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Survivor: The role of innovation in firms' survival

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Abstract

This paper explores the relationship between innovation and the survival probability of manufacturing firms in the Netherlands, conditional on firm age and size. The empirical analysis combines firm level data on innovation, derived from the second Community Innovation Survey, and on the date of exit, from the Business Register of all firms active in the Netherlands. To estimate the survival probability of a firm we use a non-parametric approach, based on the calculation of Transition Probability Matrices over different time periods. The results show that innovation has a positive and significant effect on the probability of firms' survival. This effect increases over time and is conditional on firm age and size; we observe that small and young firms are the most exposed to the risk of exit, as found in earlier studies, but also those that most benefit of innovation to survive in the market, especially in the longer term.

JEL classification: L11; O30; D21; C14; L25

Keywords: Firm survival; Innovation; Firm exit; Transition probability matrices

1. Introduction

It is well known that most industries display high degrees of turbulence as new firms enter the market and existing firms exit (Caves, 1998). Innovation can play an important role in shaping the survival of firms, whether they are new entrants or incumbents. New firms are the most exposed to risk of exit, especially in the first few years after entry (Geroski, 1995; Caves, 1998). Innovation may increase the chances of new firms surviving by providing successful niche strategies. Established firms are at risk from shakeouts in the industry, brought by the changing nature of technology (Utterback and Abernathy, 1975; Gort and Klepper, 1982). Innovation activity enables well-established firms to deal with new and emerging or 'disruptive' technologies and continuously improve their existing capabilities (Banbury and Mitchell, 1995; Christensen, 1997).

A number of studies have empirically evaluated the factors that influence the probability of firms' survival in the market. At firm level, these factors have traditionally been size and age of the firm, both increasing survival probability (Evans, 1987; Hall, 1987; Dunne et al., 1989; Dunne and Hughes, 1994). At industry level, the characteristics of demand, such as market size and growth rates (Mata and Portugal, 1994), the characteristics of technology (Audretsch, 1991, 1995; Malerba and Orsenigo, 1999) and the life cycle (Suarez and Utterback,

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1995; Agarwal and Gort, 1996) have been found to be important determinants of survival. These studies, however, focus either on the structural features of the firm or on differences in the external environment. Very few empirical studies have looked at the role of innovation within the firm in shaping the probability of survival.

In this paper, we explore how innovation influences the survival probability of manufacturing firms in the Netherlands. We draw on two harmonised and comprehensive micro-economic data sets collected by the Central Bureau of Statistics (CBS). One is the Community Innovation Survey (CIS), which allows us to establish whether or not firms innovate; the other is the Business Register (BR), which provides monthly data on the entry and exit of all firms active in the Netherlands. By linking these two datasets we can study the effects of innovation on survival at the firm level for a rich sample of firms. The empirical analysis is based on a non-parametric approach using transition probability matrices. We estimate the effect of innovation on firms' survival probability, conditional on firm age, size and sector of activity. This effect can be considered the measure of the '*innovation premium*' associated with survival.

Confirming previous research, we found that the demography of firms is influenced by age and size. The firms most likely to exit and disappear from the market are small and young firms. The effect of size and age, however, is influenced by the extent that these firms engage in innovative activities. In general, we find that the ability to innovate increases the survival probabilities for all firms across most industrial sectors. We find also that the innovation premium is highest for small and young firms, which are those at the greatest risk of failure: small, young firms that innovate have a 23% greater chance of surviving than those that do not.

The paper is organised as follows: Section 2 discusses theoretical approaches and empirical studies that examine the role of firm attributes as determinants of firm survival. The data used in the empirical analysis are described in Section 3 and the methodology applied for the estimation of survival probability in Section 4. We discuss the results of the analysis in Section 5, and in Section 6 we present a robustness analysis to verify whether our results are robust to the choice of different innovation variables. Section 7 concludes.

2. Theoretical and empirical background

Various approaches in economics ultimately identify two factors underlying the decision of a firm to exit the market (Audretsch, 1997): one is the gap between firm size and minimum efficient scale, and the other is the selection mechanism of heterogeneous firms. The first characterises the mainly empirical tradition of cross-sectoral studies in industrial economics (Scherer, 1980). According to this approach probability of survival in an industry will be lower in presence of economies of scale (Audretsch, 1991; Mahmood, 1992). It is also assumed that new firms, which enter an industry at a level of production below the minimum efficient scale, experience high hazard rates soon after entry. This has been confirmed by empirical studies at firm level, which have focused on the post-entry performance of new firms and found that survival probability increases with firm size at the time of entry (Mata and Portugal, 1994; Geroski, 1995; Agarwal and Audretsch, 2001).

The second factor is highlighted in equilibrium models of firm dynamics approaches, based on Jovanovic's (1982) theory of 'noisy selection'. In Jovanovic's model, firm dynamics depend on the learning process that enables firms to discover and adapt to their particular level of efficiency, given the existence of asymmetries in efficiency and imperfect information. Over time, firms discover their levels of efficiency through operating in the industry; those that are more efficient grow and survive while for those that discover that they are relatively inefficient, production is reduced and they eventually exit the market. The model predicts that the hazard rate of a firm decreases with current size (conditional on age), as well as firm age (Pakes and Ericson, 1998). These predictions are consistent with the evidence from empirical studies in industrial economics, which shows that the probability of survival increases with age and the current size of the firm, although at a decreasing rate (Evans, 1987; Hall, 1987). Evans's study also reveals that age and size exert a positive interactive effect on firm survival: the probability of survival for large firms increases more rapidly with age and that for older firms increases more rapidly with size.

In terms of the non-linear effect of firm age and the probability of survival, other studies estimating the hazard function of different cohorts of entrants suggest that the relationship between the two variables is complex. In some cases (Mata and Portugal, 1994; Mata et al., 1995), the hazard rate was found to decrease linearly over time; in others (Wagner, 1994; Audretsch and Mahmood, 1995; Audretsch et al., 1999) it increased significantly soon after the entry of a firm, before decreasing more or less monotonically. Therefore, while there is a positive relationship between survival probability and firm age, at least for older firms, the relationship is not so clear-cut for younger firms.

Ericson and Pakes (1995) extended Jovanovic's model to include the investments of individual firms on research and development. This model contrasts a process of 'active learning' to the process of 'passive (Bayesian) learning' in Jovanovic's model, where firm efficiency levels are assumed to be constant over time (Pakes and Ericson, 1998). In Ericson and Pakes's model, firms explore the space of technological opportunities by actively investing in research, and by doing so they improve their efficiency and profitability; and ultimately their chances of survival. However, high degrees of uncertainty associated with research and development (R&D) investments may negatively affect the survival of firms. Jovanovic's and Ericson and Pakes's selection models account for the effects of firm attributes on exit behaviour by assuming that exit is the outcome of an optimising decision process. In contrast, Nelson and Winter (1982) interpret firms' exit behaviour as the result of out-of-equilibrium processes of learning and market selection. The selection mechanism transforms existing asymmetries in productivity among firms (due to the heterogeneous distribution of knowledge and capabilities) into differential rates of growth and survival. In addition, the distribution of firm productivity varies over time as an outcome of the innovation process. Through innovation, firms seek to improve their relative position in the distribution of productivity levels and their chance of success in the competition process.

