Crossing the innovation threshold through mergers and acquisitions.

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Abstract

Firms are resorting more and more to mergers and acquisitions (M&A) to bridge the gap between where they are and where they would like to be in relation to innovation and performance. This paper investigates whether involvement in M&A triggers distinct patterns of innovative behaviour across firms, and whether this effect is conditional on firm size. The analysis combines data from four waves of the Community Innovation Survey (CIS) and the Business Register of Dutch manufacturing firms. We observe that M&A influence the probability that firms will begin innovation activities or persist with them, and these effects vary at different points in the firm size distribution. In particular, by resorting to M&A firms are able to persist with the innovation efforts and output over time, and this effect is especially strong for large firms. For small firms, M&A help them to cross the 'innovation threshold', increasing the probability of the transition from a non-innovator to an active innovator. However, the M&A effect does not mitigate the tendency of small firms to be occasional innovators.

Keywords: Mergers and acquisitions; innovation; small and medium sized enterprises; dynamic random effect probit models, multiplicative interaction models

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Introduction

Building a successful innovation-based strategy requires resources and capabilities that are often difficult to develop internally (Teece 1987) especially for small firms. Firms frequently are resorting to mergers and acquisitions (M&A) to bridge the gap between their existing condition and what they would like to achieve in relation to innovation and performance (Cassiman and Veugelers, 1999, 2002; Cefis, 2010). The performance effects of M&A are generally measured in the strategy and finance literature as cumulative abnormal returns (CAR) or returns on assets (Haleblian et al., 2009). However, several studies have looked at the consequences of M&A for innovative activities and innovative performance, noting also that is not always positive (Hitt et al., 1991). Although an M&A agreement is a popular means of accessing external technologies, it can lower managerial commitment and investment in R&D and, therefore, innovative output (Hitt et al., 1990; 1991). However, a growing body of evidence (Hagedoorn and Cloodt, 2003; Cassiman et al., 2005; Cassiman and Veugelers, 2007) shows that if the merger is motivated by the goal of acquiring new technology and is complemented by an efficiently managed knowledge transfer and integration process, it can have a positive effect on innovative performance. While these studies support the notion that technology-driven M&A help firms to increase their innovation levels, less is known about how they trigger changes in the patterns of innovation over time.

This paper focuses on two properties of innovation dynamics. First, we consider the degree of persistence in innovation. Several studies show that firms that have innovated or invested in innovation activities at a certain time are more likely to continue these activities in the future (Cefis, 2003; Peters, 2009; Raymond et al., 2010). This reflects the path-dependent and cumulative nature of the innovation process in which 'success breeds success' (Dosi, 1988). The question we investigate is whether a merger or an acquisition enhances the firm's innovation persistence, that is, the ability to cumulatively exploit its knowledge base by re-combining, and creating synergies with, externally acquired resources and capabilities. Second, we investigate what is referred to in the literature as the 'innovation threshold' (Geroski et al., 1997; Cefis, 2003; Gonzalez and Pazo, 2004). Innovative activity often requires that the firm changes its pattern of resource deployment, which usually involves irrecoverable ('sunk') costs - in new R&D facilities, the hiring and training of new personnel, and the marketing efforts required to launch a new product - associated with high levels of uncertainty about whether these investments ultimately will pay off. As a consequence, there is a minimum level of innovation, for example, the first product introduced to the market (Geroski et al., 1997) or the first patent granted (Cefis 2003) that is more difficult for the firm to achieve than further innovations of similar impacts. We want to understand whether M&A, by giving access to additional resources and capabilities whose value has been proved in the acquired organisation, serve to lower the innovation threshold for the acquiring firm.

Most studies of M&A concentrate on transactions involving large publicly traded firms (Haleblian et al., 2009). However, M&A vary. In large firms the motivations for engagement in M&As are mainly financial or to achieve market dominance. In these cases, it is likely that the costs incurred by the post M&A integration process absorb energy and resources that could have been devoted to increasing the efficiency of other activities (De Man and Duysters, 2005), and the process reduces innovative activity and produces negative effects on both capital and R&D spending (Schenk, 2006). Conversely, when the merging parties have complementary technologies and are motivated by value improvements, then the merger can generate innovations that otherwise would not have been achievable (Cassiman and Veugelers, 2007). These technology-driven M&A are becoming especially important for small and medium sized enterprises (SME). For SMEs, which tend to be less persistent innovators and to face more concrete 'innovation threshold' than large firms (Geroski 2000; Cefis and Orsenigo, 2001; Cefis, 2003; Peters, 2009; Raymond et al., 2010), M&A may represent a viable strategy to overcome their innovative threshold. Following this line of reasoning we investigate whether involvement in M&A triggers distinctive innovation dynamics in firms of different size.

The empirical analysis relies on an extensive dataset of Dutch manufacturing firms with 10 or more employees, in the period 1994-2002, derived from two different sources: four waves of the Community Innovation Survey (CIS), and the Dutch Business Register (BR). The analysis focuses on the degree of 'state dependence' in the firm-level innovation dynamic, as represented by a Markov stochastic process. The objective is to establish whether innovation state dependence differs conditional on having engaged or not in an M&A for firms in different size classes. For this purpose we calculate transition probability matrices (TPM) for M&A active and non-active firms and estimate a dynamic random effects (RE) discrete choice model. A firm's innovative status in defined by two complementary indicators: engagement in innovative activities, and realisation of innovative sales (or turnover). By analysing the dynamic properties of innovation conditional on M&A involvement and firm size, this study highlights the specific effects of M&A on innovation in relation to the ability to innovate persistently and to cross the innovation threshold in a context of varying resource constraints. The study provides new insights on post-merger performance and contributes to the growing literature on the role of innovation in the M&A process.

1. Theoretical background

Although widely accepted as an important element of the firm's competitive strategy, M&A are generally not analysed in conjunction with innovation (Cassiman et al. 2005; Schulz 2007). The focus in the M&A literature is mainly on the benefits deriving from economies of scale and scope on the one hand, and the costs of concentrated economic power among rival firms on the other (Burkart and Panunzi, 2008). However, scholars of innovation management have observed that because of the increasing complexity in innovation, firms are relying more and more on external sourcing strategies, including M&A.

Despite the increased attention in the strategy and economics literature to the possible existence of a link between M&A and innovation, the question of whether M&A create, destroy or redistribute value related to innovation among the merging parties remains open.

The literature proposes several alternative views on the ways that M&A can affect the innovative potential of firms. Scholars writing in the Resource Based View of the firm posit that M&A increases innovative performance by enlarging the acquirer's knowledge base, technological know-how and technical capabilities (Ahuja and Katila 2001). The acquiring firm gains access to new, valuable knowledge, which when combined with its own knowledge base, generates innovations that otherwise would not have been achievable (De Man and Duysters, 2005; Gerpott, 1995). From an economic perspective, expectations of a positive effect of M&A on innovation are based on the possibilities to exploit economies of scale and scope in R&D (Cassiman et al., 2005). A merger also may allow the firm to redeploy resources to more productive use (Ahuja and Katila 2001).

On the other hand, in non-technology driven M&As, initiated for financial reasons or to achieve market dominance, the costs incurred in the integration process may absorb managerial and organizational resources that otherwise would have been devoted to other activities (Hitt et al., 1991; De Man and Duysters, 2005). In these cases, M&A may be detrimental to innovative activity, and lead to negative effects on R&D inputs and outputs (Hitt et al., 1991; Schenk, 2006).

The industry organization literature assesses the impact of M&A on innovation in the context of post-merger R&D expenditure, or by investigating a series of research inputs, outputs and dynamic efficiencies simultaneously (for a review see Cefis et al., 2007 and Schulz, 2007). However, empirical evidence shows a generally negative impact on post-acquisition innovative inputs, outputs and dynamic efficiencies in acquiring firms (Cassiman et al., 2005; Cefis et al., 2007, for a review). Note though that most studies focus on transactions involving only large firms (Schenk, 2006), and ignore the small firm context.

