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Landmarks as lighthouses: firms' innovation and modes of exit during the business cycle☆

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A B S T R A C T

We revisit the relationship between innovation and survival, tracking how innovation types (product, process, organizational, and marketing innovation) relate to exit routes (closure, failure, M&A) during different phases of the business cycle (i.e. normal times, the 2007–08 financial crisis and subsequent recovery). In particular, we implemented a new (to the economic field) econometric approach, landmark analysis, to include time-varying covariates in survival models with competing exit routes on our representative sample of Dutch firms (obtained merging monthly register data with biennial innovation surveys, for 2006–2015). Our most straightforward result is that each type of innovation, across the different phases of the business cycle, affects, in a substantially different way, the likelihood to exit the market through different modes of exit. Innovations seems to grant some innovation premium, but no common pattern appears between the evolution of the relationships between different types of innovation and exit routes across the business cycle.

1. Introduction

At the national level, private investment in innovation is an important driver of productivity growth and economic development, although at the firm-level the incentives to invest in R&D are affected by uncertainty regarding the amount and timing of returns, and threats from rivals. Indeed, not all firms benefit from investments in innovation, and some avoid innovation altogether. As a response to perceived underinvestment in innovation by firms, most governments have elaborate policies in place to provide incentives to (potential) innovators. The incentives to innovate are especially crucial during an economic crisis, such as the recent 2007–08 financial crisis or the contemporary 2020 Covid crisis. There is evidence that the crisis is killing longer-term investments, such as R&D (Garicano and Steinwender, 2016), as firms shorten their planning horizons as a reaction to heightened uncertainty. Therefore, there is considerable interest in the fates of innovative firms during the crisis (Filippetti and Archibugi, 2011; Archibugi, 2017).

While some studies suggested that innovation enhances survival (Cefis and Marsili, 2005, 2012; Wagner and Cockburn, 2010; Colombelli et al., 2013), more recent work has shown that innovative activity can sometimes increase the probability of exit, because of the extra risks brought on by innovation (Fernandes and Paunov, 2015; Hyytinen et al.,

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2015; Howell, 2015). Indeed, innovation is uncertain, with regards to the overall gains and the payback time (Malerba and Orsenigo, 2000; Klette and Kortum, 2004). Innovative firms may also be more likely to exit, if entrepreneurs with high human capital and attractive outside options accelerate their firms towards either rapid success or failure, rather than persisting with an unexceptional performance (Arora and Nandkumar, 2011). The relationship between innovation and firm survival therefore remains worthy of further investigation, especially when considering periods of high instability.

Recently, some papers have studied the effects of innovation on firms' survival during the 2007–08 financial crisis given the uncertain and risky nature of innovation. Among others, Landini et al. (2020), Cefis and Marsili (2019), and Cefis et al. (2020) find that there still exists an innovation premium in terms of survival even if it differs with respect to the one enjoyed in normal times. This premium is also differently qualified with regard to the different types of innovations, with technological innovation being more rewarding than non-technological innovation (Cefis and Marsili, 2019; Fernandes and Paunov, 2015). In all these papers, innovations or intangible assets (Landini et al., 2020) are captured at the beginning of the crisis and they are time-invariant, as if they were an "initial condition"[1] that would influence the firms' survival during and after the crisis. Furthermore, even if they include different types of innovations (Fernandes and Paunov, 2015; Cefis and Marsili, 2019; Cefis et al., 2020), they do not consider different exit routes, or they are focused only on subsamples of firms, e.g. start-ups. Therefore, there is still need of a study that can put together the different dimensions (in particular: types of innovation, modes of exit, and business cycle phases) that affect the relationship between innovation and firms' survival.

In this exploratory paper, we investigate in a representative sample of Dutch firms the relationship between different types of innovations and different modes of exit (namely through closure, failure, and M&A) before, during, and after the 2007–08 financial crisis. More specifically, we investigate the effects of *time-varying* innovative behaviours of firms on both the instantaneous hazard and the cumulative probability to exit the market, from an initial pre-crisis period through the peak of the crisis to the recovery. In this way, we are able to show how the relationship between innovation types and exit routes distinctively changes in the different phases of the business cycle.

To achieve our goal, we introduce to the economic field new techniques from epidemiology (Van Houwelingen, 2007; Cortese and Andersen, 2010; Putter and Van Houwelingen, 2017), that highlight these effects in a "punctuated" way (landmark analysis), rather than reporting "average" effects over the entire period of analysis (from standard estimators such as Cox models or parametric survival models such as complementary log-log regressions), while taking into consideration different causes of exit. We go beyond the current state-of-the-art in the methodology of survival regressions in economics (for a survey see Josefy et al., 2017) by improving upon competing risk models (CRMs) in two ways. First, we aim to complement cause-specific hazards with estimates of the overall probabilities of exit. Second, in this setting, CRMs have limitations on the ability of including time-varying covariates (Fontana and Nesta, 2009) because of their endogeneity. To overcome these limitations, CRMs have been estimated using only covariates which are fixed in time (Cefis and Marsili, 2012; Colombelli et al., 2013; Børing, 2015; Kato and Honjo, 2015). However, proxying time-varying covariates with constant variables (when they are not considered "initial conditions") is a misspecification (Cameron and Trivedi, 2005, p.598), as the overall evolution of such variables might be of great explanatory interest. We therefore reiterate our CRMs introducing landmark analysis (Van Houwelingen, 2007; Putter and Van Houwelingen, 2017). Landmark analysis is a natural choice in our context, where biennial innovation surveys jut out amidst the flow of monthly observations on survival. In the same landmark approach, we use an emerging (for economics) graphical methodology – Cumulative Incidence Functions – for plotting the cumulative probability of exit in the case of competing risks, that does not require independence between the competing exit routes. These CIFs show how different types of innovative activities, which change during the period, affect the probability to exit the market via alternative exit routes.

We take a representative sample of Dutch firms observed in 2006 (9667 firms) and track them for 10 years, to investigate whether various innovation types (product, process, organizational, and marketing innovation) influence their survival prospects (for three exit routes: closure, failure, and M&A) through the crisis and recovery. We build a new panel dataset starting from the cohort given by the Community Innovation Survey (CIS) in 2006 and merge it with two subsequent CIS waves (2008, 2010). We merge the resulting panel data set with the Business Register data that supplies information on demographic firms' characteristics and on different exit routes in a monthly cadence.

The new methodology constitutes our main contribution. Our results highlight how firms' innovation behavior changes during times of crisis and recovery. We capture these changes by removing the usual restriction that innovation behaviours remain fixed, thus allowing the innovation variables to vary during the study period. Our most straightforward result is that each type of innovation, comparing across normal times, crisis and recovery, affects, in a substantially different way, the likelihood to exit the market through different modes of exit. Our analysis emphasised the evolution over time of each relationship between innovation types and exit routes.

In general, no common pattern appears between the evolution of such relationships. In particular, we observe that product innovation grants a survival premium against closure both before and after the crisis, but not in the midst of it. This cautions that while innovation can generally be rewarding in normal times, rewards to innovation are lower during the crisis, exposing innovators to considerable risks. Furthermore, product innovation decreases the likelihood to exit via M&A during the crisis and recovery, but not in normal times. Therefore, product innovation arguably grants the most comprehensive survival premium. Process innovation, in normal times, reduces the likelihood of all exit events. However, this relationship is weaker during both crisis and recovery: a significant shielding effect is maintained only against closure in times of crisis. With regard to non-technological forms of innovation, they do not affect the survival likelihood as substantially and reliably as for technological innovation. Organizational innovation is generally non-significant for survival, if not detrimental. Actually, the risks of closure for organizational innovators are higher during crisis and recovery. Similarly, marketing innovation is non-significant for all exit routes during normal times. On the one hand, the negative effect of marketing innovation on the risk of failure is larger during the crisis. On the other hand, marketing innovations reduces the probability of exit via M&As during crisis and recovery phases, but not in normal times.

2. Background literature and research questions

2.1. Types of innovations and exit routes in normal times

Scholars have previously observed that innovation activities confer an *innovation premium* to firms, substantially decreasing their likelihood of exit (Cefis and Marsili, 2005). Successful innovations grant a competitive advantage (Schumpeter, 1934). More importantly, independently of the degree of success of firms' innovative efforts, innovative activities transform firms' internal competences, routines, and capabilities (Nelson and Winter, 1982), thus enabling firms to better face ongoing and future market challenges. Innovation represents a source of learning (Cohen and Levinthal, 1990), improving firms' capabilities of

[1] For example, Cefis and Marsili (2019) considered innovation variables to be constant because they capture the founding conditions of the new ventures and then they investigate the consequences of these founding conditions on survival in the following periods.

recombining existing knowledge and competences to pursue existing opportunities or to exploit new opportunities (Teece et al., 1997). Even if innovation usually benefits survival, only recently have scholars suggested that different types of innovation have different effects on survival (inter alia: Cefis and Marsili, 2012; Børing, 2015). Earlier studies[2] focused mainly on technological forms of innovation (product and process innovations) generally finding a positive effect of innovation on survival (e.g. Cefis and Marsili, 2006), while very few studies broadened the field considering also non-technological forms of innovation (Cefis and Marsili, 2019; Ortiz-Villajos and Sotoca, 2018). In line with the existing literature, we consider three main exit routes, namely closure (the voluntary termination of economic activities), failure (the dismantlement or unsuccessful restructuring of the exiting firm), and merger or acquisition (M&A: the acquisition of the firm as a target, or its merger with one or more firms into a new unit).

Product innovation is a new or substantially improved technical solution. Product innovators benefit from increased profits and market share (Nelson and Winter, 1982). They can be safeguarded from imitators through the use of intellectual property rights (Teece, 1986), which may grant a temporary monopoly power (Schumpeter, 1934; Cohen and Klepper, 1996). Overall, scholars have previously observed how product innovators are less likely to exit via closure or failure (Fernandes and Paunov, 2015; Buddelmeyer et al., 2010; Esteve-Pérez et al., 2010; Wagner and Cockburn, 2010). While beneficial, the outcomes of investments in product innovation are inherently surrounded by uncertainty (Malerba and Orsenigo, 2000; Schubert and Tavassoli, 2020). Furthermore, it requires substantial investments, mainly taking the form of sunk costs (e.g. intramural or extramural R&D, machinery, equipment, or software, Cefis, 2010). Therefore, if returns do not materialize or are lower than expected, firms may incur financial distress if unable to overcome the costs and risks linked to product innovation (Ponikvar et al., 2018a, 2018b) leading to an increased probability of exiting by closure and failure (Cefis and Marsili, 2012). Finally, the value of product innovation indicates proximity to the technological frontier, and it acts as a signal of firm's quality (Fontana and Nesta, 2009), drawing the attention of potential acquirers and therefore increasing the likelihood of exit via acquisition (Cefis and Marsili, 2012; Børing, 2015).

Process innovation improves production or delivery methods, granting an increase in quality or a reduction in costs, thus increasing profit margins (Klepper, 1996). It is often introduced through new software and machinery, usually available on the open market (Pavitt, 1984), hence reducing its appropriability (Tavassoli and Karlsson, 2015). Process innovation allows to cut production costs and enhance productive efficiency. Such benefits are immediate, because it upgrades the existing production rather than creating new products which require further marketing. Moreover, unlike product innovation, it does not require prior, substantial long-term innovation investments to be implemented, unless it concerns a radical change of the entire production process of the firm. Therefore, in general, process innovation can grant managers a quicker route to improve productivity and profitability, rather than betting on the successful development of new products or services, decreasing the overall risk of exit by closure and failure (Cefis and Marsili, 2012; Ortiz-Villajos and Sotoca, 2018). Firms adopting or developing new production processes are usually more efficient and/or on the technological frontier, becoming an interesting target for M&A (Børing, 2015).