Nelson and Winter's (1982) model of Schumpeterian competition postulates that firms that invest in innovative and imitative R&D draw from a distribution of productivity levels that on average improve on their current levels. By comparing the outcome of this random draw with the overall productivity level in the market, the firm decides whether to stay in the market or to exit, on the basis of a certain satisfying threshold. In both Ericson and Pakes's model and Nelson and Winter's model, it is the combination of the enhanced opportunities for innovation stemming from the investment in R&D, and the uncertainty of the partly random outcomes of this investment that determines survival.

Despite the role attributed to innovation in firm survival, there is little empirical evidence on the relationship between probability of survival and the innovative activities carried out within the firm (Cefis and Marsili, 2005). A few studies have empirically examined investment in R&D at firm level as a determinant of survival. Hall (1987) found that the intensity of R&D expenditure positively influences the survival probability of firms, and this effect is stronger for firms that do not patent than for firms that do. In a recent study of Spanish manufacturing firms, Esteve Perez et al. (2004) observe that firms that invest in R&D activities experience an exit risk that is 57% lower than firms that do not, and this effect is enhanced by the international orientation of the firm.

While existing studies focus on R&D expenditure as a measure of innovative input, few studies have used measures of innovative output as determinants of survival. Those that do exist are in the field of management, where the role of innovation in survival has been examined by comparing firms with different innovative performance. In a study of the disk drive industry, Christensen et al. (1998) observed that firms that entered the market by introducing an architectural innovation had a lower likelihood of exit that firms that did not introduce this type of innovation. In particular, their study showed that this effect was conditional on the timing of entry into a new market in relation to the different stages of evolution of a new technology, before and after the emergence of a dominant design. For firms active in the cardiac pacemaker industry, Banbury and Mitchell (1995) found a positive relationship between survival and the number of new products introduced in the market. These studies, however, are based on specific industries and datasets and do not allow generalisation.

The purpose of this present study is to investigate how innovative activities within the firm influence its survival probability. We take account of the findings in the literature; in particular, we control for the influence of firm age and size on the effects of innovation for firm survival. In other words, we estimate the innovation premium conditional on firm age and size. Furthermore, to account for the differences in survival across industries, we calculate the innovation premium across industrial sectors.

3. Data

The analysis draws on two micro-economic databases collected by the CBS: the Business Register database and the CIS-2 in the Netherlands. The Business Register database reports employment, sector of activity, and demographic data for all the firms registered for fiscal purposes in the Netherlands. This population includes firms with zero employees (or self-employment). From the dataset we selected all manufacturing firms present in the database at year 1996, resulting in 61,177 firms. 1996 was selected to allow comparison with the CIS-2.

We used the Business Register database to identify the date that a firm exited the population, and to estimate the survival probability. Date of exit is defined as the month that the firm appeared in the database for the last time. Because it is so comprehensive, the Business Register allows this to be narrowed down to the month that a firm exited the market. Exit dates range from January 1996 to June 2000, covering 54 months of possible existence. For each month, we built a dummy variable that was equal to 1 if the firm existed in the database, and 0 otherwise.

Using the Business Register data we also built a number of variables for the structural characteristics of a firm, which we use as control variables in the analysis of survival and innovation. First, using the date of entry, we calculated the age of a firm at 1996 according to three age classes: 0–4 years; 5–10 years; and more than 10 years. Age 0 identifies those firms that entered during 1996. Date of entry is defined as the month in which a firm was first included in the database. We also classified each firm according to the number of employees at 1996: 0–9; 10–49; 50–199; and 200 and over. Each firm was assigned a sector of activity at the two-digit level SIC code. The Tobacco sector was excluded from the analysis because of the small number of observations, namely only 13 firms. Because of technological proximity and degree of diversification of firms active in the electrical and electronics fields, these firms were aggregated into a single class, which includes computers (SIC 30), electrical equipment (SIC 31) and telecommunication equipment (SIC 32) (see Table A1 of Appendix A for definition of the sectors).

The second database used in the analysis, is the 2nd Community Innovation Survey (CIS). CIS has been employed in several European country studies to explore the determinants of innovation and its effects on economic performance, and especially in terms of productivity (Kaiser, 2002; Mairesse and Mohnen, 2002; Rouvinen, 2002; Vivero, 2002).

The Dutch CIS-2 covered the private sector firms with at least 10 employees. This was a stratified random sample drawn from the Business Register database for 1996, based on size class, region and industrial sector at the two-digit SIC code level. In manufacturing, the number of respondents to the CIS-2 was 3299, a response rate of 71%. The dataset provides information on the innovation processes of firms in the Netherlands for the period 1994–1996. On the basis of this dataset, we classified the respondents to the CIS-2 into innovators and non-innovators. An innovator is defined as a firm that introduced either a product or a process innovation in the period 1994–1996. These two CIS variables reflect the respondents' subjective perception of "being an innovator". Therefore, our definition of innovators is broad and encompassing, and leads to an underestimation of the effects of innovation on survival probability.

Of the respondents to CIS-2 3275 firms could be matched with the firms from the Business Register for 1996. Our analysis thus excludes 24 companies. These are large diversified companies for which the unit of observation in the CIS survey does not coincide with the unit of observation in the Business Register. This implies that the survival probabilities of large, old and innovative firms are underestimated.

In sum, by using the CIS-2 database we were able to identify two sets of firms, innovators and non-innovators, for a random sample of firms drawn from the Business Register of all manufacturing firms in the Netherlands at 1996. Having determined the age class, size class, industrial sector and date of exit of firms from the entire population in the Business Register, we were then able to compare the survival probability of innovators and non-innovators by controlling for age, size and sector (also in comparison with the general conditions of survival in the overall population).

4. Method

We used an approach based on Transition Probability Matrices to analyse the survival probabilities among different groups of firms. This methodology is non-parametric because it does not assume any specific functional form to model the relationship between our variable of interest (firm survival) and the possible determinants (innovation). It allows the effects on the dependent variable of an explicative variable, conditional on several other controlling variables to be captured. In our case, the methodology enables us to measure the effects of innovation on firm survival, conditional on the age and size of the firm.[1]

We measure survival probability as the probability of the firm continuing to exist, and probability of exiting the market as the probability of becoming nonexistent.