Taking account of the complexity of the innovation process, Arora et al. (2001), Ahuja and Katila (2001) and Cassiman and Colombo (2006) highlight that in technology driven M&A the emergence of technological synergies in the integration process can lead to increased ability to sustain innovation. All M&A processes involve major reorganizations in the merging parties: subdivisions are merged, divested or dissolved according to the objectives of the post-merger integration process. However, in firms engaging in technologically motivated M&A processes, post-merger integration is likely to be aimed more at achieving synergies and maximizing value. Technological M&A processes are seen as being motivated by value improvements and appropriation of the benefits from innovation. It is expected that the contribution of those firms embarking on these processes will increase the capabilities of the merged entity in terms of knowledge, human capital, financial resources, R&D laboratories, and access to intellectual property rights. Studies that focus on technology-driven M&As argue that if the merger involves technological components and motivations such as technological renewal and diversity, and a larger knowledge base, it will be more likely to have a positive impact on post M&A innovation performance (Ahuja and Katila, 2001; Cassiman et al., 2005; Cassiman and Colombo, 2006).

Our study complements this literature by looking at changes in firms' innovation behaviour and performance following a reasonable post-merger period. A technology driven merger should result in higher innovation performance at firm level. Specifically, we expect that those firms that were non-innovators before the merger, will be more likely to be able to scale the innovation threshold. We expect also that those firms that were innovators before the merger will be more likely to continue to innovate than innovating firms that do not undertake a merger or acquisition. In other words state dependence in the innovation process will be higher for M&A active firms.

Our approach is novel in that it examines whether these patterns of entry to and persistence in innovation activities following M&A activity, are different for different firm size classes. The M&A-innovation literature so far has focused mainly on large firms, and has tended to ignore the SME sector. Our study includes a firm size component, which allows us to assess the link between M&A and innovation and to disentangle the effects of M&A activity on changes in innovative behaviour for different size classes of firms.

The design of innovation strategies differs between large and small firms (Acs and Audretsch, 1987; De Jong and Marsili, 2006; Santarelli and Vivarelli, 2007; Veugelers, 2009). Large firms are mainly involved in incremental innovation, building on existing knowledge bases and competences. They have an advantage in markets characterized by imperfect competition and are active in final goods markets based on their technological innovation efforts. They have strong market power, can support R&D and innovation costs, and can afford to consider heavy investment commitments in the expectation of higher long term pay-offs (Arrow, 2000; Dougherty and Hardy, 1996; Tether, 1998; Wagner and Hansen, 2005).

Small firms that are innovators usually are producers of radical innovations. They find it more difficult to cope with innovation uncertainties, and the costs of establishing research facilities, hiring R&D personnel and investing in R&D technologies can be prohibitive for these firms, which reduces their opportunities to engage in innovative activities. However, in certain sectors, for example biotechnology, small entrepreneurial firms may have innovation advantages in markets characterized by perfect competition. Their innovative activity is often motivated by expectations of first mover advantage (Rosenberg, 1990). Thus, small and medium sized innovators are often rapid and/or radical innovators, pioneering new and harder to imitate technologies. They innovate in market niches or produce radical innovations, independently developing a market for their technology and tying their growth to the growth of these smaller markets (Cosh et al., 1998; de Jong and Marsili, 2006).

SME engagement in M&A has received less research attention; however, it would seem that the reasons for SMEs agreeing to merge with other firms are very different from the reasons applying to large firms. Thousands of small M&A take place annually at the national level, and it is likely that these smaller transactions not only are driven by different rationales but result in different innovation effects (Cefis et al., 2007). Small firms that face higher resource and capability constraints in pursuing an innovation strategy and conducting continuous innovation, may be more likely to rely on external sourcing for their innovation activity, and to choose a 'buy' rather than 'make' policy (Cassiman and Veugelers, 1999). Their involvement in M&A may take the form of innovation driven strategic alliances aimed at providing complementary knowledge, competences and technologies that otherwise would be difficult to build internally. M&A may constitute a strategic tool that provides access to the right mix of resources to cross the innovation threshold, pursue a long-term innovation strategy, and maintain the pace of the innovation activity. These technology-driven M&As are more likely to trigger innovative outputs, especially when the absolute size of the acquired knowledge base is large (Ahuja and Katila, 2001). Cassiman and Colombo (2006: 163) show that 'where innovation is itself the main motive of the M&A activity, the results can often be positive and sometimes extremely so'.

To evaluate the accuracy of this statement, we break down the effect of M&A activities along size classes and investigate whether small firms engage more often than large firms in technological driven M&A transactions and, therefore, have a higher probability of deriving innovative gains. First, we analyse whether M&A can be used by SME to pass the innovation threshold and make the transition from a non-innovator to an active innovator. Second, we analyse whether M&A help to reduce the barriers to innovation faced by SME, and facilitate long term innovative activity.

2. Data and method

2.1. The data

We use a longitudinal dataset that combines economic and firm-level data from two different data sources, elaborated by the Central Bureau of Statistics (CBS) in the Netherlands: the CIS and the BR. The CIS collects data on activities related to product and process innovation, innovation strategies and sources, and M&A activity. The CIS data allow a broader identification of firm level patterns of innovation than other innovation indicators because they cover various sectors and forms of innovation (see among others, Cassiman and Veugelers, 2002; Mairesse and Mohnen, 2002; Kleinknecht, 1996; Kleinknecht et al., 2002).

The CIS is a (mostly) four-yearly survey and gathers information on the activities of firms in the previous three years. However, in the Netherlands, CIS surveys are conducted every two years, which enables analysis of successive waves starting from the period 1994-1996 (CIS 2).[1] Since our analysis focuses on post-merger innovative performance and CIS 4 does not provide information on M&A activities, we use data from the first four waves: 1994-1996 (CIS 2), 1996-1998 (CIS2.5), 1998-2000 (CIS3), 2000-2002 (CIS3.5).[2] These firm-level data on innovation and involvement in M&A activities are combined with firm specific demographics, such as firm age and size, derived from the BR database. The BR covers all firms registered in the Netherlands for fiscal purposes. It is a

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[1] The CIS1 dataset for the period 1992-1994 was not available from the Dutch Statistical Office because it was administered and managed by another organization.

[2] The threshold for inclusion in the CIS is 20 or more employees for most European countries. However, in the case of the Netherlands, because two CIS waves (2.5 and 3) were sponsored by the Dutch Ministry of Economic Affairs, the threshold is 10 employees.

comprehensive register that records the date of inclusion of the firm in the register, which can be used to proxy the firm's age on the basis of the date of entry to the market (Cefis and Marsili, 2006).

The resulting unbalanced panel covers the manufacturing industry within the time frame 1994-2002. It is composed of 13,901 firm-wave observations, with an average of 134.3 employees per firm, and 707.2 standard deviation. The panel data have a two-year cadence, which allows us to account for a post-acquisition integration process when studying the effects of M&A.

2.2. The variables

Innovation activities and output

We represent the innovation dynamic of a firm as a two-state stochastic process $\{Innov_t\}_{t=1...T}$, where $Innov_t$ is a dummy variable that takes the value 1 if the firm is an innovator at time *t*, and 0 if the firm is not an innovator at *t*. The time *t* identifies the successive waves of the CIS in the set *T ={(1994-1996), (1996-1998), (1998-2000), (2000-2002)}*. We adopt two different definitions of firm innovation status. A first broad definition is based on the condition of whether or not the firm had undertaken innovative activities in a certain time period, specifically (and according to the CIS questionnaire), if the firm has introduced a technologically new or improved product, service or process, or has invested in R&D or incurred innovation expenses, at any time in the three year's prior to the survey. In investment in innovation and/or in R&D we include expenditure on intra and/or extramural R&D, patent and copyright applications, acquisitions of external knowledge, expenses related to product design and market introduction, and training of R&D personnel. The choice to use such a broad proxy for innovation is motivated by the primary aim of our study to capture whether (in any possible way) M&A help firms to become innovators.

A second and narrower definition focuses on the firm's innovative output. On the basis of responses to the question in the CIS concerning the percentage turnover of technologically new or improved products/services that the firm has achieved in the three years prior to the survey, the dummy for innovator status is equal to 1 if this percentage is greater than zero at *t,* and 0 otherwise.

