirms our contention about current investment in new-to-the-world innovations: because they are risky and yet to be evaluated by the market, they certainly don't increase the chance of firm survival.

Once we account for the difference between stocks (capital) and flows (investments) of innovative activity, the situation changes somewhat, particularly with regard to patents. Patent applications for incumbent firms become positive and significant – in other words, patent applications actually *increase* the likelihood of incumbent firm exit. However, the significance of incumbent patent applications was lower under alternative specifications of patent counts.[16] The coefficient on patent applications for new firms remains insignificant.

Patent stocks, on the other hand, act in the opposite direction – they improve the chances of survival predominantly for incumbent firms. As we know from other empirical research (e.g. Harhoff et *al*. 1999), the distribution of patent value is highly-skewed – most patents have no economic value and a tiny proportion have enormous economic value. Such a finding is consistent with our results since we show that it is not until the filter of the market has been applied that we observe any strong, systematic benefits of holding a patent. This reinforces the importance of being able to separate current investments, many of which will not be successful, from past, partly successful

[16] We alternately specified the IP variables as: 1/0 dummies for whether the firm has applications and stocks greater than zero; a set of dummies for between 2 to 5 groupings of the number of applications and stocks; and the log of the number of applications and stocks plus 1 (the case presented in Table 3). In each case the appropriate test of significance (z or likelihood ratio test) found that the IP variables were jointly significant. However, the significance of the variable(s) to represent incumbent patent applications was more sensitive to the specification of the IP variables. When the IP variables were represented as 1/0 dummies or continuous variables, the incumbent patent variable was significant at the 5 per cent level. If the IP variables were represented as a series of dummy variables, their significance fell to about the 20 per cent level.

investments. Including trade mark stocks reduces the magnitude of the trade mark applications coefficient for both new and incumbent firms. The coefficient on TMSTOCK is negative and significant for both types of firm, but at least twice as large in absolute size for new firms. The relative sizes of the new-versus-incumbent stock coefficients on the stock variables implies that having innovation capital is more important for new firms than incumbents.

Our second set of findings relates to the intensity of innovation in the industry. Are newborn firms more/less likely to survive in industries where competition occurs though rapid technological change and what does this tell us about the gale of creative destruction? This is an important empirical issue on which there is substantial existing evidence suggesting that new firms (entrants) have a substantial advantage over established firms (incumbents) in industries where there is technological turbulence – that is, a lot of technological change. Although there is precious little evidence to explain why this observation holds, the standard line of argument is that new firms are small and are able to use their agility to find a niche in rapidly-evolving markets and gain a foothold in the market. While existing firms do have an incentive to "destroy" existing technology, perhaps the incentive to be proactive is much weaker than that for new entrants. We are unable to shed light on whether this is true (or how entrants are able to outmanoeuvre existing firms), but we provide important confirmatory evidence suggesting that entrants are agents of change.

Similar to our treatment of firm-level innovation variables, we estimate the model both with and without our index of industry innovativeness. As shown in Model 3, the INDINNOV variable is significant but different for each type of firm. For incumbent firms, rapidly-changing technological change (under our broader meaning) has no effect on the likelihood of exit, while it actually reduces it for newborn firms. In the presence of rapidly-changing technology, it appears that new firms prosper – they thrive in such conditions. For new firms, technological change brings opportunity. This has important implications for how we explain industry evolution since it implies that new entrants enter turbulent industries (presumably carrying new technology), and survive. Thus, it is not the case that new firms enter an industry, stay a short time and then exit (the "revolving door"). Rather, technological progress relies on entrants to come up with innovations, enter the market and displace (or at least offer an alternative) to existing technology.

In and of itself, this is not a new finding since many other studies have previously argued that entrants play the pivotal role in the gale of creative destruction (see Sarkar et *al*. 2006 for the most recent contribution on this front). But our study takes an important step forward: we introduce a measure of technological conditions which is time-varying. An important limitation of the Sarkar et *al*. (2006) study is that "…our measure of technology intensity is time-invariant, in that each industry is characterized as highly technology intensive, or not, for its entire life cycle" (p.536). Gans, Hsu and Stern (2002) previously concluded that start-ups are important spurs to the gale of creative destruction in a few key industries. Here, we find similar evidence across a much broader spectrum of industries.