Among a finite population of firms (firms that existed at 1996), at each point in time there is a cross-section distribution of firms that do exist and those that no longer exist. The objective is to describe the evolution of this distribution over time, to allow us to analyse the intra-distribution mobility of firms, which supplies the information about the firm's relative situation and its movement over time (Cefis, 2003).

To study the evolution of this distribution it is necessary to hypothesise a law of motion for the cross-section distribution within a more formal structure.

Let F_t denote the distribution of firms at time t; and let us describe $\{F_t\text{: integer } t\}$'s evolution by the law of

[1] With respect to a (semi-parametric) proportional hazards Cox model or to a (parametric) accelerated time model, this non-parametric approach has the advantage of calculating the effects on survival of innovation not simply controlling for characteristics, but conditioning on the operating of intervening (or moderating) variables.

motion:

$$F_{t+m} = PF_t \tag{1}$$

where P maps one distribution into another, and tracks where points in F_t end up in F_{t+m}. Eq. (1) is a first step for analysing the dynamics of $\{F_t\}$. If we assume a finite state space $S=\{s_1, s_2, \ldots, s_r\}$, where s_i ($i=1, \ldots, r$) are the possible states that firms can occupy, P is simply a Transition Probability Matrix (TPM). P encodes the relevant information about mobility and persistence of firms within the cross-section distributions. In this study, we are interested in analysing the movements of firms among two states: the state 1 (existence state) that corresponds to firms being active in the market (or, more precisely, being registered in the BR); and the state 0 that corresponds to firms exiting the market (non existence state). In other words, our state space is $S=\{0, 1\}$. Furthermore, we can observe in which state a firm is at the discrete moments of time $n=1, 2, \ldots, 54$, that is each month from January 1996 until June 2000.

Let X_n denote the state in which firms are at time n. The one-step transition probability is defined by:

$$p_{ij} = P(X_{t+m} = j | X_t = i) \tag{2}$$

where $t=1996, 1997, 1998$; $m=24, 30, 36, 42$ months and i, j denote the states.

The transition probability matrix $\mathbf{P}$ is the matrix with p_{ij} as elements measuring the probability of moving from state i to state j in one period (Hoel et al., 1987).

The focus of our analysis is to estimate the probability of firm survival, defined as the probability that a firm remains in existence (or in the existing state). Therefore, we estimate the following probabilities:

$$\hat{P}(X_{t+m} = 1 | X_t = 1) = \hat{p} \tag{3}$$

$$\hat{P}(X_{t+m} = 0 | X_t = 1) = 1 - \hat{p} \tag{4}$$

The probabilities (3) and (4) are computed on four different period lengths (for different m): (i) 24 months; (ii) 30 months; (iii) 36 months; (iv) 42 months. These different transition periods allow us to capture the dynamics of the survival probability of firms, and to study how it evolves over time.

It should be noted that in order to perform the survival analysis we assume that firms are homogeneous. One way to take account of the heterogeneity among firms, arising from their belonging to different sectors or different size or age classes, is to split the overall sample into sub-samples according to industry classification, size and age. However, in our sub-samples firms are assumed to be homogeneous; using our methodology, we cannot control for heterogeneity at firm level.[2]

We conducted the analysis on the entire sample, and then on sub-samples based on size, age and industry classification. Furthermore, we initially performed our analysis considering these firm-specific characteristics separately, in order to identify the effects only of size, age and technological specificities on survival probability. We successively repeated the analysis controlling contemporaneously for these firm characteristics jointly.

In order to test whether the difference between two estimated probabilities were statistically significant, we applied the following test.

Let $\hat{P}_1$ and $\hat{P}_2$ be the survival probabilities estimated in the samples of size n_1 and n_2 (for example, the survival probabilities for innovators and non-innovators in the CIS) drawn from their respective populations with probabilities p_1 and p_2. The null hypothesis is that there is no difference between the survival probabilities of the populations, that is H_0: $p_1=p_2$, and thus the samples are really drawn from the same population with survival probability p. The test statistic is the difference in the estimated probabilities: $\hat{P}_1 - \hat{P}_2$. Given the fact that the size of our samples is sufficiently large (with at least $n>80$), under the null hypothesis, the standardised variable

$$Z = \frac{\hat{P}_1 - \hat{P}_2 - 0}{\sigma_{\hat{P}_1 - \hat{P}_2}}$$

is approximately distributed $N(0, 1)$, where

$$\sigma_{\hat{P}_1 - \hat{P}_2} = \sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}$$

Given that p_1 and p_2 are unknown and for the null hypothesis $p_1=p_2=p$, the estimator of $\sigma_{\hat{P}_1 - \hat{P}_2}$ is

$$S_{\hat{P}_1 - \hat{P}_2} = \sqrt{\hat{P}(1-\hat{P})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}$$

where $\hat{P}$ is the estimator of the survival probability of the population given by the arithmetic weighted average of $\hat{p}_1$ and $\hat{p}_2$:

$$P = \frac{n_1\hat{P}_1 + n_2\hat{P}_2}{n_1 + n_2}.$$

We tested the differences in the survival probabilities of different sub-groups of firms and the test results are reported in Tables A2 and A3 of Appendix A.

[2] An extension of this analysis could be to test for endogenous group heterogeneity.

Table 1
Descriptive statistics of the number of employees of manufacturing firms at 1996 by sample

	N	Mean	Std Dev	Kurtosis	Skewness	Median
All firms in BR	60792	16.7	197.4	24648.7	133.8	2
All firms in BR with at least 10 employees	12260	74.1	434.9	5157.6	61.7	23
All firms in BR with at least 10 employees not in CIS-2	9036	58.1	480.7	4694.5	61.5	19
All firms in CIS-2	3275	117.2	261.0	112.0	9.0	54
Innovators in CIS-2	2075	139.5	280.6	83.6	7.8	68
Non innovators in CIS-2	1200	78.5	217.9	230.1	13.2	35

Note: Datasets: Business Register (BR), Second Community Innovation Survey (CIS-2).

Table 2
Survival probabilities of firms by sample and transition period

	Number of months			
	24	30	36	42
All firms in BR	0.85	0.82	0.79	0.77
All firms in BR with at least 10 employees	0.92	0.90	0.88	0.86
All firms in BR with at least 10 employees not in CIS-2	0.90	0.88	0.86	0.84
All firms in CIS-2	0.95	0.93	0.92	0.91
Innovators in CIS-2	0.96	0.94	0.93	0.93
Non innovators in CIS-2	0.93	0.91	0.90	0.89

Note: Datasets: Business Register (BR), Second Community Innovation Survey (CIS-2).