Organizational innovation is managerial rather than technological (Birkinshaw et al., 2008; Mol and Birkinshaw, 2009). It directly concerns the organization of employees and the configuration of business activities, affecting routines and procedures and the utilization of a firm's knowledge base. Organizational innovation is internally initiated by managers and can therefore be undertaken in relative autonomy, without requiring validation from demand-side actors (such as for product innovation). Managers pursue organizational innovation with the intent of improving the internal flow of information and division of labour (Volberda et al., 2013; Ballot et al., 2015), increasing internal efficiency and performance when successful (Birkinshaw et al., 2008; Mol and Birkinshaw, 2009). However, the transformation of internal organization and knowledge structure might be hindered by resistance from internal actors (Tavassoli and Karlsson, 2015) and trigger a period of disruption and uncertainty when implemented. While high capacity utilization and internal resistance decrease the desirability of organizational innovations in normal times, its introduction can prove beneficial for such innovators, decreasing their likelihood of exit via closure and/or failure (Ortiz-Villajos and Sotoca, 2018). Organizational changes may be introduced without following formal steps or procedures, or codified strategies, making them less detectable by potential acquirers. Furthermore, socially embedded resources and routines are more difficult to preserve in corporate transactions such as acquisitions, often being disrupted in the subsequent integration phase (Ranft and Lord, 2002; Graebner et al., 2017), making organizational innovators less-desirable targets, thus decreasing the likelihood of organizational innovators to exit via M&A.

Marketing innovation affects the relationship between market orientation and firm performance, offering an affordable "*quick fix*" to reinvigorate performance and tune profitability (Naidoo, 2010, p.1311). Changes to the marketing strategy are crucial in determining the appeal of products in the reference market, or in promoting their entry into unexplored ones. Building on existing products, marketing innovation tends to be incremental (Grewal and Tansuhaj, 2001; Naidoo, 2010). Since it can be easily outsourced to consultants, it is not a source of long-lasting competitive advantage (Barney, 1991) and its appropriability is low (Tavassoli and Karlsson, 2015). However, it does not require the costly and time-consuming internal development of resources and competences specific of other innovative activities. Given its incremental nature and relatively lower costs compared to other innovation types, marketing innovation can decrease the chances to exit via closure (Buddelmeyer et al., 2010; Helmers and Rogers, 2010), but empirical findings remain mixed, probably due to its mostly short-term focus (Ortiz-Villajos and Sotoca, 2018).

Overall, the previous arguments and the findings of the extant literature remain mixed, particularly if firms' exit is unpacked, not discriminating between exit routes on the basis of their specific economic/business meanings (Schary, 1991; Balcaen et al., 2012; Wennberg and DeTienne, 2014; Cefis et al., 2021). Therefore, our first research question investigates the relationship between each innovation type and exit route in "normal times", i.e. times of prosperity that are neither recession nor recovery:

Research question 1 (RQ1): How does each type of innovation affect each exit route in normal times?

2.2. Types of innovations and exit routes throughout the business cycle

The 2007–08 financial crisis was an unexpected shock that slammed the Dutch economy, causing the largest economic contraction since World War II.[3] During a crisis characterized by a demand shock and a credit crunch, firms are forced to adapt to the new environmental conditions (Steenkamp and Fang, 2011). Innovative activities are usually promptly re-examined, with firms adjusting their investments in R&D (Garicano and Steinwender, 2016). The available resources for innovation dry up: firms' accumulated profits are depleted, demand remains low, and fewer resources are available from the credit market, linked to the risk-aversion of both investors and consumers. Emerging from the recession phase, prospects improved as demand started to pick up again (albeit slowly) and credit constraints became less binding. However, the

[2] We have included a literature table on firm innovation, exit routes, and survival which is provided in Appendix A.

[3] For details, see the Online Supplementary Materials, Appendix OSM1.

competitive environment remained different (OECD, 2014). Surviving firms were presumably more adaptive and efficient than those existing before the crisis, because of the well-known 'cleansing effect' of recessions (Caballero and Hammour, 1994; Bartoloni et al., 2020). Recovery changes the rules of competition impelling firms to introduce any available innovative techniques, overcoming the usual resistance to change (Tavassoli and Karlsson, 2015).

In line with the previous sub-section, we consider the extant literature on the four types of innovation and the three main exit routes during crisis and recovery.

Product Innovation. While higher unemployment, lower wages, and a weaker factor market make R&D cheaper, creating slack resources that can be allocated towards R&D projects (Barlevy, 2007; van Ophem et al., 2019), a financial crisis causes a sudden credit shortage. The unforeseen 2007–08 crisis sharply increased the level of environmental uncertainty, imposing adaptation costs alongside missing revenues, further increasing the risks associated with product innovation. Investors might avoid bearing the uncertainty of innovation projects, preferring instead safer assets and a shorter-term investment horizon (Baker and Wurgler, 2007). Scholars have also recently observed that the novelty of patents decreased during the 2008 crisis (Silvestri et al., 2018), because innovators respond to the heightened environmental uncertainty by focusing on local search and more incremental (and less uncertain) improvements on existing products. This blurs the positive signalling effect of product innovation, decreasing the likelihood of acquisitions. As previously observed, during the 2008 crisis, firms relied on acquisitions as a mechanism to close the performance gap created by the jolt, targeting mainly domestic firms operating in the acquirers' core markets (Cerrato et al., 2016).

While potentially beneficial in normal times, product innovation can be financially burdensome. On top of requiring substantial investments and imposing sunk costs, Lahr and Mina (2021) observed that product innovation is the only form of innovation that directly generates financial constraints for innovating firms. Therefore, product innovators do not benefit from a survival premium against closure during the crisis (Cefis et al., 2020; Kato et al., 2022). Furthermore, such additional burden can irreversibly compromise the position of fragile innovators, increasing their risk of failure (Kato et al., 2022).

While process innovations focus on the cost side, product innovations require a warm reception from customers. Product innovations, therefore, depend crucially on demand conditions. Periods of crisis, however, are unsuitable times for product innovations, because consumers' reduced confidence leads them to cut or delay expenditures, while shifting their tastes away from new and riskier products (Quelch and Jocz, 2009). Thus, firms may optimally sit on their discoveries and keep them secret until demand picks up after the crisis, during times of recovery (Fabrizio and Tsolmon, 2014). This suggests that product innovations boost survival in normal times, while performing relatively badly in times of crisis, yet being more suitable in times of recovery.

Process innovations allow firms to cut costs, boost productivity, and increase efficiency (Klepper, 1996), safeguarding against financial distress (Ponikvar et al., 2018a, 2018b). The benefits of process innovation are relatively immediate because they improve existing production processes, since it can substantially decrease the likelihood of closure in times of crisis (Cefis et al., 2020). Although beneficial in decreasing exit overall (Cefis and Marsili, 2019), firms facing shrinking demand and difficulties in accessing credit may struggle to counterbalance these negative effects relying on process innovation alone. Scholars observed how production efficiency is not alone sufficient to support firm survival during the crisis, but must be paired with knowledge and skills accumulation, allowing firms to cope with the new environmental conditions (Bartoloni et al., 2020). Consequently, process innovation could prove ineffective for those firms at risk of failure throughout the crisis.

During the recovery phase, cutting costs via process innovation could be insufficient to thrive in the new competitive environment, which may require more radical adaptations, and not simply a relief against financial distress. This makes process innovations a blunt instrument to lower the risk of closure or failure, and less attractive for potential acquirers (Cefis and Marsili, 2019).

Organizational Innovation. Scholars previously argued that economic downturns are opportunities to 'clean up', introducing productivity-enhancing *organizational* changes (Caballero and Hammour, 1994). Production activities are less profitable compared to normal times, and lower capacity utilization confers some slack, decreasing the opportunity cost of diverting resources to reorganisations or workers' re-skilling (Geroski and Walters, 1995; Nickell et al., 2001). However, organizational innovations require substantial time to become effective (Birkinshaw et al., 2008). Social norms, routines and procedures are sticky and difficult to change, since they crystallise inside the firm, resulting in rigidities and lock-in effects (Nelson and Winter, 1982). Organizational innovation could therefore be destabilizing, since it disrupts such internal routines and procedures without providing immediate returns. On the one hand, when considering new entrepreneurial firms, organizational innovations could be detrimental for survival because they create excessive instability for firms whose internal organization is poorly-structured, and whose environment is already highly unstable (Cefis and Marsili, 2019). On the other hand, while larger organizations possess more resources, they are "ossified" by established norms, rules, and internal structures involving numerous actors and ties (Hannan and Freeman, 1984). Such complexity, paired with inertia, makes change more difficult and complicated, decreasing success rates, especially in an uncertain environment. Therefore, introducing organizational innovations during or in the aftermath of a crisis may prove ineffective for a firm's survival prospects, if not detrimental for the more fragile firms (Cefis and Marsili, 2019).

As previously argued, M&A events often imply the restructuring and redesigning of routines and processes inside the target firm, leading to the loss and disruption of socially embedded resources and practices (Eliason et al., 2020; Graebner et al., 2017). This makes organizational innovation less valuable than technological innovations to potential acquirers, leaving the probability of exit via M&A unaffected across the business cycle.

Marketing innovation. Marketing innovations are less resource-demanding compared to other forms of innovation, and can provide an affordable and immediate instrument to support sales (Naidoo, 2010). During a downturn, customers cope with economic adversities adopting different behaviours, which prompt firms to adjust their marketing instruments accordingly (Dekimpe and Deleersnyder, 2018). Marketing scholars confirmed how firms undertaking a proactive marketing response can outperform struggling competitors, turning recessions into opportunities (Srinivasan et al., 2005). Increased advertising during recessions can drive profit and market share relatively more than in expansions (Frankenberger and Graham, 2003; Steenkamp and Fang, 2011). Therefore, marketing innovation can support firms in decreasing the risk of closing. However, during downturns, customers tend to be less responsive to other forms of marketing outside pricing (Van Heerde et al., 2013). Furthermore, marketing scholars observed that while firms adopting a proactive marketing strategy in difficult times can benefit from a performance boost, such effect is negatively mediated by the severity of the downturn (Srinivasan et al., 2005). Consequently, while potentially beneficial, given the unprecedented contraction in demand, marketing innovation is unlikely to suffice in preventing exit during the crisis (Cefis and Marsili, 2019). In the following recovery, the external environment grows competitive. As more firms actively engage with customers and adapt to the new market conditions, long-term investments in R&D and technical innovations become again the key sources of competitive advantage. Marketing innovation should therefore not significantly influence the risk of exit (Cefis and Marsili, 2019).

Presumably, such an important environmental jolt affected the relationships between innovation types and exit routes. However, the existing literature does not punctually characterise such relationship across the two phases of the business cycle: crisis and recovery. Our analysis aims to examine how the relationships previously highlighted change during the crisis and the recovery, answering our second research question:

Research question 2 (RQ2): How do the relationships between the innovation types and exit routes evolve during times of crisis and recovery?