It would appear that there is a *prima facie* case for endogeneity of the INDINNOV variable, if we assume that new firms are on average more innovative than incumbent firms. In this case, any industry-year in which new firms have a higher survival rate, for whatever reason (compared with incumbents), will also appear to be more innovative.[17] However, the most plausible, systematic reason why a new, innovative firm will have a higher probability of surviving is because it is a more successful innovator in its environment.

With respect to the two other measures of industry competition we found that new firms are <u>more</u> likely to survive in industries that are 'more risky' than incumbent firms, *ceteris paribus*. The relative coefficients on GROSSENTRY showed that new firms are <u>less</u> likely to survive in industries where a lot of competition arises from new firms entering the industry, *ceteris paribus*. We suggest that GROSSENTRY is indicative of low barriers to entry.

The third and final area of analysis relates to the importance of aggregate economic fluctuations on the likelihood of firm survival. In order understand the importance of these cyclical factors on survival, we separately identified three factors: the change in the growth of GDP, the interest rate and the growth in the stock market. Each variable

[17] Even, this is less clearly the case when we consider the timing of the death and INDINNOV variables. A death, for the purposes of the hazard estimation, is the last year in which the firm is alive. As such, a higher exit rate of non-innovators will impact primarily on the following year's INDINNOV variable and not the current year.

was included in Models 1, 2 and 3 and show remarkably robust results across all three estimations. Our first, and arguably most important, result is that new firms are considerably more sensitive to macroeconomic, interest rate and external equity conditions than established firms. An increase in interest rates is likely to have adverse implications for the survival of both new and incumbent firms. However, the effect is much more pronounced for newborn firms. Conversely, improvements in macroeconomic conditions and abundance of external equity are likely to nurture both newborn and incumbent firms; that is, all firms are more likely to flourish when the economy is growing strongly. But, once again, the effect is much stronger (both economically and statistically) for new firms than for incumbents.

Despite the fact that our results are generally intuitively appealing, some puzzles remain. Most of the literature tends to find that the ownership structure matters; for instance, that newborn firms which are subsidiaries of existing firms (*de alio* births) have systematically different survival rates than newborn firms which are independent entities (*de novo* births) primarily because of initial endowments and other market entry conditions (see Khessina and Carroll 2002 for a discussion). While we find no evidence of the widely-supported view that *de alio* firms outlive *de novo* firms, we have no explanation of our result. One plausible explanation may be that existing firms spin-off risky parts of their business and let them "sink or swim". While there may be some transfer of tacit knowledge to the new firm, the parent ultimately refuses to underwrite the risk associated with the fledgling firm.

5. Conclusions

Much research has been dedicated to describing and understanding the powerful evolutionary forces that shape product markets and industries. In the process, much has been learnt about the causes and effects of entry, growth and exit of firms. In this article, we take a new look at the role that firm, industry and macro-specific factors play in shaping firm survival. Our particular focus is on the role the firm's innovative activity and the innovativeness of its industry plays in determining survival. At the firm level, we include innovation with different risk profiles to consider how market uncertainty affects firm survival. Adopting such an approach enables us to overcome some of the selection bias that has often been encountered in other studies which find that successful innovation causes survival.

While we find, consistent with other studies, that young firms are more prone to early death, we also find that new firms are more advantaged in certain contexts. Compared with incumbents, new firms' stocks of low-risk capital is their major source of comparative advantage vis-à-vis incumbents. At the industry level, we develop the notion that the intensity of innovation has differential effects for entrants and incumbents. Although this idea is not novel – it forms the basis of Nelson/Winter's technological regimes – we construct a novel time-varying index of the underlying technological conditions. We therefore improve upon previous studies which use simple binary variables to examine whether an industry's stage of development (formative/mature) influences the likelihood of an entrant surviving (and thereby effectively destroying the incumbent technology). Our results are consistent with the thesis that new firms thrive in more uncertain and innovative climates compared with their established counterparts. However, they are comparatively disadvantaged in industries where there is evidence of low barriers to entry. This apparent new-firm advantage in innovative industries may occur either because new firms are more agile than incumbents or because in less innovative industries, the conventional systematic forces in survival such as size and financial assets dominate over the unpredictable forces associated with change and newness.