The percentage of turnover from innovation represents the most restrictive definition of the 'innovative status' of the firm, where a firm is positioned along the innovation process, in contraposition with the broadly defined innovative activities. In this way the two measures capture distinct stages of the innovation process, and therefore can bring to light different mechanisms by which M&A can affect innovation. With innovative sales we observe the firm at the end of the innovation process, as a product or service has been developed and successfully commercialized, when some sales have been realized beyond the simple market introduction. It is therefore possible that acquisitions may influence innovative behavior, a firm engaging in an innovative project (the innovative status as broadly defined), to a different degree that it affects the ability to bring the project into full realization by achieving first sales (the innovative status as narrowly defined). Using two alternative indicators of innovative status serves a double purpose. As narrow and broad measures of innovation, and as such expected to be correlated to a certain degree, they allow assessing the robustness of the analysis and the model. As well, being indicative of different stages of the innovation process, they can highlight somewhat different types of effects of M&A, on the decision of a firm to engage in innovative activities, and on its ability to realize them successfully.

For each indicator, the combination of the corresponding dummy variable of innovative status at successive time periods (i.e. CIS waves) defines four alternative dynamic patterns of innovation, according to the occurrence or non-occurrence of a change in firms' innovative behavior. Specifically, 'new-entrant innovators' are firms that change their status from non-innovators in one CIS wave to innovators in the subsequent wave. 'Persistent innovators' are firms that maintain their status of innovators from one CIS to the subsequent one, while 'exiting innovators' are those that lose their innovative status from one wave to the next. Finally, 'persistent non-innovators' consist of firms that are non-innovative in one CIS wave and remain in the non-innovative status in the successive wave.

M&A involvement

We are interested in whether the innovative activities and performance of acquiring firms change after the M&A, based on a post-acquisition analysis of firm-level innovativeness. The challenge for acquiring companies is to integrate the knowledge bases, competences and capabilities they acquire, with their own resources, in order to improve post-M&A innovative performance (Ahuja and Katila, 2001). For a merger to result in significant positive static and dynamic efficiency, we need to allow for a reasonable post-merger integration period. The integration process is complex, and to enable an efficient transfer of strategic capabilities requires intensive early planning, clear definition of corporate differences and communication of goals, and continuous attention to maintain optimal interaction during the post-merger integration process (Haspeslagh and Jemison, 1991; Jansen, 2002). The complexity of the post-merger integration process demands a minimum time span of 2-3 years.

To proxy for M&A activity we construct a dummy variable for whether or not the company has acquired or merged with another firm(s) during the three years covered by the CIS. The dummy variable $M\,\&\,A_t$ takes the value 1 if the firm is active in the M&A process in the period *t* of the CIS wave (where $t \in T$) and 0 otherwise. In analysing the effects of M&A involvement on innovation we apply two time-lag structures, in accordance with the way the firm's innovation status is identified. The two indicators of a firm's innovation status (activities and sales) capture distinct stages of the innovation process and, therefore, observing a post-merger effect in one or the other case requires a different time frame. In the case that innovation status is defined broadly as engagement in innovative activities, including initiation of an innovative project which could be possible within a relatively short time after the post-merger period, we use a one period time lag and compare adjacent waves of the CIS. We assume that the effects of M&A on innovative activities, such as on the decision to start a new project, are likely to be observable within a short time period after the merger. With a longer time lag, this type of effect may not be detected from the data, or if any change is observed it might not be associated with the M&A. Specifically, the firm's innovative activity at time period *t* (i.e. CIS wave *t*) is related to its innovation activity at time period *t*-1 (CIS wave *t*-1), conditional on having or not carried out M&A at time period *t*-1 (CIS wave *t*-1). Conversely, in the case of innovation status defined more narrowly on the basis of innovation turnover, we allow for a two period lag assuming that a longer time period would be necessary to observe significant post-acquisition changes in output due to time of commercialization. A longer time period after the merger is more likely to bring to light those cases of firms that achieve post-merger commercial success due to innovation. In this case, the dynamic model compares innovation and M&A in non-adjacent CIS waves, over a seven-year period. Specifically, the firm's innovative performance at time t (CIS wave t) is related to innovation performance at time t-2 (CIS wave t-2), conditional on having or not engaged in a M&A at time t-2 (CIS wave t-2). While adjacent CIS waves overlap one year, there is one full year between the time periods of non-adjacent CIS waves[3]. This setting allows us to assess the robustness of the observed patterns of state dependence since lower levels of persistence can be expected with the narrower definition of innovation and longer time lag, as well as to capture different types of effects of M&A on innovation dynamics, which relate to the innovation status of a firm as observed at different stages of the innovation process.

Sector specificity and firm heterogeneity

The multivariate analysis includes variables to control for sector and firm specificities. To capture and control for differences in the nature of the technology, organizational sectoral specificities and opportunity conditions (ease of innovation in some fields compared to others; possibility of targeted industry innovation policies) (Mairesse and Mohnen, 2002), we apply a refinement of Pavitt's taxonomy of firms (1984) proposed in Marsili (2001) and de Jong and Marsili (2006). Pavitt assigns a bigger role to large firms than to SME, which means that his original categories do not account for intra-industry differences across firm size classes. The refinement proposed by Marsili classifies firms according to their innovative behaviour, accounts directly for firm size and includes small and micro firms. We thus obtain five technology classes that can be used to map the entire Dutch manufacturing

[3] In the case of adjacent CIS waves, there is the possibility that data on the innovation status overlap in the central year of the 5-year period. This may lead to slightly overestimating the probability of a firm to be persistent innovator when considering the innovative activities variable, while it would not affect the estimated probability when considering the innovative sales variable, because the innovative sales indicator refers to firms sales of only the last year of each CIS wave, so there is no overlapping even when considering adjacent waves. Furthermore, the estimated probability of becoming an innovator after the merger is not affected for both of the variables.

sector: science based, fundamental process, complex (knowledge) systems, production engineering, and continuous process. The Appendix to this paper provides a comprehensive overview of these technological regimes. Figure 1 depicts the percentage of innovators across technological regimes. The majority of SME innovate mostly in production engineering, and a large share of small firms fall into the science-based or fundamental process innovation category. The production engineering technological cluster is characterized by a medium to high level of technological opportunity, low entry barriers and not high levels of persistent innovativeness, but a very high diversity of technological trajectories.

We account for characteristics such as firm size and age, to analyse changes in firms' innovative behaviour. We identify three firm size classes according to number of employees: small - 10 to 49 employees; medium - 50 to 250 employees; and large – more than 250 employees. We construct this variable using firm-level yearly data taken from the Dutch BR. In the multivariate analysis, the logarithm of number of employees per year is used to proxy for firm size. Firm age is calculated in months, based on date of entry in the BR, and the variable is expressed in logarithm values. The evidence from studies on the relationship between firm size and innovation activity is somewhat mixed, but tends towards a positive but not necessarily linear trend (Cohen and Levin, 1989; Kamien and Schwartz, 1982; Evangelista et al., 1997). The impact of firm age has been shown to be highly non-linear, with low volatility along size classes – typically, innovation is higher in young and recently established firms, and decreases as firms age (Huergo and Jaumandreu, 2004). Table 1 summarizes the description of the variables and the various patterns of innovative behaviour considered in the analysis

< Insert Table 1 about here >

Panel structure

Table 2 presents the composition of the panel constructed from the four waves of the CIS for manufacturing firms by innovation, M&A involvement and size class. Taking the broader definition of innovation, the percentage of firms that are innovators varies from a minimum of 52.2% in CIS3.5 to a maximum of 63.4% in CIS2, with this proportion decreasing to values ranging between 37.1% in CIS3.5 and 57.2% in CIS2, if we apply the narrower definition of innovative output. Overall across the CIS waves, the share of firms engaged in M&A varies between 8.5% and 21.6%. The distribution of firms by size classes among the 13,901 observations in the panel varies between 41.5% to 57.2 % of small firms, 34.5% to 47.9 % of medium firms, and 8.3% to about 11% of large firms.