3. The exploratory approach

The previous subsections provided some background to the topic of innovation and survival, by drawing on previous theoretical and empirical contributions that discuss the various innovation types (product, process, organizational and marketing innovation) and exit routes (closure, failure, M&A) at various phases of the business cycle (normal times, recession, recovery). One approach could be to formulate hypotheses for each of these $4 \times 3 \times 3 = 36$ cases. However, for three reasons discussed below, it seems inappropriate to formulate a set of 36 hypotheses.

First, existing theoretical and empirical contributions are not sufficiently detailed to provide a basis for elaborating clear specific predictions for each of these 36 contingencies. While theoretical predictions may be relatively easy for some cases (e.g. product innovation and failure in normal times), predictions may be more difficult, and sometimes contradictory, in other cases (e.g. organizational innovation and M&A during a recovery). On the empirical side, previous research in this broad area has, at best, shown evidence from different samples using different econometric techniques.[4]

Second, a major contribution of this article is the application to innovation data of a new econometric technique: landmark analysis. The exploratory nature of our paper means that hypothesis-testing is less appropriate (Helfat, 2007; Hambrick, 2007). Given the large policy interest surrounding innovation and survival, the formulation of hypotheses to justify why this topic might be interesting or relevant seems less urgent (Helfat, 2007). Instead, we seek to discover new empirical facts that can be useful for subsequent theory-building (Hambrick, 2007) and policy development.

Third, is the more serious issue of Hypothesizing After the Results are Known (HARKING) which has been identified as a 'questionable research practice' (QRP) affecting the validity of research in innovation studies (Martin, 2016; Bruns et al., 2019; Hall and Martin, 2019) and related disciplines (Cox et al., 2018; Craig et al., 2020; Salandra et al., 2021). HARKing can lead to mis-interpreting and over-theorizing of false positives and spurious results that emerge from data-mining (Denton, 1985; Kerr, 1998). While HARKing may improve researchers' chances of finding statistically significant results, due to misinterpreting the meaning of *p*-values, it leads to the situation whereby papers end up resembling "works of creative fiction" rather than rigorous contributions to knowledge (Cox et al., 2018, p.926). HARKing can also lead to ignoring false negatives that may be of genuine theoretical interest. HARKing is therefore considered to be detrimental to knowledge accumulation in innovation studies (Hall and Martin, 2019). Instead of lengthy hypothesizing (HARKing) ahead of the results, exploratory empirical papers such as ours are encouraged to shift the front-end theory-based discussion of the topics to a post-hoc discussion of results that precedes the conclusion (Bamberger and Ang, 2016).

4. Research design

4.1. Data

The dataset is built matching two independent micro-economic databases managed by the Netherlands' Central Bureau of Statistics (CBS): the General Annual Business Register (ABR) and Community Innovation Surveys (CISs).

The ABR is a comprehensive longitudinal dataset on the population of companies established in the Netherlands. For each firm,[5] it reports demographic data, such as the number of employees or the SIC industrial sector, paired with the dates of market entry and exit. These events are processed with monthly frequency. Since the ABR is built for administrative and fiscal purposes, the event timing is remarkably precise. Together with the date of exit, the ABR reports the mode of exit. We distinguish three broad exit routes, defined as follows:

- *Exit by closure*: this includes exits due to the voluntary termination of activities.
- *Exit by failure*: this comprises all exits resulting from a failed corporate restructuring or which took the form of firms' dismantlement, with the consequent break-up of the initial productive unit.
- *Exit by M&A*: this consists of exits due to mergers or acquisitions. Such firms lost their identity in the process, becoming part of an already-existing unit (in case of an acquisition) or of a new productive unit (in case of a merger).

The CISs are harmonized questionnaires carried out since the 1990s by the Central Statistical Offices of EU member states under the coordination of Eurostat. CIS data have already proven valuable in investigating the determinants of innovation and its impact on firms' economic performance (Mairesse and Mohnen, 2002; Cassiman and Veugelers, 2002; Laursen and Salter, 2006). CISs are designed to collect comprehensive data on firms' innovative activities, in accordance with the guidelines of the Oslo Manual (OECD and Eurostat, 2005). Every CIS wave is built around a core questionnaire and is accompanied by a proper set of definitions and methodological recommendations, ensuring quality and comparability across waves. The CIS dataset has a longitudinal structure. The CBS distributes the CIS questionnaire in 2-years waves to a representative sample of firms with at least 10 employees at the time of sampling. The sample is stratified over size classes, 2-digit SIC industrial sectors, and geographical locations.

[4] Perhaps the closest-related paper to ours is Cefis and Marsili (2019), who use different econometric techniques and who focus on entrepreneurial firms (young firms under 6 years old, and small firms) instead of a representative sample of the full population.

[5] In line with Eurostat guidelines, in both the ABR and CISs the unit of analysis is the firm, also called 'enterprise'. It is defined as "*an organizational unit producing goods or services which has a certain degree of autonomy in decision-making, especially for the allocation of its current resources*" (Council Regulation (EEC) No 696/93). It therefore differs from the firm intended as a unique financial entity. In our database, this is defined as an 'enterprise group', a group of enterprises bound together by financial links. We control for this in our analysis by including an appropriate set of variables.

4.2. Sample cohort

We develop a cohort study, taking into consideration the cohort constituted by all firms that were sampled in the CIS 2006. They could be new ventures that entered during the year 2006 or firms already existing at the beginning of 2006. From the starting CIS 2006 representative sample, 9935 firms, we exclude firms belonging to the following sectors: Research and Development, Public administration, Education, Sports and other Social Activities.[6] We further exclude outliers in terms of number of employees. The resulting sample is composed of 9667 firms. We follow this cohort over 10 years, from the 1st of January 2006 until the 31st of December 2015. Given the longitudinal dimension of the CIS dataset, we were able to update, as we move over time, the data regarding the innovation activities contained in the CIS, using the data included in CIS 2008 and 2010.

Table 1 reports the number of exits distinguishing by type of exit. Overall, the years characterized by the highest number of exit events are 2007, when the financial crisis hits the Dutch economy, and 2009, its immediate aftermath. The three exit modalities present different patterns over years. M&A events peak in 2009. By contrast, exits by closure are more evenly distributed over years, with local peaks in 2009 and 2013. Finally, 415 out of 966 failure events are registered in 2007, at the very beginning of the crisis period. The marked differences in the incidence of the three types of exit highlight how different in nature they are and how heterogeneous was the impact of the financial crisis on the population of firms.

Table 2 reports the mean and standard deviation of the variables considered in the analysis, together with the correlation matrix estimated using ABR and CIS data in 2006. The firms composing the sample are on average 21.6 years old and have 134 employees. Nearly half of the firms in our sample (46.6 %) are, in some ways, innovators in 2006. Organizational innovators are the most numerous category (28.8 %), marketing innovators the least (11.3 %). A substantial share of the firms in our sample (56.6 %) are part of either a domestic or foreign group. As indicated by the correlation coefficients, younger and smaller firms are less likely to be part of a group. Interestingly, both group dummies are only weakly correlated with the innovation variables, with firms part of a group with a foreign headquarter being slightly more innovative. While size is positively correlated with all innovation variables, age is

Table 1
Composition of sample at landmark 2006, number of exits (by mode of exit) and number of surviving firms by year, over the period 2007–2015.

Year	M&A	Closure	Failure	n° exits at the end of each year	n° survivors at the beginning of each year
2007	156	248	415	819	9673
2008	139	273	108	520	8854
2009	841	293	80	1214	8334
2010	233	225	80	538	7120
2011	95	163	52	310	6582
2012	77	138	91	306	6272
2013	69	204	45	318	5966
2014	64	173	49	286	5648
2015	48	134	46	228	5362
Total	1722	1851	966	4539	5134

[6] We exclude the 'Research and Development' sector from the analysis because data on product and process innovations (and all the other type of innovations) are missing since the firms operating in this sector are R&D Lab or Research Institutes not directed to commercialise their product/services in the market. Firms belonging to the other sectors are excluded because they operate with a non-market rationale or are public institutions, altering inevitably their survival probabilities.

Table 2
Descriptive statistics and correlation matrix, landmark CIS 2006.

		Statistics		Correlation matrix													
	Variables	Mean	StdDev	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	Age	21.6	18	1													
(2)	Size	135	341	−0.0421*	1												
(3)	N. establishments	3.1	14.9	−0.0204*	0.3910*	1											
(4)	Limited-liability	0.863	0.344	0.0253*	−0.0668*	0.0174	1										
(5)	Total sales	38,581	225,450	−0.0246*	0.3613*	0.1067*	−0.0581*	1									
(6)	Sales unchanged %	0.95	0.151	0.0081	−0.0299*	0.0248*	−0.0422*	−0.0458*	1								
(7)	Domestic group	0.364	0.481	−0.0441*	0.0614*	0.0430*	0.1632*	0.0283*	−0.0113	1							
(8)	Foreign group	0.195	0.396	0.0006	0.1067*	0.0311*	0.0502*	0.0706*	−0.0791*	−0.3723*	1						
(9)	HHI	0.413	0.995	−0.0858*	0.0387*	−0.0132	−0.0566*	0.0401*	−0.0717*	−0.0087	0.0343*	1					
(10)	Haltiwanger ind.	0.19	0.17	−0.1859*	0.0059	0.0111	−0.1926*	0.0111	0.0277*	−0.0171	−0.0271*	0.3772*	1				
(11)	Product inn.	0.237	0.425	0.0242*	0.1122*	−0.0224*	0.0399*	0.0882*	−0.5933*	0.0312*	0.1461*	0.0962*	−0.0501*	1			
(12)	Process inn.	0.23	0.421	0.0208*	0.1175*	0.0064	0.0374*	0.0963*	−0.3098*	0.0681*	0.0814*	0.0653*	−0.0311*	0.4927*	1		
(13)	Organizational inn.	0.288	0.453	−0.0136	0.1423*	0.0170	0.0141	0.0725*	−0.2047*	0.0642*	0.0937*	0.0641*	−0.0072	0.3030*	0.3580*	1	
(14)	Marketing inn.	0.113	0.317	−0.0065	0.1034*	0.0236*	0.0144	0.0912*	−0.2502*	0.0128	0.0979*	0.0332*	0.0090	0.3433*	0.3063*	0.3497*	1

Note: * Significance level at 0.05.

only significantly correlated with product and process innovation.

4.3. Dependent variable

The dependent variable is firms' survival time separating firms' presence in the cohort CIS 2006 from firm's exit or censoring. All survivors' times are censored at 31st December 2015. Survival time is measured in months, since we have monthly observations.

4.4. Independent variables

Variables on innovative activities are contained in CIS surveys and defined according to the Oslo Manual guidelines (OECD and Eurostat, 2005, pp.48–51). CIS innovation variables have been extensively used in the literature (among others Mairesse and Mohnen, 2002; Cassiman and Veugelers, 2002; Laursen and Salter, 2006; Raymond et al., 2010; Hottenrott and Peters, 2012). *Product innovation* is a dummy with value 1 if the firm introduced new (or significantly improved) goods and/or services, and 0 otherwise. *Process innovation* takes value 1 if the firm introduced new (or significantly improved) manufacturing methods, input distribution or supporting activities. *Organizational innovation* is a dummy capturing the introduction of new knowledge management systems, changes in the organization of work or in external relations. Finally, *marketing innovations* signals significant changes to product design, packaging or new distribution methods.