We also find that entrants are more sensitive to fluctuations in aggregate macroeconomic conditions such as the growth of aggregate demand, interest rates and the stock market. We cannot tell from our analysis whether those that fail do so because of their underlying lack of fundamentals, such as poor technical and market knowledge, industrial capabilities and sub-optimal scale of operations, or from short-term cash-flow problems. Nonetheless, there is no reason why during macroeconomic downturns firms are less intrinsically productive that during macroeconomic upswings. Accordingly, downturns will see the loss of firms that have more potential than those that survive during an upswing.

6. Appendix

To capture the various dimensions of innovation, a multiple indicator approach has been adopted. We used factor analysis to constructed single measures of industry R&D (based on three R&D)[18], and industry IP (based on patent, trademark and design applications).[19] Together with a measure of industry labour productivity,[20] we then estimated the following equation using random-effects Generalised Least Squares regression, with adjustments for autocorrelation and heteroskedasticity for the period 1990 to 2003[21]:

$$ROE_{it} = \alpha_i + \hat{\lambda}_1(R\&D_{it}) + \hat{\lambda}_2(IP_{it}) + \hat{\lambda}_3(P_{it}) + u_{it}$$

Where *ROE* is return on equity,[22] α is the firm-specific effect, *R&D* is the factor of R&D activity, *IP* is the factor of IP applications, *P* is labour productivity, *i* is the industry, *t* is year and *u* is a random disturbance term. The estimated coefficients, λ, are used to weight the index for each industry in each year. Separate R&D data for Wholesale Trade; Retail Trade; Electricity, Gas and Water; Construction; Transport and Storage; Communications; Health and Community Services; Cultural and Recreational Services and Personal and Other Services, were not available prior to 2002. From 1990 to 2001, R&D expenditure and persons were interpolated from the data and from 1990 to 2003, R&D researchers were interpolated from the data in these industries. No R&D data are available for Agriculture, Forestry and Fishing and the implied weight for this factor is zero.

This, however, does not give us an index which is comparable across industries since we know that for reasons associated with the composition of the industry by firm size, some industries will report more of their innovative activity as formal R&D than others and some industries are more inclined to apply for IP. For our INDINNOV series to be operable we need at least one year to serve as an anchor point to make the index comparable across industries. Accordingly, we used the only existing survey of

---

[18] ABS catalogue 8104.0 various years.
[19] IP Australia data.
[20] ABS catalogue 520614.wks, 629105.xls.
[21] The modified Bhargava, Franzini and Narendranathan Durbin-Watson = 1.19 and Baltagi-Wu LBI = 1.48 both reject the hypothesis of no autocorrelation. The LR test (chi2(5) = 33.46) suggests that adjusting for heteroskedasticity improves the fit of the data.
[22] ABS catalogue 8140.0.55.002.

innovation in Australia that provides industry-comparable information (ABS cat 8158.0 2003). This provides data on the percentage of businesses innovating by industry, and for these firms, expenditure on innovation as a percentage of total business expenditure in 2002. We calibrate the raw index for each industry so that the data for 2002 is in proportion to the data from the ABS survey.

References

Agarwal, R. (1998), "Small firm survival and technological activity", Small Business Economics 11: 215-224.

Agarwal, R. and Audretsch, D. (2001), "Does entry size matter? The impact of the life cycle and technology on firm survival", Journal of Industrial Economics 59: 21-43.

Almus, M. (2004), "The shadow of death – An empirical analysis of the pre-exit performance of new German firms", Small Business Economics 23: 189-201.

Audretsch, D. (1991), "New-firm survival and the technological regime", Review of Economics and Statistics 73(3): 441-450.