5. Results

5.1. Overall set of firms

In this section, we compare the general characteristics of the different samples we used in the analysis. Table 1 presents the descriptive statistics of the number of employees in the different samples and Table 2 the corresponding survival probabilities for the different transition periods. First, we observe that the 10-employee threshold is important. As can be seen from Table 1, this threshold excludes about 80% of all the firms in the population of the Business Register (BR). The large majority of firms are small, or even very small firms (BR includes firms with 0 employees). These very small firms are not included in the Community innovation survey. The CIS is a stratified random sample of firms with at least 10 employees.[3] Furthermore, based on a threshold of 10 employees, the survey tends to capture the largest firms. The average size of firms within the CIS is equal to 117.2 employees, while the average size of firms in the BR with more than 10 employees is 58.1 (see Table 1). In addition, in the CIS, innovative firms tend to be larger than non-innovative firms: their average sizes being 139.5 and 78.5 employees, respectively.

The importance of the 10-employee threshold for the survival probability can be seen in the first two rows of Table 2. There is a difference between the entire BR population and the BR population of firms with more than 10 employees, with the former lower than the latter by about 0.08 (equal to 9.8%). This difference is statistically significant at the 1% level, independent of the transition period. However, the difference increases with the length of the transition period, ranging from 0.07 for 24 months, to 0.08 for 30 months, and 0.09 for 36 and 42 months.

To answer our main question about the effects of innovation on survival, we compared the survival probabilities between innovators and non-innovators in the CIS sample. The survival probability of innovators is persistently higher than for non-innovators. The difference is on average equal to 3.6% across the four transition periods considered, and statistically significant at 1%. This is initial evidence, at very aggregate level, that there is an innovation premium.

The CIS includes a high percentage of innovators as can be seen from Table 1 (2075 firms are innovators; 1200 are non-innovators). This could stem from two factors: one, an overestimation on the part of the respondent that the firm is an innovator; second, innovators are more likely to respond to the survey than non-innovators. This suggests that the CIS tends to capture the majority of innovators. Indeed, for firms with more than 10 employees (i.e. the threshold for the CIS sample), the survival probability based on BR data without CIS records is lower than the probability for the entire BR. This difference is statistically significant, and equal to 0.02 and is persistent along time (24, 30, 36 and 42 months). Thus, there is evidence of a self-selection problem in the innovation survey: if this were not the case, the two probabilities would have been the same. This is further

[3] Among the European participants in the CIS, only the surveys for the UK and the Netherlands set the threshold at 10 employees; all the other countries set it at 20 employees.

Table 3a
Survival probabilities of innovators and non-innovators by size class and transition period

Size class	Number of months							
	Innovators				Non-innovators			
	24	30	36	42	24	30	36	42
Small	0.95	0.94	0.93	0.92	0.93	0.91	0.90	0.89
Medium	0.96	0.95	0.95	0.94	0.94	0.93	0.92	0.91
Large	0.95	0.93	0.92	0.91	0.93	0.92	0.90	0.88

Table 3b
Survival probabilities of innovators and non-innovators by age class and transition period

Age class	Number of months							
	Innovators				Non-innovators			
	24	30	36	42	24	30	36	42
Young	0.92	0.90	0.88	0.87	0.88	0.85	0.83	0.81
Grown-up	0.96	0.95	0.93	0.92	0.92	0.90	0.89	0.88
Old	0.96	0.95	0.94	0.93	0.94	0.92	0.91	0.90

indication of the existence of an innovation premium for survival.

5.2. Patterns by age and size

The results of the analysis of the survival probabilities by age and size classes are presented in Tables 3a and 3b. Controlling for age and size independently, innovation has a positive effect on survival probability. In fact, Table 3a shows that the difference in probability between innovators and non-innovators is on average equal to 3% for small and medium firms and to 2% for large ones. These differences are also persistent over time. Specifically, the survival probabilities are highest for medium firms in the group of innovators or non-innovators. Small firms have the lowest survival probabilities among non-innovators. However, among innovators the probability of survival of small firms is higher than for large firms. That is, the innovation premium is highest for small firms.

With regard to age class (Table 3b), the innovation premium becomes even more pronounced. The effect of innovation on survival probability is 6% on average for young firms, 5% for grown-up firms, and 3% for old firms. The differences are statistically significant at the 1% level across all the transition periods, and increase over time. Overall, innovation appears to be more important for the survival of young firms.

As would be expected, old firms are those with the highest survival probability, based on either innovators or non-innovators. At the other extreme, the probability of survival is lowest for young firms. However, the gap between young and old firms decreases when considering the group of innovators. Among innovators, young firms have a survival probability an average 6% lower than large firms, ranging from 5% in 24 months to 7% in 42 months. Among non-innovators, the difference is 8% on average, increasing from 6% in 24 months to 10% in 42 months. All these differences are statistically significant at the 1% level. Grown-up firms' probability of survival is more similar to that of old firms than young firms, especially for the group of innovators, where the difference between grown-up and old is marginal.

5.3. Interactive effect of age and size

The literature tells us that not only does the probability of survival increase with the size and age of a firm, but that the two variables exert a positive interactive effect on this probability. To control for this interactive effect we calculate the survival probabilities for a cross-tabulation of age and size classes. These are illustrated in Figs. 1 and 2, respectively for innovators and non-

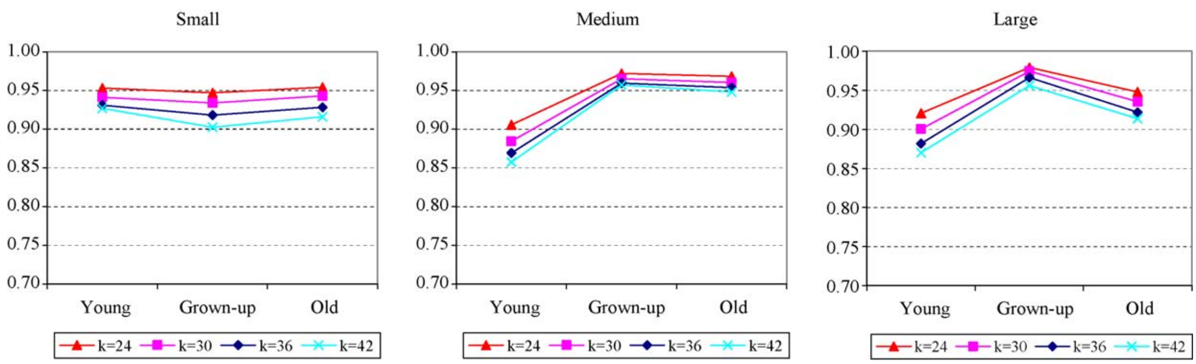

Fig. 1. Survival probabilities of innovators by size class and age class for different transition periods.