As control variables, we consider demographic information derived from the ABR. They include firms' age and size, which are crucial determinants of survival (Evans, 1987; Hall, 1987; Dunne et al., 1988; Thompson, 2005). *Firm size* is calculated as the logarithm of the *number of employees* plus 1, to include the self-employed. Size was consistently found to increase the probability of survival, since larger companies are more likely to operate closer to the minimum efficient scale (Audretsch and Mahmood, 1995), and can access more resources (Aldrich and Auster, 1986). We further control for the *number of establishments*, plus 1 and log-transformed, as an additional way to account for size and for a firm's structure. *Firm age* is calculated as the logarithm of the number of years of permanence in the register. Scholars identified younger firms as more vulnerable to exit (Stinchcombe, 1965; Freeman et al., 1983), with exit risk potentially following an inverted-U pattern (Brüderl and Schussler, 1990). Age has also been used as a proxy of learning-by-doing and capabilities, significantly supporting firms' survival (Agarwal and Gort, 2002). We then control for whether firms are part of a group, distinguishing between Dutch and foreign groups. Using CIS data, we define *domestic group* as a dummy variable equal to 1 for firms part of a group with headquarters in the Netherlands, and 0 otherwise. If the headquarters are located abroad, we set the dummy *foreign group* equal to 1. Group membership grants access to additional resources (Audretsch and Mahmood, 1994, 1995), which can boost performance (Chang and Hong, 2000) and support innovation (Chang et al., 2006; Choi et al., 2011), but may increase exit rates during severe economic downturns (Bradley et al., 2011). Resource endowments, competences and incentives can differ substantially between foreign and domestic actors (Douma et al., 2006), having different implications on firms' performance (Yang and Tsou, 2020), innovation (Dachs and Peters, 2014), and survival (Mata and Portugal, 2002; Kronborg and Thomsen, 2009). We also control for firms with a *limited liability* legal form using a dummy variable. Since the firm itself is liable for any debt, this legal form grants more flexibility to founders and managers, allowing for a smoother exit route if needed (Harhoff et al., 1998; Lee and Cho, 2020). Finally, we control for firms' performance. First, we include the log of firms' *total sales*, measured at the first reference year of each CIS in order to minimise their endogeneity with a potential exit. Second, we consider the *share of total sales from unchanged good and services*, a variable taking values from 0 to 1 which controls for the extent to which sales are generated by existing (rather than innovative) goods and services.

In addition to firm-level variables, we leverage the ABR to construct environmental-level variables at the population level. First, we add a control for *sectoral employment dynamics* computing the employment growth rate measure proposed by Haltiwanger et al. (2013)[7] at the level of technological macro-sectors.[8] Growth rates (g_{st}) are calculated over the 2 years preceding each landmark time as $g_{st} = (E_{st} - E_{st-2})/(0.5^*(E_{st} + E_{st-2}))$, where E_{st} is the total number of employees in sector s in year t. We then control for the level of market concentration using the *Herfindahl-Hirschman index* (HHI), calculated for technological macro-sectors at each landmark time. Sectors characterized by higher levels of concentration tend to be less competitive and to contain structural barriers, affecting firms' survival likelihood (Lin and Huang, 2008; Kim and Lee, 2016). Finally, we included a set of *sectoral and geographical dummies* to control for any residual heterogeneity. Sectoral dummies are defined at the 1 digit level of the Standard Industrial Classification 2008, while geographical dummies are defined at the provincial level.

5. Methodology

Our analysis focuses on how firm's innovative activities relate to different exit routes throughout the business cycle. To investigate this complex relationship, we augment standard competing risks models (CRM) analysis in two ways. First, we complement cause-specific hazards estimates with Cumulative Incidence Functions (CIFs), which report the overall probability of exit over time. Second, we account for firms' innovation dynamics by estimating the role of time-dependent (TD) covariates using a landmark analysis approach. In this way we can control for the selection bias generated by the inclusion of firms' TD covariates in survival models and obtain punctual, dynamic estimates of covariates' effects over time.

5.1. Local vs global parameters: the cumulative incidence function

Survival data can be characterized either by a 'local' parameter, the hazard function *h(t)*, or by a 'global' parameter, the cumulative incidence function *F(t)* of exit (also called cumulative distribution function). The first captures the exit rate, the instantaneous risk of exit in the infinitesimal time interval $t + d$, given survival at time *t*; the latter describes the evolution over time of the probability of exit, providing complementary information on the effect of covariates on the incidence of exit. In a competing risks setting, however, the interpretation of such effects requires caution.

When there is a unique cause of exit, the 'global' characterization is informationally equivalent to the 'local' one. There exists a one-to-one correspondence (Andersen et al., 2012) between the hazard function *h(t)* and CIF *F(t)* (and its complement to 1, the Survival Function *S(t)*), which is defined through the cumulative hazard function *H(t)*:

$$F(t) = 1 - S(t) = 1 - e^{-H(t)}, \textit{where } H(t) = \int_0^t h(u)du \tag{1}$$

Such correspondence is reflected in the Kaplan-Meier and Nelson-Aalen estimators often seen in Economics and Management studies (e.

[7] "This growth rate has become standard in analysis of establishment and firm dynamics because it shares some useful properties of log differences but also accommodates entry and exit" (Haltiwanger et al., 2013, p.353).

[8] Our macro-sectors classification follows the Eurostat technology level regulation of NACE where manufacturing and services are classified as follows: according to the technology level (High, Medium, and Low-Tech) for manufacturing, and into Non-market services, Market services except financial intermediaries, and Financial intermediaries for services. To those sectors we have added Agriculture, Water management, Energy and Construction.

g. Kahn, 1993; Bernard and Sjoholm, 2003; Santarelli and Lotti, 2005; Key and Roberts, 2006).

When dealing with competing risks, this one-to-one correspondence no longer occurs for the CIF and hazard function, even if referring to the same cause of exit. This happens because the CIF of a specific cause of exit (*j*) also depends on the cause-specific hazards of the competing causes:

$$F_j(t) = \int_0^t S(u) \cdot h_j(u) \cdot d_u \tag{2}$$

where *S(t)* is calculated using the cumulative hazard functions of all *k* causes, with $k = 1, \ldots, n$ and $j \in k$.

$$S(u) = e^{-\sum H_k(u)} \tag{3}$$

This has two consequences. First, a CIF estimator based on the Kaplan-Meier estimator is upward-biased because it disregards competing events as a source of censoring (Andersen et al., 2012; Latouche et al., 2013). Instead, CIFs estimates based on Eqs. (2) & (3) are always feasible and, as a further advantage, do not require independence between competing causes.[9] Second, the joint interpretation of covariates effects on hazards and CIFs is not straightforward, since a covariate can have opposite-signed effects on the hazard and CIF of the same exit cause (Latouche et al., 2013). With this caveat in mind, we calculate CIFs considering sub-samples defined using innovation dummies and represent them graphically.

5.2. *Firm's internal time-dependent covariates and landmark analysis*

Including firms' internal time dependent (TD) covariates is, on the one hand, a source of precious information, since they are crucial predictors. On the other hand, internal TD covariates introduce a selection bias (Peters et al., 2017; p. 7), since they can only be observed only if firms survive until the time of observation (Thompson, 2005). Survival could be due to the TD covariate in which we are interested. Therefore, if internal TD covariates are to be included, as in our case the innovative activities of the firms, "*then it is possible to estimate cause-specific hazards, but prediction of the cumulative incidences and survival probabilities based on these is no longer feasible*" (Cortese and Andersen, 2010, p. 139).[10]

Including TD covariates in survival models requires caution. Recalling the distinction proposed by Kalbfleisch and Prentice (2002, p.196), we define a TD covariate for firm *i* as $X_i(t) = \{x_i(u); 0 < u \leq t\}$. $X_i(t)$ encompasses all the covariate history from the beginning of the spell up to time *t*. Kalbfleisch and Prentice distinguish two broad categories of TD covariates: *external* and *internal* TD covariates, which are often referred to as *exogenous* and *endogenous* TD covariates (Cortese and Andersen, 2010). Formally, external covariates satisfy the following condition:

$$Prob\ \{T \in [u, u + \Delta u)\ | X(u)\ , T \geq u\} = Prob\ \{T \in [u, u + \Delta u)\ | X(t)\ , T \geq u\} \tag{6}$$

which is equivalent to

$$Prob\ \{X(t)\ | X(u)\ , T \geq u\} = Prob\ \{X(t)\ | X(u)\ , T = u\}, 0 < u \leq t \tag{7}$$

The idea is that the future path of an external covariate to any time $t > u$ is not affected by the occurrence of exit at time *u*, even though this variable influences the rate of exit over time.[11]

An internal TD covariate does not satisfy this condition. Therefore, it is endogenous to firm's survival, because its observation requires the survival of the firm and, consequently, its path carries information on the firm's exit time (or lack of it). Estimating a model of survival probability that includes endogenous TD covariates would therefore require specifying a joint model for the distribution of the stochastic process generating the endogenous TD covariates and survival time itself (Cameron and Trivedi, 2005, p.598), since "*the survival function is not any more a function only of the hazard rate, but also of the random development of the covariates*" (Cortese and Andersen, 2010, p.141).[12]

We solve the problem of TD covariates following Cortese and Andersen (2010), applying *landmark analysis* (van Houwelingen, 2007; Putter and van Houwelingen, 2017), which does not require specifying any specific stochastic model for *X(t)*. These survival model techniques have been mainly applied in Biostatistics and are little-known in Economics and Management. The core intuition is to divide the period of analysis into segments delimited by *landmark* times. At each landmark, the cause-specific hazards and CIFs are re-estimated with the covariate values kept fixed 'between landmarks'. The two major advantages of landmarks are "simplicity and transparency" (Klein et al., 2016: p.454; Dafni, 2011). On the one hand, landmark models are estimated applying existing methods on an apparent framework. On the other one, this stepwise analysis allows researchers to provide a much clearer interpretation by explicitly discretizing changes in both covariates and the risk pool, which would otherwise be assimilated into a unique model.

Specifically, our "*landmark analysis*" shows how *X(t)* (here, the firms' innovative activities over time) dynamically affects the CIF and the CRM estimates. This approach consists in estimating a series of CRMs with time-fixed covariates conducted at various *landmarks s* and estimating the corresponding CIF. More specifically, we estimate

$$P(T \leq t, Z(T) = j\, | T \geq s, X(s)\,) \tag{8}$$

where $j = 1, \ldots, m$ are the competing exit routes, and *X(s)* are the firms' innovative activities (i.e. product, process, organizational and marketing innovation, and a combined "innovation" variable) at each landmark. We estimate the CIF given the status of our endogenous TD covariate at the landmark *s*, considering only firms alive at *s*. We estimate this for s = 0, our initial state (CIS 2006), but also repeat it for later values of *s*, (CIS 2008 and CIS 2010). Computing these probabilities at different landmarks *s* requires using the restricted samples of firms still alive at each *s*. For *s* = *0*, the probability in Eq. (8) is the usual cumulative incidence given *X(0),* while, for later values of *s*, we have conditional cumulative incidence given survival until *s* and given *X(s)*.

Importantly, *X(s)* is a time-constant covariate when Eq. (8) is estimated at each *s*. In fact, for a given landmark *s*, it is only the covariate value at *s*, *X(s)* = *1* or *X(s)* = *0* that is accounted for, while future values of *X(u), u* > *s*, are not considered. However, the covariate *X(s)* is allowed to vary between the sequence of landmarks s. Thus, by setting the landmarks s at respectively, 31 Dec. 2006, 31 Dec. 2008, and 31 Dec. 2010, the sequence of probability.