< *Insert Table 2 about here* >

For the panel of 13,901 observations across the four CIS waves we report in Table 3 the cross-tabulated frequencies according to the two binary indicators used to identify a firm's innovative status, based on innovative activities and innovative sales. Of the total observations 6,706 (equal to 48.2%) are innovators with respect to both indicators, 5,940 (42.7%) are non-innovators however defined, and the remaining 1,255 observations are firms that engage in innovative activities of some kind but do not report greater than zero sales from innovation (equal to about 9% of the sample). The statistical tests reported at the bottom of Table 3, with a Cramer's phi of 0.83, indicates that the association between the two indicators is statistically significant, consistent with the fact that they are both expression of the innovative process of a firm. However, despite the association between the two variables, Table 3 also shows that 15.8% of all observations are of firms that carry out innovative activities but register non-positive innovative sales. Accordingly, the choice of indicator for the innovative status of a firm might also have an influence on the type of innovation dynamics observed, since, given the definition of innovative activities and innovative sales, it captures distinct stages of the innovation process. .

< *Insert Table 3 about here* >

Finally, we consider the distribution of innovators and non-innovators defined on the basis of both indicators of innovative status, separately for firms that engaged in a M&A in at least one of the time periods of the CIS, and for the group of firms that did not engage in a M&A (Tables 4a and 4b). In the panel the presence of innovators is higher among M&A active than M&A non-active firms, with a difference of above 20 percentage points for both indicators of innovative status.

< Insert Table 4a and 4b about here >

2.3. Transition probabilities

Traditionally studies of the determinants of innovation focus on the distribution of innovative and non-innovative firms at a certain time. However, a cross-section distribution can coexist, with different patterns of mobility within the distribution, as firms over time move from one innovation status to another. While some firms continue to innovate or not, from one time to the next, some firms become innovators while others cease to innovate. These dynamics, which distinguish persistent from occasional innovators, can be analysed using a Transition Probabilities Matrix (TPM) (Cefis, 2003). The TPM framework is a non-parametric method based on the assumption that the distribution of firms among a set of possible states (in this case innovators and non-innovators) at time *t* is generated by a random Markov process, that is, by a stochastic process in which the conditional probability of a certain state at time *t*, is a function only of the previously observed state (and not of the sequence of all preceding states). If F_t is the distribution of innovators and non-innovators at time t, the one-period transition probability matrix *P* defines the law of motion of the distribution according to:

$$F_{t+1} = P \cdot F_t \tag{1}$$

where the generic element of the matrix is defined by

$$P_{ij} = \Pr(Innov_{t+1} = j \,|\, Innov_t = i), \quad \text{with } i,j = 0,1 \tag{2}$$

Under this assumption, it is possible to estimate the probability of the following four events occurring at time *t+1*, conditional on the firm's innovative status at time *t*:

P_{01} : innovative entry for innovators at time *t+1* not performing any innovative activity at time *t*

P_{11} : persistence of innovation at time *t+1*, for firms already innovative at time *t*;

P_{10} : innovative exit for non-innovators at time *t+1* that are active innovators at time *t*

P_{00} : persistence of non-involvement in innovation of firms not performing any innovative activity at time *t+1* and at time t.

Some studies use the TMP approach to measure degree of persistence in innovation as proxied by various indicators, such as patents, R&D expenditure, introduction of new products and processes, and compare the resulting patterns among alternative indicators (Cefis, 2003). However the degree of persistence can vary systematically among firms, because of underlying asymmetries in the dynamic capabilities and heterogeneous behaviour of individual firms. In particular, we want to explore whether differences in persistence can be attributed to the choice of external knowledge sourcing through M&A, and if this relationship varies with firm size. We begin our analysis by comparing the transition probability matrices of firms that are involved in M&A and those that are not, computed separately for small, medium and large-sized firms. The transition period corresponds to the timing of the Dutch CIS waves. We are interested in two dynamic properties of innovation: the probability that firms progress from being non-innovators to becoming active innovators (crossing the innovation threshold); and the probability that firms continue to innovate (innovation persistence). The other two probabilities complement one of these values in a two state TMP.

In order to test whether there are statistically significant differences in innovation dynamics conditional on firms' engagement in M&A, we apply a test for differences in proportions (Cefis and Marsili, 2006). If $\widehat{P}_1$ is the estimated probability in the sample of n_1 firms active in M&A, and $\widehat{P}_2$ the estimated probability in the sample of n_2 firms non active in M&A, the test statistic is defined as:

$$Z = \frac{\widehat{P}_1 - \widehat{P}_2}{S_{\widehat{P}_1 - \widehat{P}_2}} \text{, approximately distributed as N(0,1)} \quad (3)$$

where $S_{\widehat{P}_1 - \widehat{P}_2} = \sqrt{P(1-P)\left(1/n_1 - 1/n_2\right)}$ is the estimator of the standard deviation $\sigma_{\widehat{P}_1 - \widehat{P}_2}$, and

$P = \frac{n_1 \widehat{P}_1 + n_2 \widehat{P}_2}{n_1 + n_2}$ is the estimated probability under the null hypothesis $P_1 = P_2$.

3. Dynamic probit model

The TMP approach allows depiction of the properties of innovation dynamics conditional on certain firm characteristics (specifically engagement in M&A). In order to test whether a shift in the innovation dynamic of a firm occurs in response to the firm's involvement in M&A at a certain time, we estimate a dynamic random effects (RE) probit model. In the dynamic RE probit model, the probability of an event depends on the outcome observed for the event occurring at a previous time, and on unobserved heterogeneity. The model allows 'state dependence' to be represented in the innovation process $\{Innov_t\}$ after controlling for unobserved heterogeneity and a set of observable variables that influence the probability of being an innovator at time *t*. More specifically, we want to analyse whether the pattern of 'state dependence' changes at a certain time because the firm has acquired or merged with another firm. For this purpose, in our regression model we introduce interaction effects between the dummy variable indicating involvement in a merger or acquisition in the previous period $(M\&A_{t-k})$ and two different innovation dummies. This is in line with Wright (1976) and Brambor et al.'s (2006) formulation of an interaction model in the specific case of a discrete modifying variable. The two interaction terms are used to predict a firm's capacity to cross the innovation threshold or its ability to engage in continuous innovation, in relation to the firm's involvement in M&A. Accordingly, we estimate the influence of M&A in shaping: (a) the probability of transition from non-innovator at time *t-k* to innovator at time *t* by the coefficient of the interaction $(M\&A_{t-k} \times NONInn_{t-k})$, with $NONInn_{t-k} = 1$ if the firm was not an innovator at time *t-k;* and (b) the probability of maintaining persistent innovation activity by the coefficient of the interaction $(M\&A_{t-k} \times Innov_{t-k})$, with $Innov_{t-k} = 1$ if the firm was an innovator at the time period *t-k*. The RE probit model is thus formulated as:

$$\begin{aligned} \Pr(Innov_{it} = 1) = \Phi[\alpha + \beta_1 Innov_{i,t-1} + \beta_2 (M\&A_{i,t-1} \times NONInn_{i,t-1}) + \\ + \beta_4 (M\&A_{i,t-1} \times Innov_{i,t-1}) + \mathbf{Z}_{it}\psi + \mu_i + \varepsilon_{it}] \end{aligned} \quad (4)$$

where μ_i is the unobserved firm-specific heterogeneity, and ε_{it} is the idiosyncratic error. The vector of observable control variables $\mathbf{Z}_t$ includes dummy variables for technological regimes (in line with Marsili's taxonomy), firm lagged R&D intensity, firm size and firm age. The squared terms of age and size are also included since we expect a non-linear relationship between both age and size and innovation. We add an interaction term age-size to test for possible heterogeneity in the effect of size as firms mature.