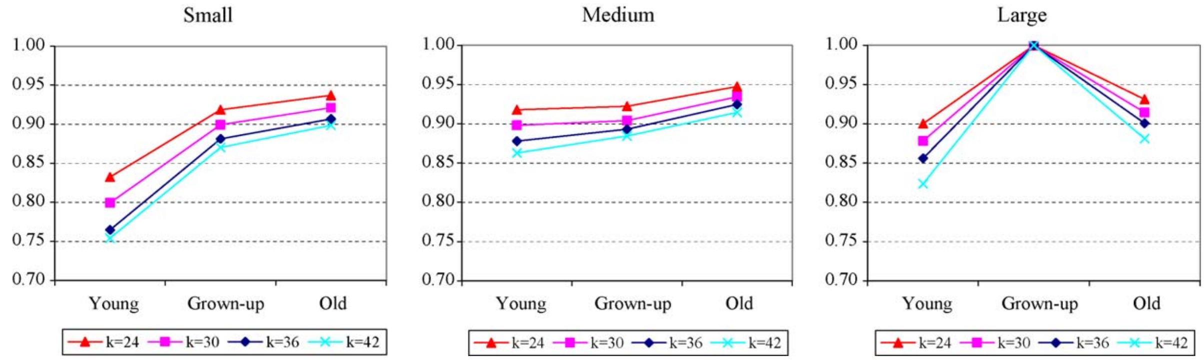

Fig. 2. Survival probabilities of non-innovators by size class and age class for different transition periods.

innovators. Our results confirm the earlier evidence for the set of non-innovators. Indeed, for this set, the probability of survival of young and small firms is always lowest across all classes, and regardless of transition period. Looking at the young firms across the different size classes, we see that the probability of these firms surviving increases significantly with size (to an increment of between 8 and 15%) in all transition periods. Among young firms, the survival probability for small firms is significantly lower than that for medium and large firms, at the 1% significance level, while the difference between medium and large firms is not statistically significant—also at the 10% level. On the other hand, if we look at small firms across different age classes, we note that survival probability increases with the age of the firm (between 10 and 19%). In this case, all the differences across age classes are statistically significant at the 1% level.

However, our results do not support the evidence from the literature of a positive relationship between firm survival, and the age and size of the firm, for the set of innovators. Repeating the analysis for innovators, we notice first that the survival probability of young and small firms is no longer the lowest among the classes in any transition period. Indeed, it is equal or even slightly larger than the survival probability of large and old firms, which the literature would lead us to expect to have the highest probability of survival. Furthermore, the difference is not statistically significant, even at the 10% level. On the contrary, for the sample of non-innovators the survival probability of large and old firms is always higher than for young and small firms, about 15% on average, and statistically significant at the 1% level, across all the transition periods.

Conditional on the size class of small firms, the probability of survival is invariant across age classes in every transition period (none of the differences are statistically significant at the 10% level). On the other hand, conditional on the age class of young firms, survival probability decreases with size (between 3 and 7%) independent of the transition period (the differences for small firms with respect to medium and large firms are statistically significant at the 1% level, while the difference between medium and large firms is generally not significant). This trend is the reverse of what we observed for non-innovators. A possible interpretation of this result is that young and small innovators enter the market with more novel ideas (leading to more radical innovations) than firms entering with a large scale of production. The literature shows that entry to the market can occur at different sizes. Greenfield entries are generally associated with smaller size than entries via diversification of existing firms. We could then argue that young and small firms are start-ups that enter based on an innovative idea, while young and medium–large firms are created as the result of diversification of existing firms (which provide the resources necessary to enter on a larger scale), and are more likely to introduce incremental or less radical innovations. Our results suggest that for this latter category of entrants, innovation is less important for survival than it is for start-ups. In sum, our results show that among young firms the innovation premium is much more important for small firms than larger firms.

In general, the survival probability of innovators is higher than that of non-innovators, independent of size and age classes.[4] Therefore, there is an innovation premium after controlling for size and age differences. For example, considering the longest time period, we can see that the survival probabilities for non-innovators and innovators are respectively 0.75 and 0.93 for young and

[4] The only exception is the case of grown-up and large firms in which the non-innovator probability is equal to 1, while the innovator probability is equal to 0.97. This is probably due to the small number problem because there are only seven firms in this class within the group of non-innovators.

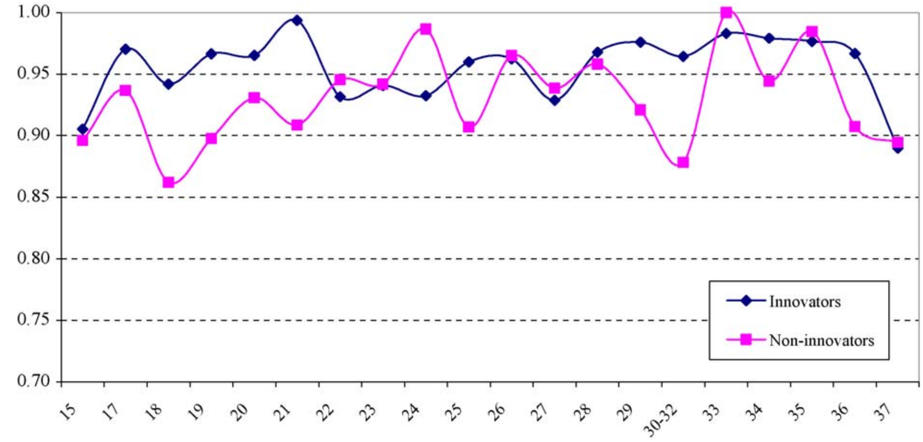

Fig. 3. Survival probabilities of innovators and non-innovators by sector (transition period of 24 months).

small (23% difference, significant at 1%), 0.88 and 0.96 for grown-up and medium firms (8% difference, significant at 1%) and 0.88 and 0.91 for old and large firms (4% difference, significant at 5%). Across the all combinations of age and size classes, only the differences between innovators and non-innovators in the categories of young and medium firms, and young and large firms are statistically not significant at the 10% level. The conditional effect of innovation on survival probability for young and small firms (equal to 23%) is considerably higher than the unconditional effect after controlling for age and size, which we estimated equal to 11%, in a related study (Cefis and Marsili, 2005).

This positive effect increases over time. In general, the survival probabilities for innovators and non-innovators diverge over time. A possible interpretation of this observation is that firms innovate especially in order to overcome the selection process in the market and survive in the long term, rather than just pursuing temporary monopoly profits. As shown in Figs. 1 and 2, the difference between the survival probability of innovators and non innovators increases over time: for example, for young and small firms, it increased from 0.12 for 24 months, to 0.14 for 30 months, and 0.17 for 36 and 42 months. For grown-up and medium firms, it increased from 0.05, to 0.06 and then to 0.07. For old and large firms these differences are virtually invariant over time.