[9] "The latter technique solely relies on the definition of cause-specific hazards as the time-local rate of occurrence of events that are mutually exclusive (or more precisely on the resulting likelihood factorizations) and not on any independence assumption" (Andersen et al., 2012, p. 869).

[10] The same limitations apply in the regression approach also in the "subdistribution hazard" models for cumulative incidence as in Fine and Gray (1999) (as has been emphasised, among others, by Latouche et al., 2013; Beyersmann and Schumacher, 2008).

[11] External covariates may be furtherly differentiated in three types. They are '*fixed*' when they are constant over time. Secondly, they are '*defined*' when their evolutionary path is pre-determined (a clear example is the variable 'age'). Finally, an exogenous covariate is '*ancillary*' when it is "the output of a stochastic process that is external to the individual under study" (Kalbfleisch and Prentice, 2002, p.197) or, in other words, that it does not involve the parameters of the studied model. An example might be a variable describing the fluctuation of the exchange rate between the Dollar and the Euro. Clearly, the last two type of external covariate are time-varying, but they contain information on variables that are not generated by the behavior of the firm over time.

[12] In the case of categorical covariates, Andersen (1986) and Andersen et al. (1991) proposed a joint model for *X(t)* and *T*.

$P(T \leq t, Z(T) = 1 \mid T \geq s, X(s) = 0)$, and $P(T \leq t, Z(T) = 1 \mid T \geq s, X(s) = 1)$,

may be compared, thereby elucidating how firms' time-dependent innovative activities (*X(s)*) affect the competing risks of exit (Cortese and Andersen, 2010).

Landmark analysis has two main drawbacks. First, an arbitrary definition of landmarks can affect the estimates: choices of landmarks must be motivated. Our landmarks fit the data structure following the CIS survey years. Second, landmark analyses lose power if we consider landmarks far (in terms of time) from the initial landmark, due to the reduction in sample size: at each landmark only survivors are kept. Nevertheless, the landmark analysis remains one of the cleanest approaches to address TD covariates and sample selection.

5.3. Model specifications

We estimate CRMs with three final states (closure, failure, M&A) on a series of landmarks *s* (31st Dec 2006, 31st Dec 2008, and 31st Dec 2010). At each landmark *s*, a competing risk regression analysis is performed only on firms still alive at *s*. Cause-specific hazards are modelled using Cox regressions (Cox, 1972), where TD covariates are included as landmark-fixed regressors. This is a semi-parametric model widely used in survival analysis for its power and flexibility. Its main advantage is that no functional form is imposed a priori on the baseline hazard, which is instead directly inferred from the data. This property is particularly desirable when the hazard is expected to assume unique or peculiar shapes, as in periods of severe economic crisis. In our landmark environment, the cause-specific hazard for firm $i = 1, \ldots, n$ and cause of exit $j = 1, \ldots, m$ is modelled using a Cox regression of the form

$$h_{ij}(t, x_i(s), z_i) = h_{0j}(t) exp\left(\beta_j^T x_i(s) + \gamma_j^T z_i\right)$$

where x_i is a vector composed by exogenous time-varying variables and landmark-specific TD covariates, z_i a vector of time-invariant covariates and β and γ vectors of coefficients. The hazard h_{ij} is assumed to have two components. The first is the cause-specific baseline hazard $h_{oj}(t)$, "*an unspecified nonnegative function of time*" (Therneau and Grambsch, 2000, p. 38) common to all units in the sample. The second is the cause-specific relative risk $exp\left(\beta_j^T x_i(s) + \gamma_j^T z_i\right)$, which is a function of (different combinations of) covariates and it multiplicatively shifts the baseline hazard. The quantity of interest is the hazard ratio, defined as the ratio between the hazard rates of two firms (a and b):

$$\frac{h_{aj}(t, x_a(s), z_a)}{h_{bj}(t, x_b(s), z_b)} = \frac{exp\left(\beta_j^T x_a(s) + \gamma_j^T z_a\right)}{exp\left(\beta_j^T x_b(s) + \gamma_j^T z_b\right)}$$

Time enters the Cox regression only in the baseline hazard, which cancels out in the calculations. Consequently, the hazard ratio is constant. Accordingly, the Cox regression is a model of *proportional hazards*. The PH assumption is crucial for the unbiasedness of the estimated hazard ratios (Bellera et al., 2010). It can be violated for different reasons: i) time-varying covariates which are wrongly assumed to be fixed-in-time; ii) the effects of covariates may actually change over time; or iii) hazard ratios have a "built-in selection bias" because, over time, they are calculated only on surviving firms (Hernán, 2010). For these reasons, the longer the period of analysis, the more fragile and case-specific are the Cox estimates. Under these premises, a landmark survival analysis seems the most suitable choice, since it minimizes the influence of the aforementioned sources of bias. We test the 'proportional-hazards assumption', which guarantees the correct specification of the Cox models, performing an analysis of the Schoenfeld (1982) regression residuals generalized by Grambsch and Therneau (1994).[13]

[13] Results are available upon request from the authors.

In our analysis, time is "discretised" monthly. The high frequency with which events are registered in the ABR minimizes the presence of ties in our dataset. To deal with monthly ties, we estimate Cox regressions with the Breslow approximation (Breslow, 1974). We estimated several model specifications to analyse how survival is related to the presence of different innovative activities at different landmarks. Models (1)–(3) focus on product and process innovation, while Models (4) and (5) on organizational and marketing innovations. Finally, Model (6) includes all innovation types.

6. Results and discussion

6.1. Univariate analysis: CIF graphs

CIF plots provide a preliminary fine-grained view of the scaling of exit probabilities over time for innovators and non-innovators, albeit without taking into account control variables. Fig. 1 shows the case of product innovators; CIFs are calculated for each landmark (defining the start of each sub-period) and mode of exit (namely M&A, closure and failure).

Focusing on landmark 2006, we observe minor divergences between the two exit probabilities. Product innovators benefit from an increasingly lower probability of closing compared to non-innovators, while a survival premium against M&A emerges only from 2010 onwards. Conversely, product innovation marginally increases the probability failure over the entire observation period. At landmark 2008, innovators' relatively lower probability of exit due to acquisition is more pronounced and remains roughly constant after the second half of 2009. Likewise, innovation usually reduces the probability of exit due to closure. For failure, the two CIFs are intertwined, suggesting that innovation is not consistently related to the probability of failing. Finally, at landmark 2010 the probabilities of exit significantly diverge over time only in the case of closure and M&A, having the most marked effect on the latter.

The CIFs for the three other innovation types are available in the Online Supplementary Materials (Appendix OSM2) and provide comparable results. The curves follow broadly similar patterns, although there are some differences. Overall, technological innovations decrease the probabilities of exit more consistently than non-technological innovations, with product innovation usually granting slightly higher survival benefits than process innovation. However, compared to non-innovators, process innovators benefit from even lower probabilities of closure at all landmarks. Conversely, for organizational innovators we observe that the two probabilities of exit tend to overlap at all landmarks and for all exit routes. This suggests that organizational innovation is the least beneficial form of innovation, both in the short and in the long run.

Perhaps the most visible result from the CIFs analysis corresponds to the divergence between exit probabilities after around 2010. In our sample, in all three landmark subperiods, innovators (of all four types) are *less* likely to be acquired, which is different from some previous work[14] and is probably due to the financial crisis, which pushes some vulnerable non-innovators to become relatively attractive 'cut-price' M&A targets. Indeed, the nature and interpretation of M&A events changes in the years preceding the crisis.[15] Regarding exit by closure, the differences are less marked, although innovators are overall slightly

[14] For example, Cefis and Marsili, 2012. Possible reasons for the discrepancy include the effect of the financial crisis on M&A exits, as well as different sample compositions (Cefis and Marsili, 2012 focus on small firms during 'normal' times, while the present paper focuses on all firms during a recession).

[15] In further analysis (available upon request), we note that M&A targets have a smaller median size, an older median age, and a lower mean productivity. Hence, while M&A might be an attractive exit route for young promising firms in periods of prosperity, M&A events in the crisis appear to be more necessity-driven and more likely to involve older and lower-productivity firms.

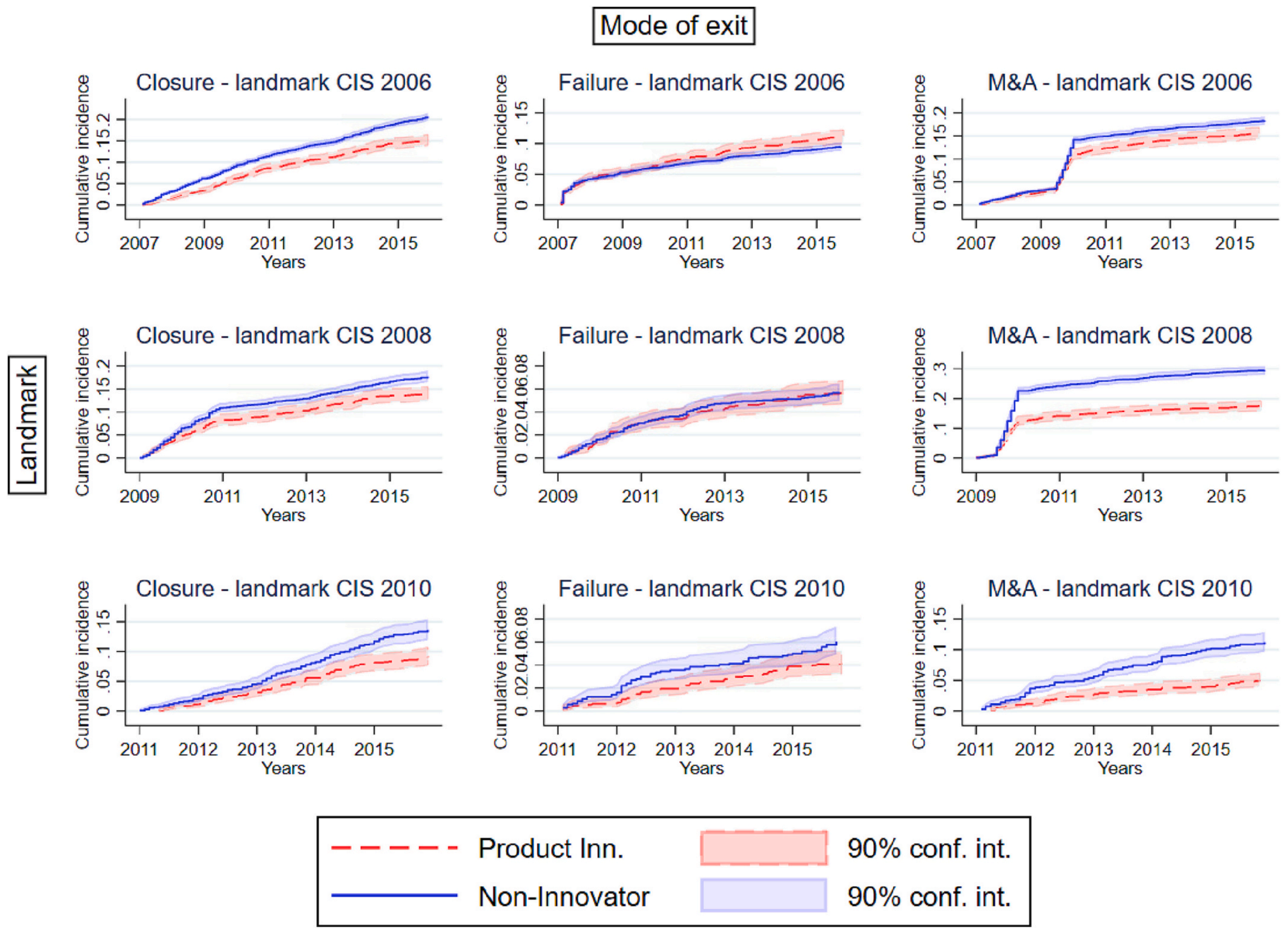

Fig. 1. Cumulative Incidence Functions for product innovators and non-innovators, by landmark and mode of exit.
Note: we use as reference category non-innovator, defined as firms not introducing any kind of innovation and without ongoing innovation projects. They represent the clearest reference category.

less likely to close. Concerning failure, there is no detectable survival premium; innovators essentially have the same (unconditional) failure chances as non-innovators. This interesting result highlights the destructive power of the onset of the crisis for innovative firms.