Estimating a non-linear dynamic model with unobserved heterogeneity presents what is known as the initial condition problem, due to the presence of the lagged value of the dependent variable among the regressors (see Hsiao, 1986, for a review). It is likely that the initial conditions for the dependent variable, that is, the firm innovation status in the initial time period under investigation $(Innov_{i0})$, are not randomly distributed among firms, but instead are correlated with the unobserved firm-specific heterogeneity. Not accounting for this and assuming the initial conditions $(Innov_{i0})$ to be fixed parameters across observations lead to inconsistent estimators (Wooldridge, 2005). Various methods have been developed to address the initial condition problem. Most of them are based on trying to 'integrate out' the unobserved effects by finding the density of the joint distribution of $(Innov_{i0},...,Innov_{iT})$, given the set of explanatory variables. An alternative solution has been proposed by Wooldridge (2005), which specifies the unobserved effects as a function of the initial conditions, $Innov_{i0}$, and uses the density of the joint distribution $(Innov_{i1},...,Innov_{iT})$ conditional on the initial state and the set of explanatory variables. Under the assumption of strictly exogenous control variables the model has a similar structure to the standard RE probit model, with the exception that it incorporates the initial state of the dependent variable as an additional explanatory variable (Wooldridge, 2005). Following this approach, our model assumes that initial innovative status is randomly distributed and firm unobservable heterogeneity depends on the initial innovative condition. We thus substitute $\mu_i = \gamma\, Innov_{i0} + a_i$ in equation (4), where $Innov_{i0}$ identifies the presence or absence of innovative activities by the firm in the first CIS wave when the firm was observed.

In choosing an RE model, we assume that the individual firm effects are strictly non-correlated with our regressors (Greene, 2003). This assumption was tested based on a Hausman test[4] and is

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[4] The Hausman tests for fixed and RE and for RE and ordinary least squares (OLS) regressions are based on the parts of the coefficients' vectors and the asymptotic covariance matrices that correspond to the slopes of the coefficients in the models. Our results showed that we cannot reject the hypothesis that individual effects are uncorrelated with the regressors. Thus, the

appropriate for large longitudinal surveys, such as those represented by our dataset, of large populations of firms.

As a sensitivity analysis, and to account for possible different effects of M&A at distinct stages of the innovation process, we estimated the RE probit model using the tighter definition of innovation based on the sales of innovative products, in place of the broad range of innovative activities. In this case we estimate the model with a two-period time lag, equivalent to comparing two non-adjacent CIS waves, because a longer time delay may be necessary for the M&A to have an impact on the firm's innovative output. Furthermore, because of this time set, it is likely that the lagged innovative state overlaps with the initial state, making application of Wooldridge's method problematic. Therefore we excluded the initial condition, $Innov_{i0}$, from the model specification with the binary variable based on innovative sales as dependent variable. Conversely, in this case we use the Mundlak (1978) correction to account for possible correlation between unobservable heterogeneity and observable firm characteristics. Accordingly we set $\mu_i = \overline{Z}_i\xi + a_i$ in equation (4), where $\overline{Z}_i$ is the vector of the time averages for all the observable control variables, excluding those such as the technological regime that are invariant over time.

4. Results

4.1. Innovation persistence and M&A involvement

Table 5 presents the estimated transition probabilities in the two groups of M&A active and M&A non-active firms, separately by firm size class - small, medium and large. The values are calculated for innovation activity (Table 5a) and innovation sales (Table 5b). These values show some general patterns in innovation mobility and persistence that are consistent for the two indicators of innovation. With regard to persistence (of innovative and non-innovative status) we observe that the

RE model appears to be the best choice. As sensitivity checks, we ran pooled OLS and cross-sectional regression models; the results were similar to those obtained from the RE model. (All results available on request from the authors.)

probability of being a persistent innovator is lowest for small firms, equal to about 60% on average, is gradually increasing for medium firms (74%), and for large firms is about 83%. Thus, the persistence of innovation, from one wave to the next, increases steadily at around 10% along size categories. Symmetrically, persistence of non-involvement in innovation declines with firm size. Small firms are the most likely to remain non-innovators, with a probability of 78% on average compared to 69% for medium firms and 53% for large firms. With regard to mobility between innovative and non-innovative status, we observe that the probability of entry to innovation is about 22% on average for small firms, 31% for medium firms, and 47% for large firms. Conversely, small firms are the most likely to exit from innovation, with a 40% probability on average, compared to 26% for medium firms and 17% for large firms. When comparing innovative entries and exits, it is evident that more medium and large firms make the transition from non-innovative to innovative status (31% and 47% respectively) than transfer from innovative to non-innovative (26% and 17%), while the opposite holds for small firms. Indeed significant proportions of small firms (37 to 44%) loose their innovative status, while much smaller proportions make the transition from being non-innovators to innovators (15 to 28%). These findings confirm studies that show, using alternative indicators such as patent counts, that small firms are more likely to be occasional innovators and face a higher innovation threshold (Geroski et al., 1997; Malerba et al. 1997; Malerba and Orsenigo, 1999; Cefis, 2003). Small firms encounter stronger barrier to innovative entry because they are generally resource constrained and need to invest in innovative activities that often have the characteristics (e.g. R&D, distribution and marketing of new products, etc.). As well small firms experience greater difficulty to sustain innovation inter-temporally through the exploitation of 'dynamic economies' of scale and scope; their portfolios of innovative activities are smaller and less diversified, and therefore offer less opportunity for cumulative learning (Geroski et al., 1997) and for shifting resources across rapidly changing markets (Helfat and Eisenhardt 2004).

< *Insert Tables 5a and 5b about here* >

We are especially interested in differences in the innovation dynamics between M&A active and non-active firms, across size classes. Starting with the indicator of innovative activities, Table 5a shows heterogeneity among size classes. In the case of small firms, those involved in M&A are marginally (2 percentage points difference) more likely to be persistent innovators than firms not involved in M&A, and are more likely, to a greater extent, in medium firms (7.6 percentage point difference between the two groups). The reverse applies to large firms: M&A active firms tend to be less likely to be persistent innovators than M&A non-active firms (-4.3 percentage points difference). Small and medium firms show similar patterns of innovative entry. For both size classes, the probability to cross the innovation threshold is higher for M&A active than non-active firms (1.6 and 5.6 percentage points difference respectively). We observe no noticeable difference for large firms. Overall, the dynamics of innovative activities indicate that the rates of persistent innovation and new entry to innovation are higher for M&A active than non-active firms in the case of SME. In contrast, for large firms persistence is lower for firms that are active in M&A compared to those that do not engage in M&A.

Taking innovation sales as an indicator of innovation output (Table 5b), the pattern is different. In the case of innovation output rates of persistence in and entry to innovation are higher for M&A active than non-active firms across all size classes not just small and medium sized firms. Also, the gap between M&A active and non-active firms is more clear-cut between small and large firms, especially in relation to rates of entry to innovation. Small firms that engage in M&A compared to their counterparts that do not invest in M&A, have a higher probability of innovating persistently (7.5 percentage points difference) and of crossing the innovation threshold (13.0 percentage points difference). There is a similar or even better defined pattern characterizing large firms, where the percentage points difference for M&A active versus non-active firms is 8.8 for innovation persistence, and 28.0 for innovative entry. To assess whether the observed differences are statistically significant and could be considered to represent systematic differences in the transition probabilities shaping the underlying stochastic innovation process for M&A active and non-active firms, Table 6 reports the results of the z-statistic as in equation (3) for the indicator of innovation sales. The results show that the differences are generally statistically significant, and are more marked for small and large firms, confirming our previous observation.

< *Insert Table 6 about here* >

Overall, our analysis of transition probabilities indicates that for small firms involvement in M&S activity is associated with innovation dynamics that are more persistent and easier to initiate in terms of both engagement in innovative activities broadly defined, and the ability to extract value from these activities. In contrast, in large firms, the difference and possible advantages of M&A involvement seem to concentrate on innovation output.

4.2. State dependence and M&A in a dynamic model of innovation

To test whether the variety of innovation dynamics observed between M&A active and non-active firms can be considered an effect of the firm's engagement in M&A, we estimate a dynamic probit model. Table 7 presents estimates of the coefficients of the probability that the firm will carry out innovation activities, broadly defined, at time *t*, as a function of the firm's previous involvement, at time *t*-1, in innovative activities and in M&A activity, of its initial innovation state, and of a set of control variables.