5.4. Sectoral patterns

Looking at survival probabilities at sectoral level, we can see that in general innovation has a positive effect on firm survival. This effect increases with the length of the transition period. As shown in Figs. 3 and 4, the differences between the probabilities for innovators and non-innovators are larger for the 42-month transition period than for 24 months. As can be seen at the aggregate level, innovation tends to be more important

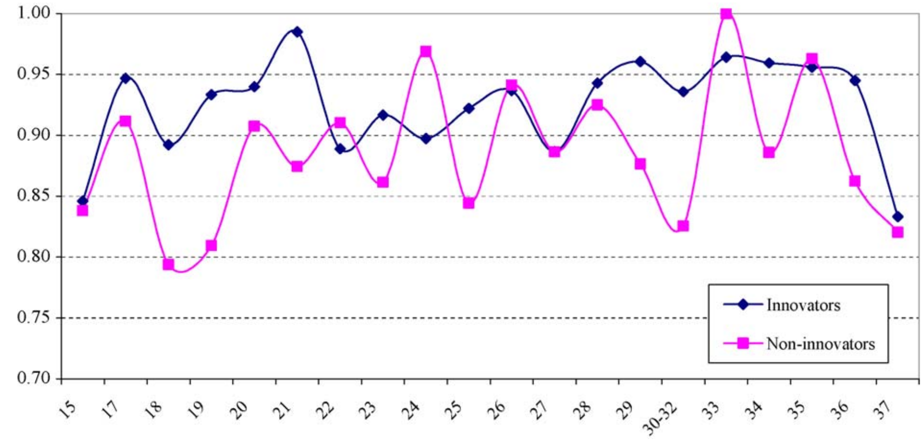

Fig. 4. Survival probabilities of innovators and non-innovators by sector (transition period of 42 months).

for survival in the longer term, within each individual sector.

Across sectors, we observe a great deal of heterogeneity in the effects of innovation on the probability of survival. Not only does the effect vary in intensity, from a minimum of 0 to a maximum of 15%, but also in direction. While in most cases the effect is positive and statistically significant (at the 1% level), it is negative and statistically significant (at 1 and 5%) in three sectors, namely publishing, chemicals, and instruments.

In publishing this is perhaps because the sector is dominated in the Netherlands by very large firms (such as Kluwer, Elsevier and Vnu). During the fifth worldwide wave of mergers and acquisitions, 1996–2000 (Schenk, 2002), these firms all made major acquisitions. This process involved acquisition of smaller (compared to the acquiring firms) and innovative firms and accounts for a number of exits from our database of innovative firms, since they lost their legal identities. These exits lower the survival probability of the innovators group quite considerably.

Chemicals are the sector where the negative difference is most pronounced. In the Netherlands, this sector is mainly constituted by bulk chemicals, with pharmaceuticals being small and relatively less important. Such a composition implies that the sector as a whole has more of the characteristics of bulk chemicals than of pharmaceuticals. Traditionally bulk chemicals exploit economies of scale to produce mature and basic products. This probably means that innovation plays a minor role in shaping the survival probability of chemicals firms.

Focusing on the sectors where the effect is positive, we find it is largest in leather (15%) followed by electrical–electronics, pulp and paper and textiles (13%); and machinery (10%). These sectors belong to different technological groups: pulp and paper, and leather and textiles are low-tech industries. They are at the mature stage of their product life cycles (Klepper, 1996); these industries have undergone a shakeout, and only the most efficient firms have survived. Therefore innovation, which occurs mainly in the production processes, is crucial for the existence of firms (innovation is a neces-

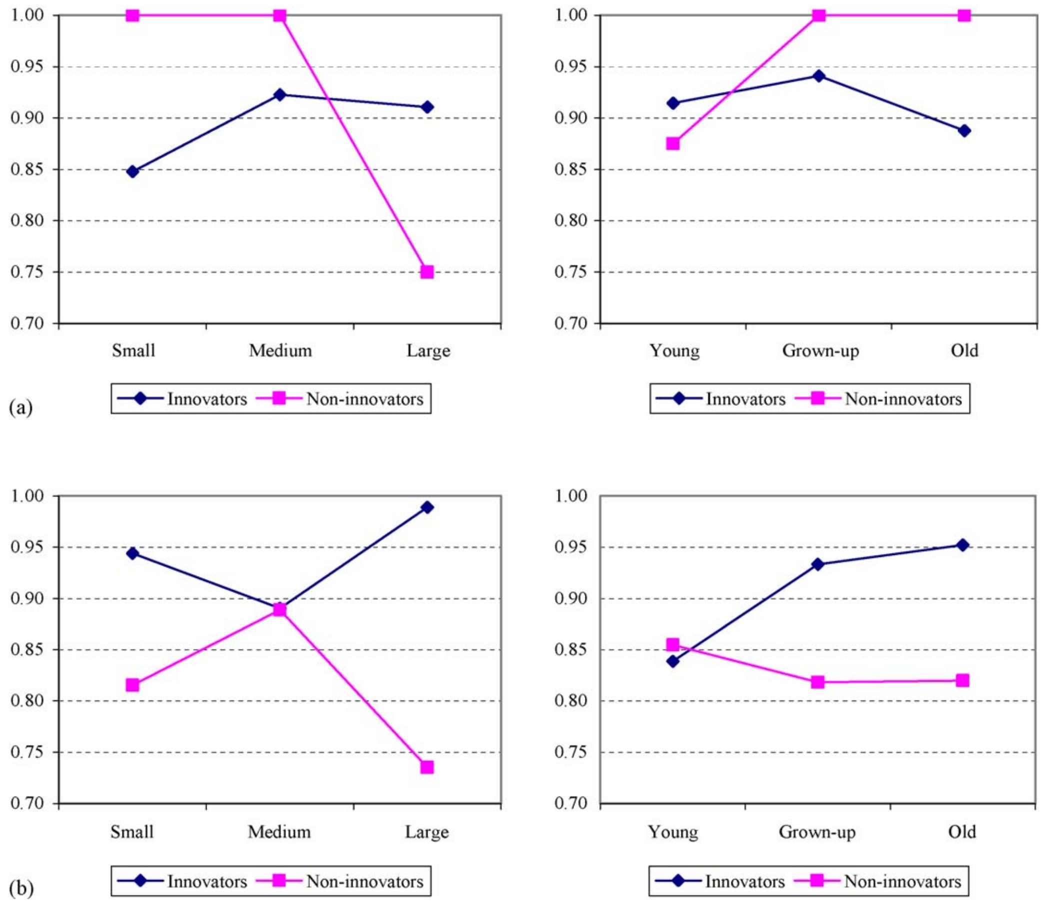

Fig. 5. Survival probabilities by size and age class by sector: (a) chemicals; (b) electrical–electronics.