Audretsch, D. (1995), Innovation and Industry Evolution, MIT Press, Cambridge, Mass. and London.

Audretsch, D., Houweling, P. and Thurik, A.R. (2000), "Firm survival in the Netherlands", Review of Industrial Organization 16: 1-11.

Audretsch, D. and Mahmood, T. (1995), "New-firm survival: New results using a hazard function", Review of Economics and Statistics 77(1): 97-103.

Australian Bureau of Statistics (ABS) (2003), Innovation in Australian Businesses, cat 8158.0, Table 10.4

Baldwin, J. and Rafiquzzaman, M. (1995), "Selection versus evolutionary adaption: Learning and post-entry performance", International Journal of Industrial Organization 13: 501-522.

Bickerdyke, I., Lattimore, R. and Madge, S. (2000), "Business failure and change: An Australian perspective", Productivity Commission Staff Research Paper, Canberra.

Boeri, T. and Bellman, L. (1995), "Post-entry behavior and the cycle: Evidence from Germany", International Journal of Industrial Organization 13:483-500.

Caves, R.E. (1998), "Industrial organization and new findings on the turnover and mobility of firms", Journal of Economic Literature 36, 1947-1982.

Dunne, P. and Hughes, A. (1994), "Age, size, growth and survival: UK companies in the 1980s", Journal of Industrial Economics 42: 115-154.

Dunne, T., Roberts, M. and Samuelson, L. (1988), "Patterns of firm entry and exit in US manufacturing industries", RAND Journal of Economics 19: 495-515.

Gans, J.S., Hsu, D.H. and Stern, S. (2002), "When does start-up innovation spur the gale of creative destruction?", RAND Journal of Economics 33(4): 571-586.

Griliches, Z. and Ragev, H. (1995), "Firm productivity in Israeli industry 1979-1988", Journal of Econometrics 65: 175-203.

Hall, B. (1987) "The relationship between firm size and firm growth in the US manufacturing sector", Journal of Industrial Economics, 35, 583-606.

Harhoff, D., Narin, F., Schere, F.M. and Vopel, K. (1999), "Citation frequency and the value of patented inventions", Review of Economics and Statistics 81(3): 511-515.

Heiss, F. and Koke, J. (2004), "Dynamics in ownership and firm survival: Evidence from corporate Germany", European Financial Management 10: 167-197.

Khessina, O.M. and Carroll, G.R. (2002), "Product dynamics of de novo and de alio firms in the world wide optical disk drive industry, 1983-1999", Presented at the Academy of Management Meetings, Denver.

Klepper, S. and Simons, K.L. (1997), "Technological extinctions of industrial firms: An inquiry into their nature and causes", Industrial and Corporate Change 6(2): 379-460.

Mata, J., and Portugal, P. (1994), "Life duration of new firms", Journal of Industrial Economics 42(3): 227-245.

Mata, J., Portugal, P. and Guimaraes, P. (1995), "The survival of new plants: Start-up conditions and post-entry evolution", International Journal of Industrial Organization 13: 459-481.

Nelson, S.G. and Winter, S. (1978), "Forces generating and limiting concentration under Schumpeterian competition", Bell Journal of Economics 9(2), 524-548.

Porter, M.E. (1979), "The structure within industries and companies' performance", Review of Economics and Statistics 61: 214-227.

Sarkar, M.B., Echambadi, R., Agarwal, R. and Sen, B. (2006), "The effects of the innovative environment on exit of entrepreneurial firms", Strategic Management Journal 27: 519-539.

Segarra, A. and Callejon, M. (2002), "New firms' survival and market turbulence: New evidence from Spain", Review of Industrial Organization 20: 1-14.

Thompson, P. (2005), Selection and firm survival: Evidence from the shipbuilding industry, 1825-1914, Review of Economics and Statistics 87: 26-36.

Tripsas, M. (1997) “Unravelling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry”, Strategic Management Journal, 18: 119-142.

Tveretas, R. and Eide, G.E. (2000), “Survival of new plants in different industry environments in Norwegian manufacturing: A semi-proportional Cox model approach”, Small Business Economics 14: 65-82.