< *Insert Table 7 about here* >

In the model estimated for the full sample of firms, the coefficient of the lagged innovative status $(Innov_{i,t-1})$ is statistically significant and positive, indicating the presence of serial correlation in innovation activities, for firms that did not engage in M&A at *t*-1. With respect to these firms, firms that engaged in M&A at time *t*-1, have a higher probability of continuing to innovate post-merger as indicated by the positive and statistically significant coefficient of the interaction term $(M\ \&\ A_{i,t-1} \times Innov_{i,t-1})$. Also, firms that were involved in M&A at time *t*-1, have a higher probability of advancing from non-innovator to innovator, than firms with no M&A activity, indicated by the positive and statistically significant coefficient of the interaction term $(M\ \&\ A_{i,t-1} \times NONInnov_{i,t-1})$.

Therefore, firms involved in M&As are more likely, post-merger, to cross the threshold of innovation or to persist in their innovative activity, compared to firms that do not engage in M&A.

When estimating the model separately for small, medium and large firms, we find strong heterogeneity in post-merger innovative patterns across size classes. The coefficient of $Innov_{i,t-1}$, is statistically significant across size classes indicating a general degree of persistence in innovative activity for firms with no M&A activities. However, when considering the interaction effect $(M\ \&\ A_{i,t-1} \times Innov_{i,t-1})$, which captures variation in the persistence of innovation for M&A active firms, the coefficient is statistically significant and of comparable size, for medium and large firms; it is not statistically significant for small firms. Small firms do not seem to benefit from involvement in M&A as a way to increase their ability to maintain innovative activities over time. Differences among size classes also emerge in relation to the probability of post-merger innovative entry. In this case, the coefficient of the interaction term $(M\ \&\ A_{i,t-1} \times NONInnov_{i,t-1})$ is positive and statistically significant for small and medium firms, but not statistically significant for large firms. Therefore, the strongest effect of M&A in helping firms to overcome the innovation threshold is for the sample of small and medium firms, while there is no statistically significant effect for large firms.

The estimates for the control variables display sector specificity for firms' innovative behaviour: the coefficients of the dummy variables for technological regimes (Marsili, 2001) are statistically significant in most cases. In contrast to what we expected, firm age and firm size, and firm lagged R&D intensity do not seem to have a statistically significant effect. This might be because we use the broad definition of innovator in this model specification. The definition is based on engagement in innovative activities, which is not limited to the introduction of new products or processes, but includes any type of innovation expenditure, for which differences between structurally different firms could be relatively less relevant. Note that the firm's initial innovation status positively and significantly affects its current innovation status, confirming the path-dependent nature of innovation. This applies across all size classes.

To assess the robustness of the observed patterns with respect to the measurement of innovation and the time lag, we estimate the model, using turnover from innovative products to identify a firm as an innovator, and a two-time periods lag. Thus, we compare M&A involvement and post-merger innovation output over non-adjacent CIS waves. Table 8 reports the estimates. The coefficient of the lagged innovative state $(Innov_{i,t-2})$ is statistically significant for the whole sample and the sample by size classes, confirming the general persistent nature of innovation in the reference group of firms that do not undertake M&A. Compared to this group, engagement in M&A seems to confer an advantage in innovation persistence, which however is mainly concentrated in large firms. In fact the coefficient of the interaction term between the M&A dummy and the dummy variable for an innovator is statistically significant for the whole sample, and for large firms only among the size classes. The effect of M&A involvement on innovative entry appears to be stronger. In this case a statistically significant coefficient of the interaction term between the M&A dummy and the dummy variable for a non-innovator, is observed in the whole sample and across all size classes, although, as in the case of innovation persistence, the effect is more pronounced for large firms. Overall, for the returns that firms are able to realize from the commercialization of innovation, large firms seem to benefit the most from M&A in order to sustain innovation over time or to cross the innovation threshold.

< Insert Table 8 about here >

With regard to the control variables, sector specificities are statistically significant and are captured by the dummies for technological regimes. Firm size and its square term have statistically significant effects in the whole sample and the group of medium-sized firms. However, the coefficients show the opposite sign, suggesting that there is a general positive tendency as firm size increases to be innovators up to a certain threshold, with the highest probability of being an innovator for medium-sized firms. The coefficient of firm age is negative and statistically significant, in the full sample and in central size class, indicating that the probability of being an innovator is higher for relatively young firms, especially among medium-sized firms. Overall, innovators seem to be concentrated among firms that are young, but have achieved a certain amount of growth. Furthermore, the positive and statistically significant effect of the time average of firm age reflects the influence of a longer persistence of the firm across CIS waves. With regard to R&D intensity, the coefficients are generally statistically significant, with a negative sign on the lagged value and positive sign for the time average. This indicates that firms are more likely to be innovators when they invest more in R&D as a general trend, and in particular when their R&D intensity has increased over time (in this case their initial lagged value would be lower). This suggests that it is not only the level but also the dynamic of R&D investment that matters.

5. Discussion and conclusions

This paper provides new evidence on patterns of entry and persistence in innovative activities across firm size classes, and highlights how these patterns are affected by engagement in M&A. We used non-parametric analysis, that is, TPM, to examine whether or not the observed innovation patterns differ between M&A active and non-active firms. We employed parametric analysis, a dynamic RE probit model, to analyse whether M&A act as incentives/determinants of firms crossing the innovation threshold and/or continuing to innovate. We constructed a longitudinal dataset of manufacturing firms in the Netherlands for the period 1994-2002, matching innovative performance data from four CIS waves with firm demographic characteristics from the BR.

Both the non-parametric and parametric analyses show that previous involvement in M&A influence the dynamic of firm innovation. We find that M&A involvement increases both the probability of making a transition from non-innovator to innovator and the probability of continuing to be an innovator conditional on having innovated in the previous period. The effects of an M&A, therefore, can be valued in terms of enhanced ability to cross the innovation threshold and to maintain innovation over time. This is a general effect observed in the whole sample of manufacturing firms, for both indicators of innovative activities and innovative output. At the same time, there are differences across size classes showing that firm size influences the way engagement in M&A activity can change innovation dynamics.

Small firms tend to be occasional innovators. For them, M&A activities offer the possibility to overcome the innovation threshold: M&A involvement increases the probability of their making the transition from non-innovator to innovator, in the case of both initial investment in innovative activity or achieving a first sale of an innovative product. For persistence in innovation, our results show that M&A involvement is not enough for small firms to become persistent innovators, either in terms of performing innovative activities or achieving innovative output. Small firms encounter the greatest difficulty to be innovative on a continuous basis and not even additional sources of knowledge and capabilities gained through an M&A would seem to enable this.

In medium-sized firms, M&A activity seems to have a more diffuse impact on innovative activities and performance. These firms profit from M&A activities in relation to overcoming the innovation threshold (i.e. becoming innovators after an M&A having not innovated in the previous period) and, to a certain extent, of persisting in innovation, by conducting innovative activity but not necessarily producing innovative output.

Finally, large firms, which are the most persistent innovators, are those that most benefit from M&A activity as a strategy to promote persistent innovation. Despite the evident benefits of M&A for large firms that are already innovators, the implications for those that were non-innovators on the probability to make the transition to innovator, are more nuanced. Our findings show that non-innovative large firms that engage in M&A display a higher probability to achieve a positive turnover from innovative products some time after the merger, but are not more likely to undertake innovative activities. This asymmetric outcome in innovation dynamics, compared to what we observed for small and medium sized firms, would seem to support the idea that the motivations for undertaking a M&A in relation to innovation differ between large and small firms. In SMEs, innovation seems to drive M&A as a way to provide an external source of new knowledge and resources that enhances internal innovative capabilities. Conversely, in the case of large firms, M&A occur for other reasons such as achievement of market dominance or entry into new sectors, and innovative performance could be achieved through the acquisition of firms with innovative products to bring to the market.