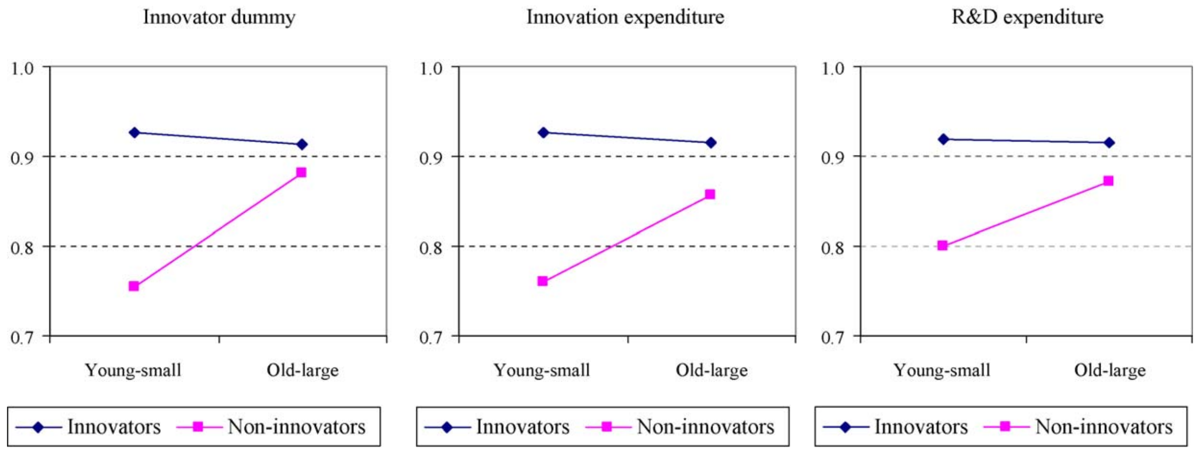

Fig. 6. Survival probabilities by innovation indicator.

sary condition for survival in the market). On the other hand, machinery and electrical–electronics, which are high-tech industries, are at the stage of expansion of their product life cycles, and must compete by introducing new products. Consequently innovation also plays a major role for these firms.

In general heterogeneity across sectors is to be expected (Marsili, 2001). When we analyse the effects of innovation on survival, controlling for sectors and an additional dimension, size or age of the firm, we notice that the patterns of these effects differ across sectors. From the graphs of the survival probabilities by age across sectors, and by size across sectors, a broad variety of patterns with distinctive characteristics can be identified. Fig. 5a and b illustrate this diversity of patterns. The chemicals sector (Fig. 5a), as previously observed, displays a rather distinctive pattern. In the classes of relatively small and old firms, non-innovators are more likely to survive than innovators. However, innovation increases the probability of survival for large firms. In electrical–electronics (Fig. 5b), innovation has a generally positive effect on the probability of survival across size and age classes. This effect is more evident in large and long established firms.

In sum, by controlling for sector differences, we find that in general an innovation premium exists in most industries, varying in intensity across industries. However, when we estimate the innovation premium conditional on age and size within a specific sector, it is not possible to define any type of relationship between innovation and survival. The conditional effects of innovation on survival can be positive or negative or non-linear depending on the sector. Furthermore, no relationship can be established between survival and size and between survival and age. Thus, industrial sectors affect not only the relationship between innovation and survival, but also the well-established relationship between survival, size and age. The dominant technological and market characteristics in a sector appear to shape the way innovation influences the survival prospects of firms of different age and size.

6. Robustness analysis

In order to assess the robustness of our results against alternative definitions of innovative firms, we use two more criteria to identify the set of innovators and the set of non-innovators. Our original dummy variable classified an innovator as a firm that introduced either a product innovation or a process innovation in the period 1994–1996. Here, we construct new dummies for innovators and non-innovators based on (i) total expenditure of a firm on innovative activities, and (ii) R&D expenditure. First, we define innovators as firms with total innovation expenditures greater than zero. These include expenditure in R&D (in-house and outsourced), industrial design, licences, and marketing and training related to the introduction of a new product and/or process. Second, we define innovators as firms with positive (in-house) R&D expenditure. This definition is more restrictive than the other two, and this set of innovative firms is a subset of the previous one.

We replicated the previous analysis using the new definitions of innovators and concentrating on the effects of innovation conditional on size and age. In particular we estimated the survival probabilities for the two contrasting classes of young and small firms (see Section 2 for definitions) and of old and large firms.

From Fig. 6 and Table 4 we can see that independent of the definition of innovators, and confirming previous

Table 4
Survival probabilities of innovators and non-innovators by innovation indicator

Size class	Innovator dummy			Innovation expenditure			R&D expenditure		
	Innovators	Non innovators	z-Statistic	Innovators	Non innovators	z-Statistic	Innovators	Non innovator	z-Statistic
All firms	0.926	0.894	10.4***	0.924	0.885	12.8***	0.924	0.894	10.4***
Young (small)	0.927	0.754	4.7***	0.927	0.760	6.8***	0.918	0.800	4.7***
Old (large)	0.914	0.881	3.6***	0.914	0.856	4.2***	0.915	0.871	3.6***

Note: Number of months equal to 42; *Statistically significant at 10%; **Statistically significant at 5%;
*** Statistically significant at 1%.

results, there is an innovation premium, which is especially pronounced for young and small firms. Indeed, in this class, the survival probability is 23, 22 and 15% higher for innovators than for non-innovators, based respectively on the innovator dummy, the total expenditure dummy and the R&D dummy. For old and large firms, the survival probability is 4, 7 and 5% higher for innovators than for non-innovators. While the innovation premium for old and large firms remains approximately invariant across definitions, the innovation premium for young and small firms decreases as the definition of innovators becomes more stringent.

As Table 4 highlights, the survival probability for innovators does not change across definitions. The innovation premium decreases because it is the survival probability of non-innovators that changes. This is due to the fact that moving from the broadest definition of an innovator to the most restrictive one, firms that originally were defined as innovators become non-innovators, increasing the average survival probability of the non-innovator subset (as the innovators are those with higher survival probabilities).

The definition of innovation that most restrict the set of innovators, positive R&D expenditure, reduces the innovation premium for young and small firms in particular, while for old and large firms it even slightly increases. Young and small firms are less likely to have formal R&D laboratories and even when they conduct in-house R&D activities they tend not to record them in their profit and loss accounts (Patel and Pavitt, 1995).

7. Conclusions

In this paper, we analysed the effects of innovation on the survival probability of manufacturing firms, conditional on firm attributes such as age and size, and sector of activity. The analysis is based on micro-economic databases from two different sources: the Business Register of the population of firms in the Netherlands and the Second Community Innovation Survey. In general, we found that innovation matters for increasing the survival probability of firms, or in other words, that there is an innovation premium for survival. This effect becomes more pronounced over longer time periods, from 2 years to three and half years of survival.