The CIF plots presented so far provide unconditional estimates of the cumulative probabilities to exit, for different groups of firms. In order to control for the potentially confounding role of firms' characteristics, we now present survival regression models.

6.2. Regression results: Cox models, by landmarks

Cox models are estimated for each landmark and for each exit route. The full regression results are presented in Tables 3–5, while the coefficients of interest for the innovation types (product, process, organizational, and marketing innovation) across exit routes and landmark periods are summarized in Fig. 2.

Focusing first on RQ1 regarding normal times, there is evidence of a survival premium for technological innovators; product and process innovations generally help avoid closure (see Fig. 2 and Table 3). The survival premium granted by product innovations is consistent with previous findings (Fernandes and Paunov, 2015; Buddelmeyer et al., 2010; Esteve-Pérez et al., 2010; Wagner and Cockburn, 2010). Process innovations are negatively associated with all three exit routes (closure, failure, and M&A). In line with previous evidence (Cefis and Marsili, 2012; Ortiz-Villajos and Sotoca, 2018), the reduction in the chances to close or fail are presumably driven by lower costs and/or higher quality, advantages conferred by process innovations in normal times. Furthermore, process innovation may also proxy for firms' expectations regarding the size and attractiveness of the overall market, thereby being associated with higher survival (Fernandes and Paunov, 2015, p.645). Interestingly, it is the only form of innovation significantly associated with M&As, but with a negative rather than positive coefficient as found in Børing, 2015. A possible explanation could be that M&As have different meanings in different contexts (e.g., M&As are procyclical in USA, but countercyclical in Japan) because M&As can either correspond to acquisitions of high-potential startups, or "rescue mergers" of failing companies that can be acquired at a low price (Coad and Kato, 2021).

With regard to organizational and marketing innovations, there is generally no statistically significant survival premium in normal times coming from their introduction, with the only exception being that marketing innovation reduces the likelihood of closure in Table 3 column (5). These latter results are interesting given that previous research focused on technological (rather than non-technological) innovation. Overall, our findings suggest that while, theoretically, innovations pursuing improvements in the internal flow of information, division of labour, and managerial practices may bolster efficiency and performance (Volberda et al., 2013; Birkinshaw et al., 2008; Mol and Birkinshaw, 2009), their benefits do not materialize for the average firm. Similarly, while achieving fit with the reference market plays a crucial role in defining a firms' profitability, marketing innovations' incremental nature (Grewal and Tansuhaj, 2001; Naidoo, 2010) and low appropriability (Tavassoli and Karlsson, 2015) prevent them from being pervasively positive. This is partially in line with previous results by Buddelmeyer et al. (2010) and Helmers and Rogers (2010), who identify a distinct positive effect for newly registered trademarks.

Finally, with regard to lack of a significant effect on M&As, our results are consistent with the idea that innovations which remain embedded into a firms' routines and social capital or product portfolio are not only more difficult pieces of information to evaluate, but are also less desirable targets due to the challenge to preserve them in the integration phase following M&As (Ranft and Lord, 2002; Graebner et al., 2017).

RQ2 looks at the relationship between survival and innovation in the time of the crisis (Table 4) and the recovery (Table 5), with Fig. 2 summarizing the results. The survival premium granted by product innovation against closure mostly disappears during the crisis, as hinted by earlier studies (Cefis et al., 2020; Kato et al., 2022). This effect might be explained by the preference for short-termed and incremental projects in times of intense environmental turbulence (Baker and Wurgler, 2007; Silvestri et al., 2018) and by the financial burden directly generated by product innovation (Lahr and Mina, 2021). Overall, this dents its benefits, and blurs the positive signal associated to product innovations in normal times, ultimately decreasing the likelihood of exit via M&A. Conversely, the recovery also allows product innovators to thrive, by conferring lower risks of closure and M&A, in line with recent evidence from Grazzi et al. (2021) on the beneficial effects of patents in the recovery period. Firms that emerge from the crisis to be able to introduce product innovations during the recovery may have exceptionally resilient innovation capabilities that withstood the hardships of the crisis and that bestow an enviable market position in the new recovery environment. An alternative explanation could be that firms that introduce product innovations during the recovery have kept their previous ideas to one side while delaying their introduction until demand conditions improve (Fabrizio and Tsolmon, 2014, p.664).

Process innovations introduced before the crisis increase survival chances during the crisis, regarding closure and M&A (but the coefficients are never statistically significant for exit via failure). Process innovation grants immediate relief against financial distress, by cutting costs and increasing efficiency on existing production (Klepper, 1996), acting as a lifeline against closure in the midst of the financial crisis (Cefis et al., 2020). During the recovery years, however, the "survival premium" for process innovators fades away (Cefis and Marsili, 2019): process innovations seem not to grant enough advantages to bestow a survival premium.

Regarding non-technological innovation, organizational innovation offers no "survival premium", in line with Birkinshaw et al. (2008)'s sobering discussions of its benefits as well as the costs. Organizational innovation sometimes actually *increases* the chances of exit during the crisis and recovery (the coefficient is statistically significant for closure

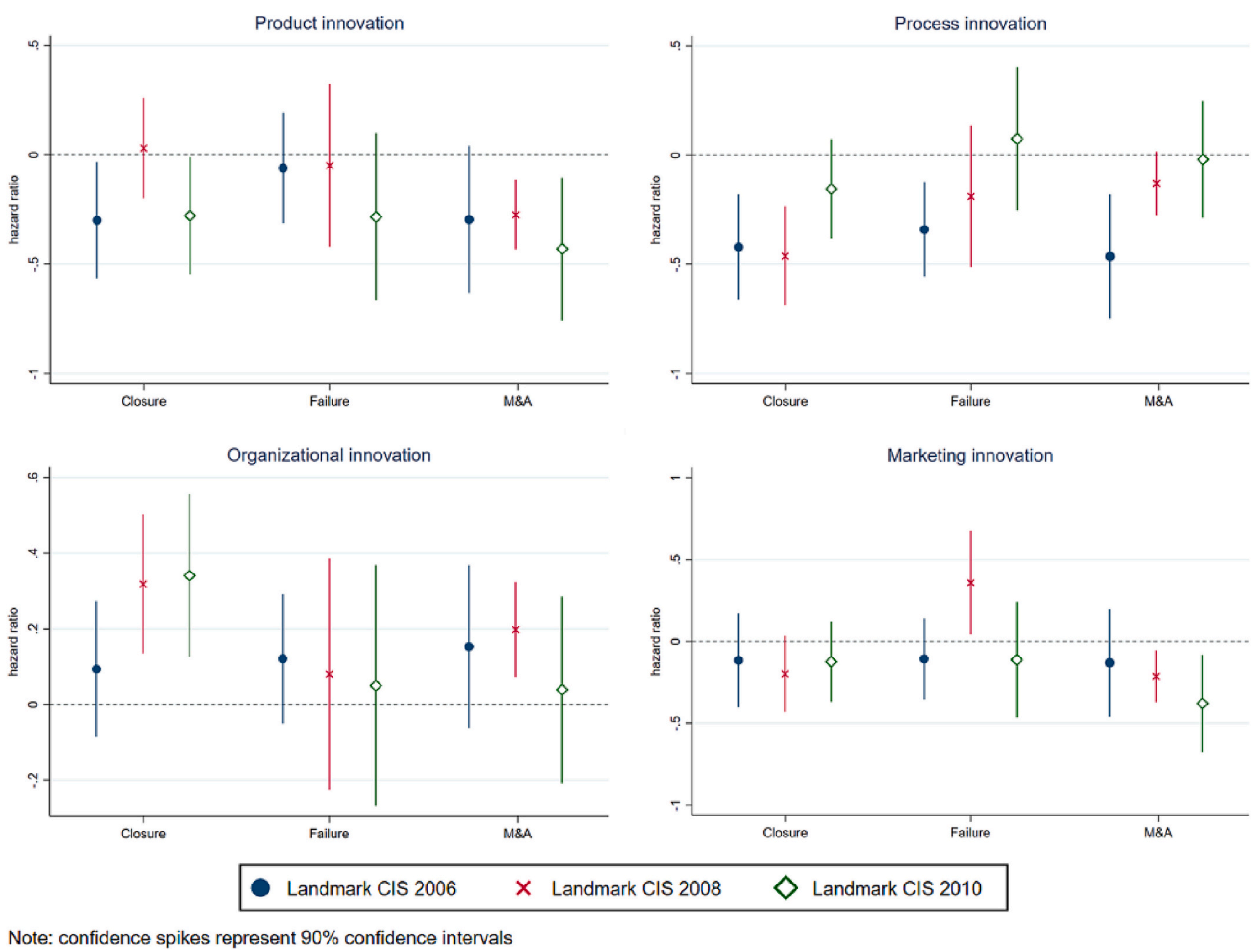

Fig. 2. Plot of hazard ratio coefficients for innovation variables, Cox model 7 (Tables 3–5).
Note: Each subgraph contains the coefficients of a specific innovation variable, grouped by mode of exit and ordered by landmark.

Table 3
Competing risks models, Cox regressions, landmark CIS 2006.