Although our study does not account explicitly for the specific characteristics of M&A deals, it points to a variety of patterns that emerge when we consider the full range of M&A across firm size classes. It provides new insights into the consequences of M&A, which management studies often examine from the perspective of large public firms (Haleblian et al. 2009). This literature has debated whether acquisitions are beneficial to the buyers as channels to access external resources and capabilities; or rather they are detrimental to organizational performance because of shift of managerial attention from core activities (Hitt et al., 1990; 1991). Our study provides evidence that through M&A buyers can enhance they ability to maintain or to activate innovative capabilities over time. Our results are based on a sample where innovators are remarkably more present in M&A active firms than non-active firms, and are consistent with the view that technology related M&A can be effective to improve innovative performance (Hagedoorn and Cloodt, 2003; Cassiman et al., 2005; Cassiman and Veugelers, 2007). As a limitation, however, our analysis, which is based on the observation of innovation patterns pre- and post-acquisition, does not account for the specific mechanisms that may explain the observed shift. In fact, other explanations than technology acquisition may be responsible for a post-merger change in innovation patterns, for example increased economic incentives to pursue innovation following post merger changes in the structure of the industry; and these incentives, as our findings suggest, may vary with firm size. A possible direction for future research could be to explore how differences in motivations and deal characteristics across the firm size distribution, might influence the outcomes of M&As for innovative performance.

Our results have implications for policy. First, they show that M&A enhance innovation persistence (true state dependence) for medium and large firms. When innovation is state dependent, policies that enhance innovation will have lasting effects since they will affect not only the current level of innovation, but will stimulate long-lasting innovation activity. Thus, large firms could argue reasons of efficiency to justify an M&A application which might provide them with a monopoly position. Further, the increased concentration of small and medium firms enabled by M&A should be welcomed since increased size of the firm and the resources available to it, could increase the possibility of producing an innovation, especially for small firms, allowing them to overcome the innovation threshold.

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Table 1. Variables and definitions of patterns of innovative behaviour

Dimension	Variable	Description
New-entrant innovators	Transition non-innovator$_t$ /innovator $_{t+1}$	Firms register a change in innovative behaviour from non-innovative status in the current CIS wave to innovative status in the following CIS wave
Persistent innovators	Transition innovator$_t$ /innovator $_{t+1}$	Firms register no change in innovative behaviour, remaining in the innovative status in the current and in the following CIS wave
Exiting innovators	Transition innovator$_t$ /non-innovator $_{t+1}$	Firms register a change in innovative behaviour from innovative status in the current CIS wave to non-innovative status in the following CIS wave
Persistent non-innovators	Transition non-innovator$_t$ /non-innovator $_{t+1}$	Firms register no change in innovative behaviour, remaining in the non-innovative status in the current and in the following CIS wave
Involvement in M&A transactions	M&A status at time $_{t-1}$	Firms have acquired another firm or been involved in a merger in the previous CIS
Marsili's taxonomy	Constructed on the basis of 3 digit SIC code	Firm taxonomy: science-based, fundamental-process, complex-systems, product-engineering, continuous process (see Appendix)
Firm size	Number of employees	Size classes: small (10-49), medium (50-249), and large (>250)
Firm age	Months since the date of entry in the Business Register	

Table 2: Composition of the CIS panel by year

	1994-96 CIS 2		1996-98 CIS 2.5		1998-2000 CIS 3		2000-02 CIS 3.5	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Based on Innovative Activities								
Innovators	2,075	63.4	2,424	56.5	1,947	56.7	1,515	52.2
Non-innovators	1,200	36.6	1,867	43.5	1,485	43.3	1,388	47.8
Total	3,275	100.0	4,291	100.0	3,432	100.0	2,903	100.0
Based on Innovative Sales								
Innovators	1,872	57.2	2,183	50.9	1,574	45.9	1,077	37.1
Non-innovators	1,403	42.8	2,108	49.1	1,858	54.1	1,826	62.9
Total	3,275	100.0	4,291	100.0	3,432	100.0	2,903	100.0
M&A active	708	21.6	925	21.6	292	8.5	Variable	
M&A non-active	2,567	78.4	3,366	78.4	3,140	91.5	not	
Total	3,275	100.0	4,291	100.0	3,432	100.0	present	
Size distribution								
Small (< 50 emp)	1,519	46.4	2,456	57.2	1,862	54.2	1,206	41.5
Medium (50-250 emp)	1,439	43.9	1,480	34.5	1,227	35.8	1,391	47.9
Large (> 250 empl)	317	9.7	355	8.3	343	10.0	317	10.9
Total	3,275	100.0	4,291	100.0	3,432	100.0	2,903	100.0

Table 3: Frequency table and measures of association between the two proxies of firm innovation

	Non-Innovative Activities		Innovative Activities		Total	
	Freq.	%	Freq.	%	Freq.	%
Non-Innovative Sales	5,940	100.0	1,255	15.8	7,195	51.8
Innovative Sales	0	0.0	6,706	84.2	6,706	48.2
Total	5,940	100.0	7,961	100.0	13.901	100.0
%	42.7		57.3			100.0

Note: Observations in CIS 2, 2.5, 3 and 3.5

Measures of association:

Pearson $\chi^2(1) = 9.7 \text{ x } 10^3$ Pr = 0.000

Likehood_ratio $\chi^2(1) = 1.2 \text{ x } 10^4$ Pr = 0.000

Cramer's V = 0.8339

Gamma = 1.0000 ASE = 0.000

Kendall's τ-b = 0.8339 ASE = 0.004

Table 4a: Number of firms by Innovative Activities and M&A

	M&A non-active		M&A active		Total
	Freq.	%	Freq.	%	
Non-innovator	5,454	45.5	486	25.3	5,940
Innovator	6,522	54.5	1,439	74.7	7,961
Total	11,976	100.0	1,925	100.0	13,901

Table 4b: Number of firms by Innovative Sales and M&A

	M&A non-active		M&A active		Total
	Freq.	%	Freq.	%	
Non-innovator	6,584	55.0	611	31.7	7,195
Innovator	5,392	45.0	1,314	68.3	6,706
Total	11,976	100.0	1,925	100.0	13,901

Figure 1: Percentage of innovators across technological clusters (CIS 2)

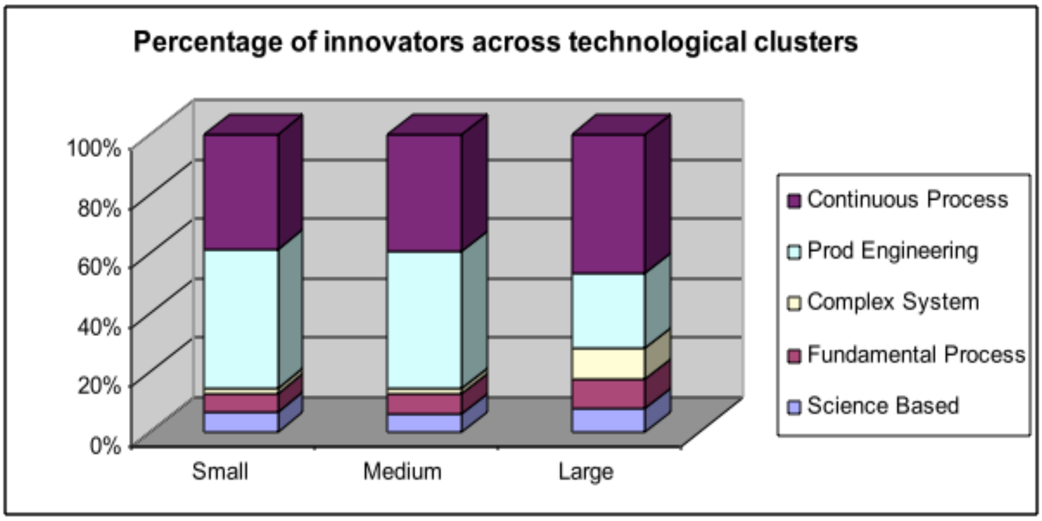

Table 5a: Transition probabilities between innovative states by M&A involvement and size class

Innovative activities	Small firms		Medium firms		Large firms	
	Time *t*+1		Time *t*+1		Time *t*+1	
Time *t*	Non-innovator	Innovator	Non-innovator	Innovator	Non-innovator	Innovator
M&A active firms						
Non-innovator	76.9	23.1	61.4	38.6	57.9	42.1
Innovator	37.8	62.2	22.8	77.2	16.3	83.7
M&A non-active firms						
Non-innovator	78.9	21.1	69.0	31.0	53.6	46.4
Innovator	39.4	60.6	28.4	71.6	15.9	84.1