We controlled for firm specific characteristics such as size and age, previously found to be important for shaping the survival of firms. The effects of innovation are especially important for small and young firms. These are the classes of firms that are generally identified in the literature as the most exposed to the risk of exit. Indeed survival probability of small, young and non-innovative firms is the lowest. In contrast, among innovative firms, the probability of survival of small, young firms is comparable to other size and age classes, and is always higher than the survival probability of non-innovators, independent of age and size. The innovation premium is thus highest for young and small firms at 23%. Based on this premium, the survival probability of young and small firms is comparable to that of old and large firms.

This paper contributes to a growing number of empirical studies that draw on the CIS to examine the effects of innovation on a firm's economic performance. However, the importance of innovation for the basic condition of survival of a firm has been rather neglected. Our results support the hypothesis that there is an innovation premium, which especially 'insures' young and small firms against the risk of failure. On this basis, it would be interesting to look in more detail into the characteristics of the innovation process in relation to firm survival, for example taking into account the distinct nature of product and process innovation.

Acknowledgements

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Appendix A

See Tables A1–A3.

Table A1
Industrial sectors

Code	Sector	NACE Rev.1 description
15	Food	Manufacture of food products and beverages
16	Tobacco	Manufacture of tobacco products
17	Textiles	Manufacture of textiles
18	Apparel	Manufacture of wearing apparel; dressing and dyeing of fur
19	Leather	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
20	Wood	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
21	Pulp and paper	Manufacture of pulp, paper and paper products
22	Publishing	Publishing, printing and reproduction of recorded media
23	Petroleum	Manufacture of coke, refined petroleum products and nuclear fuel
24	Chemicals	Manufacture of chemicals and chemical products
25	Rubber and plastics	Manufacture of rubber and plastic products
26	Mineral products	Manufacture of other non-metallic mineral products
27	Basic metals	Manufacture of basic metals
28	Metal products	Manufacture of fabricated metal products, except machinery and equipment
29	Machinery	Manufacture of machinery and equipment n.e.c.
30	Computers	Manufacture of office machinery and computers
31	Electrical equipment	Manufacture of electrical machinery and apparatus n.e.c.
32	Telecommunications	Manufacture of radio, television and communication equipment and apparatus
33	Instruments	Manufacture of medical, precision and optical instruments, watches and clocks
34	Automobile	Manufacture of motor vehicles, trailers and semi-trailers
35	Other transportation	Manufacture of other transport equipment
36	Other manufacturing	Manufacture of furniture; manufacturing n.e.c.
37	Recycling	Recycling

Table A2
Values of the z-statistic for comparison between probabilities

Comparison groups	Number of months			
	24	30	36	42
BR vs. BR with at least 10 employees	−102.1***	−100.9***	−92.2***	−78.4***
Innovators vs. non-innovators in CIS-2	17.4***	17.3***	15.5***	12.6***
BR not in CIS-2 vs. BR (≥10 employee)	−16.8***	−16.5***	−15.9***	−14.3***
Innovators vs. non innovators (Table 3a)				
Small	10.5***	10.5***	8.7***	6.0***
Medium	9.1***	9.1***	8.5***	7.7***
Large	2.5**	2.4**	2.0**	2.6***
Innovators vs. non innovators				
Young	5.7***	5.4***	5.4***	4.7***
Grown-up	7.7***	7.6***	6.4***	4.9***

Table A2 (*Continued*)

Comparison groups	Number of months			
	24	30	36	42
Old	15.4***	15.5***	13.8***	11.1***
Small vs. large firms				
Innovators	3.1***	3.2***	2.3**	1.1
Non-innovators	−0.4	−0.4	−0.5	0.7
Young vs. old firms				
Innovators	−15.3***	−15.2***	−13.2***	−10.4***
Non-innovators	−11.2***	−10.7***	−10.1***	−8.5***
Firms across size classes (S, M, L)				
S/M				
Young innovators	5.3***	4.7***	4.8***	5.3***
Young non-innovators	−6.3***	−6.0***	−5.5***	−4.2***
M/L				
Young innovators	−1.8*	−0.9	−0.7	−0.7
Young non-innovators	1.2	1.1	0.9	1.3
S/L				
Young innovators	3.7***	2.8***	3.2***	3.6***
Young non-innovators	−3.5***	−3.4***	−3.2***	−1.9*
Firms across age classes (Y, G, O)				
Y/G				
Small innovators	0.9	0.8	1.1	1.6
Small non-innovators	−7.5***	−7.2***	−6.8***	−5.3***
G/O				
Small innovators	−1.7*	−1.7*	−1.5	−1.5
Small non-innovators	−3.5***	−3.3***	−3.1***	−2.7***
Y/O				
Small innovators	−0.2	−0.3	0.3	0.9
Small non-innovators	−12.8***	−12.1***	−11.3***	−9.1***
Small and young vs. large and old				
Innovators	0.8	0.6	0.8	1.2
Non-innovators	−8.0***	−7.6***	−7.3***	−5.3***
Innovators vs. non-innovators				
Small firms				
Young	9.7***	9.2***	9.6***	9.0****
Grown-up	4.1***	4.2***	3.8***	2.8***
Old	7.3***	7.7***	6.5***	4.4***
Medium firms				
Young	−1.3	−1.1	−0.6	−0.3
Grown-up	6.7***	5.4***	5.3***	5.1***
Old	8.9***	7.5***	7.4***	7.2***
Large firms				
Young	1.5	1.0	1.0	1.6
Grown-up	−2.1**	−2.1**	−2.1**	−2.0**
Old	2.6***	2.1**	1.9**	2.4**

* Statistically significant at 10%.
** Statistically significant at 5%.
*** Statistically significant at 1%.

Table A3
Values of the z-statistic for comparison between probabilities

Comparison groups		Number of months	
SIC	Sector	24	42
Innovators vs. non-innovators			
15	Food	1.6	0.7
17	Textiles	4.9^{***}	2.6^{***}
18	Apparel	5.7^{***}	3.7^{***}
19	Leather	4.3^{***}	3.7^{***}
20	Wood	4.5^{***}	2.2^{**}
21	Pulp and paper	13.5^{***}	9.2^{***}
22	Publishing	-2.7^{***}	-2.2^{**}
23	Petroleum	0.0	1.2
24	Chemicals	-6.5^{***}	-4.4^{***}
25	Rubber and plastics	7.4^{***}	5.2^{***}
26	Mineral products	−0.4	−0.4
27	Basic metals	−0.8	0.0
28	Metal products	2.8^{***}	2.5^{**}
29	Machinery	13.3^{***}	10.3^{***}
30–32	Electrical–electronics	11.6^{***}	7.6^{***}
33	Instruments	-4.1^{***}	-3.8^{***}
34	Automobile	5.2^{***}	5.0^{***}
35	Other transportation	-1.7^{*}	−0.7
36	Other manufacturing	8.8^{***}	6.3^{***}
37	Recycling	−0.2	0.3

Notes: See Table A2.

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