Closure	(1)	(2)	(3)	(4)	(5)	(6)
ln(age)	−0.243***	−0.241***	−0.242***	−0.242***	−0.242***	−0.241***
	(0.0443)	(0.0442)	(0.0442)	(0.0442)	(0.0443)	(0.0443)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(size)	−0.0796*	−0.0727	−0.0675	−0.0902*	−0.0892*	−0.0715
	(0.0484)	(0.0486)	(0.0487)	(0.0486)	(0.0483)	(0.0491)
	[0.100]	[0.135]	[0.166]	[0.063]	[0.065]	[0.145]
ln(establishments)	−0.397***	−0.396***	−0.400***	−0.391***	−0.389***	−0.399***
	(0.133)	(0.134)	(0.133)	(0.134)	(0.134)	(0.133)
	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.003]
Domestic group	0.277***	0.285***	0.291***	0.263**	0.265**	0.289***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
	[0.010]	[0.008]	[0.007]	[0.014]	[0.013]	[0.007]
Foreign group	0.259**	0.244*	0.258**	0.236*	0.243*	0.259**
	(0.127)	(0.128)	(0.128)	(0.127)	(0.127)	(0.128)
	[0.042]	[0.056]	[0.043]	[0.064]	[0.057]	[0.043]
Limited-liability	−0.991***	−0.982***	−0.984***	−0.989***	−0.988***	−0.984***
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(total sales)	−0.0254	−0.0269	−0.0230	−0.0322	−0.0304	−0.0234
	(0.0219)	(0.0220)	(0.0222)	(0.0215)	(0.0218)	(0.0223)
	[0.246]	[0.222]	[0.302]	[0.135]	[0.164]	[0.294]
Sales unchanged %	0.329	0.781*	0.294	1.183**	1.074**	0.291
	(0.461)	(0.437)	(0.455)	(0.470)	(0.467)	(0.457)
	[0.475]	[0.074]	[0.519]	[0.012]	[0.021]	[0.524]
HHI	−0.0335	−0.0355	−0.0350	−0.0332	−0.0349	−0.0370
	(0.0687)	(0.0691)	(0.0689)	(0.0691)	(0.0697)	(0.0692)
	[0.625]	[0.608]	[0.612]	[0.631]	[0.616]	[0.593]
Haltiwanger ind.	0.480	0.499	0.502	0.465	0.477	0.507
	(0.448)	(0.447)	(0.448)	(0.448)	(0.452)	(0.450)
	[0.284]	[0.264]	[0.262]	[0.299]	[0.291]	[0.259]
Product inn.	−0.466***		−0.305*			−0.299*
	(0.157)		(0.164)			(0.162)
	[0.003]		[0.062]			[0.065]
Process inn.		−0.495***	−0.411***			−0.421***
		(0.137)	(0.144)			(0.147)
		[0.000]	[0.004]			[0.004]
Organizational inn.				−0.0404		0.0935
				(0.104)		(0.109)
				[0.698]		[0.390]
Marketing inn.					−0.245	−0.115
					(0.171)	(0.175)
					[0.152]	[0.508]
Sectoral dummies	✓	✓	✓	✓	✓	✓
Provincial dummies	✓	✓	✓	✓	✓	✓
N. observations	9667	9667	9667	9667	9667	9667
Chi-squared	289.5	307.0	308.1	282.7	284.9	310.4
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	−4605	−4602	−4600	−4609	−4608	−4600

Failure	(1)	(2)	(3)	(4)	(5)	(6)
ln(age)	−0.396***	−0.395***	−0.395***	−0.394***	−0.395***	−0.393***
	(0.0424)	(0.0423)	(0.0423)	(0.0424)	(0.0423)	(0.0425)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(size)	0.393***	0.400***	0.402***	0.383***	0.387***	0.397***
	(0.0449)	(0.0445)	(0.0450)	(0.0448)	(0.0442)	(0.0455)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(establishments)	−0.0437	−0.0442	−0.0460	−0.0367	−0.0354	−0.0432
	(0.0689)	(0.0685)	(0.0688)	(0.0693)	(0.0691)	(0.0693)
	[0.526]	[0.519]	[0.503]	[0.597]	[0.609]	[0.533]
Domestic group	0.0457	0.0551	0.0566	0.0374	0.0403	0.0516
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.108)
	[0.670]	[0.608]	[0.598]	[0.727]	[0.707]	[0.632]
Foreign group	−0.128	−0.134	−0.130	−0.140	−0.132	−0.130
	(0.133)	(0.134)	(0.133)	(0.133)	(0.133)	(0.133)
	[0.335]	[0.316]	[0.328]	[0.292]	[0.323]	[0.327]
Limited-liability	0.326**	0.328**	0.329**	0.325**	0.321**	0.329**
	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)
	[0.027]	[0.027]	[0.027]	[0.028]	[0.030]	[0.027]
ln(total sales)	−0.0472***	−0.0451**	−0.0443**	−0.0511***	−0.0494***	−0.0456**
	(0.0178)	(0.0179)	(0.0180)	(0.0176)	(0.0177)	(0.0181)
	[0.008]	[0.012]	[0.014]	[0.004]	[0.005]	[0.012]
Sales unchanged %	−0.314	−0.268	−0.349	−0.00719	−0.0866	−0.339
	(0.365)	(0.309)	(0.360)	(0.319)	(0.311)	(0.362)
	[0.390]	[0.386]	[0.333]	[0.982]	[0.781]	[0.349]
HHI	−0.0276	−0.0263	−0.0258	−0.0298	−0.0292	−0.0273
	(0.0704)	(0.0706)	(0.0704)	(0.0709)	(0.0710)	(0.0706)
	[0.696]	[0.710]	[0.714]	[0.674]	[0.681]	[0.699]
Haltiwanger ind.	0.0259	0.0162	0.0134	0.0377	0.0578	0.0170
	(0.528)	(0.529)	(0.528)	(0.530)	(0.532)	(0.527)
	[0.961]	[0.976]	[0.980]	[0.943]	[0.913]	[0.974]
Product inn.	−0.201		−0.0653			−0.0604
	(0.142)		(0.152)			(0.154)
	[0.159]		[0.667]			[0.694]
Process inn.		−0.340***	−0.319**			−0.340***
		(0.120)	(0.128)			(0.132)
		[0.005]	[0.013]			[0.010]
Organizational inn.				0.0125		0.121
				(0.0991)		(0.104)
				[0.899]		[0.245]
Marketing inn.					−0.166	−0.107
					(0.144)	(0.151)
					[0.249]	[0.479]
Sectoral dummies	✓	✓	✓	✓	✓	✓
Provincial dummies	✓	✓	✓	✓	✓	✓
N. observations	9667	9667	9667	9667	9667	9667
Chi-squared	386.0	396.7	397.9	390.5	387.6	408.1
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	−4601	−4598	−4598	−4602	−4602	−4597

M&A	(1)	(2)	(3)	(4)	(5)	(6)
ln(age)	−0.364***	−0.362***	−0.363***	−0.363***	−0.362***	−0.360***
	(0.0571)	(0.0570)	(0.0572)	(0.0567)	(0.0568)	(0.0574)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(size)	0.201***	0.206***	0.213***	0.184***	0.189***	0.207***
	(0.0615)	(0.0610)	(0.0617)	(0.0614)	(0.0605)	(0.0627)
	[0.001]	[0.001]	[0.001]	[0.003]	[0.002]	[0.001]
ln(establishments)	−0.0820	−0.0772	−0.0863	−0.0659	−0.0638	−0.0836
	(0.101)	(0.101)	(0.100)	(0.102)	(0.102)	(0.101)
	[0.416]	[0.446]	[0.391]	[0.519]	[0.533]	[0.409]
Domestic group	1.228***	1.239***	1.244***	1.216***	1.217***	1.237***
	(0.161)	(0.162)	(0.162)	(0.161)	(0.161)	(0.162)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Foreign group	0.514**	0.494**	0.511**	0.486**	0.495**	0.508**
	(0.211)	(0.212)	(0.212)	(0.211)	(0.211)	(0.212)
	[0.015]	[0.020]	[0.016]	[0.021]	[0.019]	[0.016]
Limited-liability	0.738***	0.764***	0.756***	0.750***	0.745***	0.751***
	(0.235)	(0.233)	(0.233)	(0.234)	(0.234)	(0.234)
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
ln(total sales)	−0.0311	−0.0305	−0.0259	−0.0404	−0.0379	−0.0274
	(0.0283)	(0.0286)	(0.0288)	(0.0276)	(0.0280)	(0.0287)
	[0.271]	[0.287]	[0.369]	[0.144]	[0.175]	[0.339]
Sales unchanged %	−0.574	−0.248	−0.628	0.128	0.0327	−0.606
	(0.466)	(0.413)	(0.459)	(0.437)	(0.423)	(0.461)
	[0.218]	[0.548]	[0.171]	[0.769]	[0.938]	[0.188]
HHI	−0.373***	−0.383***	−0.377***	−0.383***	−0.388***	−0.380***
	(0.142)	(0.147)	(0.145)	(0.145)	(0.148)	(0.146)
	[0.009]	[0.009]	[0.009]	[0.008]	[0.009]	[0.009]
Haltiwanger ind.	3.052***	3.107***	3.078***	3.098***	3.147***	3.072***
	(0.760)	(0.764)	(0.764)	(0.765)	(0.772)	(0.771)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Product inn.	−0.476**		−0.302			−0.296
	(0.193)		(0.201)			(0.204)
	[0.014]		[0.134]			[0.148]
Process inn.		−0.522***	−0.438**			−0.464***
		(0.164)	(0.172)			(0.173)
		[0.001]	[0.011]			[0.007]
Organizational inn.				−0.0106		0.153
				(0.130)		(0.130)
				[0.935]		[0.241]
Marketing inn.					−0.264	−0.130
					(0.194)	(0.201)
					[0.174]	[0.516]
Sectoral dummies	✓	✓	✓	✓	✓	✓
Provincial dummies	✓	✓	✓	✓	✓	✓
N. observations	9667	9667	9667	9667	9667	9667
Chi-squared	290.6	288.2	293.2	282.7	284.7	302.4
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	−2548	−2546	−2545	−2552	−2551	−2544

Notes: all coefficients are hazard ratios. Robust standard errors are reported in round brackets, p-values in square brackets.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 4
Competing risks models, Cox regressions, landmark CIS 2008.