Table 5b: Transition probabilities between innovative states by M&A involvement and size class

Innovative sales	Small firms		Medium firms		Large firms	
	Time *t*+1		Time *t*+1		Time *t*+1	
Time *t*	Non-innovator	Innovator	Non-innovator	Innovator	Non-innovator	Innovator
M&A active firms						
Non-innovator	71.9	28.1	70.4	29.6	35.7	64.3
Innovator	36.9	63.1	24.5	75.5	13.9	86.1
M&A non-active firms						
Non-innovator	84.9	15.1	74.0	26.0	63.7	36.3
Innovator	44.4	55.6	28.5	71.5	22.7	77.3

Note: Values are reported as percentages

Table 6: Test of differences in transition probabilities for the innovative output state, between M&A active and M&A non-active firms

	Small firms	Medium firms	Large firms
Innovative entry (P_{01})			
Estimated probability			
M&A active (p_1)	0.281	0.296	0.643
M&A non-active (p_2)	0.151	0.260	0.363
Sample size[a]			
M&A active (n_1)	153	253	42
M&A non-active (n_2)	635	747	91
Estimated probability under H_0 of equality (p)	0.176	0.269	0.451
z-statistic for p_1-p_2	3.78***	1.14	3.02***
Innovative persistence (P_{11})			
Estimated probability			
M&A active (p_1)	0.631	0.755	0.861
M&A non-active (p_2)	0.556	0.715	0.773
Sample size[b]			
M&A active (n_1)	260	690	244
M&A non-active (n_2)	464	1154	273
Estimated probability under H_0 of equality (p)	0.583	0.730	0.814
z-statistic for p_1-p_2	1.96**	1.88*	2.56***

Notes:
[a] Sample size is defined by the number of non-innovators at time *t*
[b] Sample size is defined by the number of innovators at time *t*
P_{01} is the transition probability from non-innovator state at *t* to innovator state at *t*+1
P_{11} is the transition probability from innovator state at *t* to innovator state at *t*+1
The z-statistic for P_{00} (non-innovator at *t* and non-innovator at *t*+1) is equal in absolute value to the figure for P_{01}. since P_{00}=1-P_{01}. As well. the z-statistic for P_{10} (innovator at *t* and non-innovator at *t*+1) is equal in absolute value to the statistic for P_{11}. since P_{10}=1-P_{11}

Table 7: Post merger patterns of innovative activities

Dependent variable	Random effect probit model Innovative state *t*							
	All firms		Small firms		Medium firms		Large firms	
	B	Std. Err.	B	Std. Err.	B	Std. Err.	B	Std. Err.
Innovative state (*t*-1)	3.19	(0.25)***	2.54	(0.69)***	3.12	(0.29)***	1.77	(1.12)***
Innovative state (t_0)	1.96	(0.17)***	1.38	(0.47)***	1.85	(0.2)***	2.50	(0.53)***
M&A(*t*-1)*Innovator(*t*-1)	1.36	(0.17)***	0.78	(0.51)	1.43	(0.2)***	1.50	(0.43)***
M&A(*t*-1)*Non-innovator(*t*-1)	3.6	(0.24)***	3.02	(0.61)***	3.87	(0.27)***	0.78	(1.06)
R&D Intensity (*t*-1)	0.06	(0.04)	4.30	(6.4)	0.05	(0.05)	3.91	(4.9)
Firm size	1.23	(1.09)	0.01	(0.01)	-1.8	(2.8)	-0.95	(5.03)
Square of size	-0.05	(0.06)	-0.75	(0.04)**	0.21	(0.25)	0.23	(0.27)
Firm age	0.25	(1.90)	3.85	(6.2)	2.43	(2.6)	-3.90	(5.4)
Square of age	-0.11	(0.16)	-0.51	(0.55)	-0.3	(0.2)*	0.46	(0.36)
Age*Size	0.22	(0.02)***	0.45	(0.15)***	0.25	(0.32)	-0.18	(0.45)
Fundamental process	2.89	(0.50)***	1.00	(2.5)	1.6	(1.03)*	2.65	(0.8)***
Science based	3.43	(0.57)***	2.35	(2.6)	1.87	(1.1)*	2.52	(1.03)***
Production engineering	3.82	(0.60)***	1.14	(2.66)	2.76	(1.14)***	3.33	(1.07)***
Complex system	3.11	(0.51)***	-0.13	(0.96)	2.14	(1.03)**	2.63	(0.91)***
Wald Chi^2	554.8***		56.78***		391.8***		71.48***	
Rho	0.91		0.9		0.91		0.89	
Number of observations	5571		976		3967		628	

Note: Standard errors in parentheses. *** 1%, ** 5%, * 1% significant.

Note: Standard errors in parentheses. *** 1%, ** 5%, * 1% significant.

Table 8: Post merger patterns of innovative sales

	Random effect probit model							
Dependent variable:	Innovative state *t*							
	All firms		Small firms		Medium firms		Large firms	
	B	Std. Err.	B	Std. Err.	B	Std. Err.	B	Std. Err.
Innovative state (*t*-2)	1.11	(0.06)***	1.17	(0.13)***	0.99	(0.07)***	0.85	(0.21)***
M&A(*t*-2)*Innovator(*t*-2)	0.18	(0.09)**	0.04	(0.2)	0.12	(0.11)	0.62	(0.27)**
M&A(*t*-2)*Non-innovator(*t*-2)	0.55	(0.13)***	0.57	(0.31)*	0.38	(0.17)**	1.40	(0.53)***
R&D Intensity (*t*-2)	-0.03	(0.01)***	-0.03	(0.01)**	-0.11	(0.02)***	0.02	(0.04)
Firm size	0.61	(0.26)**	-0.19	(1.21)	-3.04	(1.76)*	-0.25	(2.44)
Square of size	-0.03	(0.02)*	0.09	(0.11)	0.39	(0.18)**	0.02	(0.15)
Firm age	-1.41	(0.48)***	-0.34	(1.4)	-1.85	(0.72)***	-1.33	(1.7)
Square of age	0.04	(0.03)	-0.02	(0.09)	0.05	(0.04)	0.06	(0.09)
Age*Size	-0.002	(0.03	0.02	(0.18)	0.001	(0.09)	0.03	(0.15)
Fundamental process	0.18	(0.14)	-1.01	(0.44)**	-0.47	(0.26)*	0.81	(0.28)***
Science based	0.33	(0.17)**	-0.55	(0.45)	-0.8	(0.29)***	1.52	(0.52)***
Production engineering	0.19	(0.17)	-0.86	(0.47)*	-0.44	(0.3)	0.52	(0.41)
Complex system	0.32	(0.14)**	-0.91	(0.44)**	-0.35	(0.26)	1.08	(0.35)***
Time average firm size	-0.05	(0.12)	-0.18	(0.24)	-0.15	(0.17)	-0.02	(0.28)
Time average firm age	0.94	(0.21)***	0.44	(0.63)	1.24	(0.26)***	0.33	(0.56)
Time average R&D intensity	0.13	(0.01)***	0.06	(0.02)***	0.35	(0.03)***	0.14	(0.05)***
Constant	-1.37	(1.38)	-0.24	(3.93)	7.92	(4.74)	2.52	(10.28)
Wald Chi2	860.0***		139.1***		528.5***		76.5***	
Rho	0.0		0.0		0.0		0.17	
Number of observations	3236		601		2122		513	

Appendix:

Table A1: Marsili (2001) classification of technological regimes

Technological Regime	Characteristics	Typical for:
Science based	High technological opportunity High entry barriers High cumulativeness of innovation	Pharmaceuticals; electrical/electronics industries
Fundamental process	Medium technological opportunity High entry barriers Strong persistence of innovativeness	Chemistry based technologies
Complex(knowledge) system	Medium/High technological opportunity Entry barriers in knowledge/scale High degree of differentiation	Mechanical, Electrical, Electronics, Transportation
Production Engineering	Medium/high technological opportunity Low entry barriers	Mechanical engineering, non-electrical mechanics
Continuous Process	Low technological opportunity Low entry barriers Low persistence of innovativeness	Metallurgic process industry, chemical process industry (food, textiles, tobacco, paper)