	Closure						Failure						M&A					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ln(age)	−0.203***	−0.203***	−0.203***	−0.201***	−0.204***	−0.198***	−0.418***	−0.417***	−0.417***	−0.417***	−0.415***	−0.413***	−0.0752**	−0.0764**	−0.0747**	−0.0775**	−0.0771**	−0.0722**
	(0.0504)	(0.0504)	(0.0504)	(0.0502)	(0.0504)	(0.0501)	(0.0863)	(0.0863)	(0.0862)	(0.0860)	(0.0860)	(0.0856)	(0.0359)	(0.0358)	(0.0359)	(0.0358)	(0.0359)	(0.0359)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.037]	[0.033]	[0.038]	[0.031]	[0.032]	[0.044]
ln(size)	−0.560***	−0.551***	−0.551***	−0.568***	−0.556***	−0.558***	−0.0507	−0.0457	−0.0468	−0.0611	−0.0662	−0.0609	−0.589***	−0.592***	−0.587***	−0.602***	−0.591***	−0.588***
	(0.0467)	(0.0464)	(0.0463)	(0.0476)	(0.0474)	(0.0473)	(0.0974)	(0.0974)	(0.0975)	(0.0973)	(0.0971)	(0.0974)	(0.0378)	(0.0378)	(0.0380)	(0.0377)	(0.0377)	(0.0380)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.603]	[0.639]	[0.631]	[0.530]	[0.496]	[0.532]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(establishments)	−0.223*	−0.227*	−0.227*	−0.215*	−0.218*	−0.212	0.185*	0.185*	0.186*	0.190**	0.178*	0.178*	−0.332***	−0.326***	−0.332***	−0.323***	−0.322***	−0.322***
	(0.130)	(0.130)	(0.130)	(0.130)	(0.131)	(0.130)	(0.0954)	(0.0949)	(0.0955)	(0.0955)	(0.0948)	(0.0958)	(0.0938)	(0.0942)	(0.0939)	(0.0942)	(0.0948)	(0.0944)
	[0.086]	[0.081]	[0.082]	[0.098]	[0.095]	[0.104]	[0.053]	[0.051]	[0.051]	[0.047]	[0.060]	[0.063]	[0.000]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]
Domestic group	0.0380	0.0432	0.0425	0.0285	0.0392	0.0358	0.295	0.295	0.294	0.288	0.283	0.281	0.871***	0.869***	0.873***	0.860***	0.871***	0.868***
	(0.110)	(0.110)	(0.110)	(0.111)	(0.110)	(0.111)	(0.187)	(0.187)	(0.187)	(0.187)	(0.188)	(0.188)	(0.0728)	(0.0728)	(0.0729)	(0.0729)	(0.0729)	(0.0731)
	[0.730]	[0.694]	[0.699]	[0.797]	[0.721]	[0.747]	[0.116]	[0.114]	[0.116]	[0.123]	[0.132]	[0.136]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Foreign group	0.423***	0.423***	0.420***	0.398***	0.425***	0.407***	−0.163	−0.162	−0.165	−0.173	−0.188	−0.189	0.0684	0.0512	0.0706	0.0316	0.0578	0.0630
	(0.122)	(0.122)	(0.122)	(0.123)	(0.122)	(0.123)	(0.252)	(0.251)	(0.252)	(0.250)	(0.251)	(0.251)	(0.110)	(0.110)	(0.110)	(0.111)	(0.111)	(0.111)
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.518]	[0.518]	[0.513]	[0.490]	[0.453]	[0.451]	[0.536]	[0.643]	[0.523]	[0.776]	[0.603]	[0.571]
Limited-liability	−0.887***	−0.892***	−0.893***	−0.886***	−0.891***	−0.883***	0.259	0.261	0.259	0.259	0.259	0.266	0.898***	0.883***	0.894***	0.891***	0.888***	0.906***
	(0.112)	(0.111)	(0.111)	(0.112)	(0.111)	(0.112)	(0.285)	(0.283)	(0.285)	(0.283)	(0.282)	(0.284)	(0.161)	(0.162)	(0.161)	(0.162)	(0.161)	(0.162)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.364]	[0.357]	[0.363]	[0.359]	[0.358]	[0.349]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(total sales)	−0.0544**	−0.0537**	−0.0544**	−0.0604***	−0.0552**	−0.0582**	−0.0124	−0.0118	−0.0123	−0.0145	−0.0183	−0.0178	−0.0276	−0.0305*	−0.0271	−0.0340*	−0.0303*	−0.0287
	(0.0237)	(0.0238)	(0.0239)	(0.0234)	(0.0238)	(0.0239)	(0.0530)	(0.0531)	(0.0532)	(0.0526)	(0.0520)	(0.0525)	(0.0178)	(0.0179)	(0.0179)	(0.0177)	(0.0178)	(0.0179)
	[0.022]	[0.024]	[0.023]	[0.010]	[0.020]	[0.015]	[0.814]	[0.824]	[0.816]	[0.783]	[0.725]	[0.735]	[0.122]	[0.087]	[0.129]	[0.055]	[0.089]	[0.109]
Sales unchanged %	−0.606**	−0.658***	−0.621**	−0.374	−0.506*	−0.631**	−0.00262	−0.0652	−0.0112	0.0852	0.181	0.0142	−0.317	−0.00941	−0.328	0.173	0.0332	−0.334
	(0.282)	(0.253)	(0.276)	(0.268)	(0.260)	(0.279)	(0.513)	(0.463)	(0.509)	(0.485)	(0.498)	(0.519)	(0.227)	(0.222)	(0.227)	(0.227)	(0.221)	(0.227)
	[0.032]	[0.009]	[0.024]	[0.163]	[0.052]	[0.024]	[0.996]	[0.888]	[0.982]	[0.861]	[0.716]	[0.978]	[0.163]	[0.966]	[0.148]	[0.445]	[0.881]	[0.141]
HHI	−0.331**	−0.338**	−0.339**	−0.338**	−0.334**	−0.353**	0.305**	0.306**	0.307**	0.300**	0.286**	0.282**	−0.00195	−0.000367	−0.00298	0.00208	0.00319	−0.0113
	(0.148)	(0.149)	(0.149)	(0.149)	(0.151)	(0.151)	(0.138)	(0.138)	(0.138)	(0.137)	(0.136)	(0.135)	(0.0746)	(0.0751)	(0.0748)	(0.0746)	(0.0758)	(0.0760)
	[0.025]	[0.023]	[0.023]	[0.023]	[0.026]	[0.020]	[0.027]	[0.026]	[0.026]	[0.029]	[0.035]	[0.037]	[0.979]	[0.996]	[0.968]	[0.978]	[0.966]	[0.881]
Haltiwanger ind.	0.0130	−0.0139	−0.0123	0.0367	−0.00656	−0.0119	0.484	0.480	0.485	0.505	0.521	0.519	−0.0637	−0.0414	−0.0675	−0.0161	−0.0522	−0.0783
	(0.404)	(0.403)	(0.403)	(0.407)	(0.406)	(0.406)	(0.640)	(0.636)	(0.638)	(0.639)	(0.642)	(0.640)	(0.258)	(0.258)	(0.258)	(0.259)	(0.258)	(0.257)
	[0.974]	[0.972]	[0.976]	[0.928]	[0.987]	[0.977]	[0.450]	[0.451]	[0.448]	[0.429]	[0.417]	[0.418]	[0.805]	[0.873]	[0.794]	[0.950]	[0.840]	[0.761]
Product inn.	−0.143		0.0379			0.0304	−0.0110		0.0468			−0.0488	−0.336***		−0.295***			−0.274***
	(0.119)		(0.132)			(0.139)	(0.197)		(0.222)			(0.226)	(0.0874)		(0.0950)			(0.0965)
	[0.230]		[0.774]			[0.827]	[0.956]		[0.833]			[0.829]	[0.000]		[0.002]			[0.005]
Process inn.		−0.372***	−0.387***			−0.462***		−0.1000	−0.118			−0.189		−0.193**	−0.0877			−0.130
		(0.117)	(0.130)			(0.137)		(0.174)	(0.196)			(0.197)		(0.0788)	(0.0856)			(0.0889)
		[0.001]	[0.003]			[0.001]		[0.566]	[0.548]			[0.339]		[0.014]	[0.306]			[0.145]
Organizational inn.				0.126		0.319***				0.130		0.0802				0.0589		0.198***
				(0.103)		(0.112)				(0.169)		(0.186)				(0.0706)		(0.0766)
				[0.220]		[0.004]				[0.441]		[0.667]				[0.404]		[0.010]
Marketing inn.					−0.191	−0.199					0.336*	0.359*					−0.237***	−0.213**
					(0.128)	(0.141)					(0.173)	(0.193)					(0.0907)	(0.0960)
					[0.135]	[0.159]					[0.053]	[0.062]					[0.009]	[0.026]
Sectoral dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Provincial dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N. observations	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279	5279
Chi-squared	459.8	467.3	467.9	457.9	461.9	477.6	90.27	90.33	90.31	92.26	101.4	103.6	837.8	833.0	837.7	832.5	825.6	847.5
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	−4135	−4131	−4131	−4135	−4135	−4127	−1301	−1300	−1300	−1300	−1299	−1298	−8549	−8552	−8548	−8555	−8552	−8544

Notes: all coefficients are hazard ratios. Robust standard errors are reported in round brackets, p-values in square brackets.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 5
Competing risks models, Cox regressions, landmark CIS 2010.

	Closure						Failure						M&A					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ln(age)	−0.264***	−0.262***	−0.264***	−0.261***	−0.260***	−0.260***	−0.300***	−0.301***	−0.302***	−0.302***	−0.299***	−0.300***	−0.387***	−0.386***	−0.386***	−0.387***	−0.377***	−0.379***
	(0.0780)	(0.0779)	(0.0780)	(0.0781)	(0.0778)	(0.0780)	(0.111)	(0.110)	(0.108)	(0.110)	(0.110)	(0.111)	(0.0864)	(0.0860)	(0.0864)	(0.0859)	(0.0854)	(0.0858)
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.007]	[0.006]	[0.005]	[0.006]	[0.007]	[0.007]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(size)	−0.411***	−0.412***	−0.410***	−0.431***	−0.413***	−0.426***	0.0619	0.0543	0.0593	0.0549	0.0567	0.0573	−0.0884	−0.0914	−0.0865	−0.0878	−0.0852	−0.0812
	(0.0618)	(0.0620)	(0.0618)	(0.0620)	(0.0623)	(0.0621)	(0.0988)	(0.0988)	(0.0977)	(0.0999)	(0.0987)	(0.0998)	(0.0815)	(0.0811)	(0.0812)	(0.0821)	(0.0804)	(0.0812)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.531]	[0.582]	[0.544]	[0.583]	[0.566]	[0.566]	[0.278]	[0.260]	[0.287]	[0.285]	[0.289]	[0.317]
ln(establishments)	0.0943	0.0948	0.0942	0.101	0.0999	0.110	0.160*	0.163*	0.160	0.163*	0.170*	0.168*	−0.147	−0.146	−0.147	−0.151	−0.128	−0.130
	(0.100)	(0.101)	(0.100)	(0.101)	(0.101)	(0.0999)	(0.0945)	(0.0948)	(0.105)	(0.0950)	(0.0956)	(0.0964)	(0.112)	(0.113)	(0.111)	(0.113)	(0.115)	(0.113)
	[0.347]	[0.346]	[0.347]	[0.315]	[0.325]	[0.271]	[0.091]	[0.085]	[0.127]	[0.087]	[0.076]	[0.082]	[0.187]	[0.195]	[0.186]	[0.182]	[0.264]	[0.249]
Domestic group	−0.0304	−0.0283	−0.0274	−0.0502	−0.0300	−0.0397	−0.0521	−0.0559	−0.0548	−0.0550	−0.0490	−0.0534	0.554***	0.557***	0.556***	0.560***	0.566***	0.565***
	(0.125)	(0.126)	(0.125)	(0.126)	(0.126)	(0.126)	(0.189)	(0.189)	(0.190)	(0.189)	(0.188)	(0.189)	(0.153)	(0.154)	(0.153)	(0.154)	(0.153)	(0.153)
	[0.808]	[0.822]	[0.827]	[0.690]	[0.812]	[0.752]	[0.782]	[0.768]	[0.773]	[0.771]	[0.795]	[0.777]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Foreign group	−0.118	−0.127	−0.116	−0.158	−0.130	−0.141	−0.367	−0.379	−0.369	−0.378	−0.373	−0.370	0.108	0.0920	0.109	0.0977	0.101	0.114
	(0.164)	(0.165)	(0.164)	(0.166)	(0.164)	(0.166)	(0.250)	(0.251)	(0.248)	(0.251)	(0.251)	(0.251)	(0.197)	(0.199)	(0.198)	(0.198)	(0.198)	(0.197)
	[0.471]	[0.442]	[0.481]	[0.341]	[0.431]	[0.396]	[0.142]	[0.132]	[0.136]	[0.133]	[0.137]	[0.141]	[0.585]	[0.644]	[0.581]	[0.622]	[0.612]	[0.563]
Limited-liability	−0.513***	−0.525***	−0.515***	−0.516***	−0.522***	−0.504***	1.093***	1.083***	1.098***	1.083***	1.083***	1.100***	−0.109	−0.130	−0.112	−0.124	−0.118	−0.106
	(0.181)	(0.181)	(0.181)	(0.181)	(0.180)	(0.182)	(0.354)	(0.356)	(0.368)	(0.356)	(0.356)	(0.355)	(0.211)	(0.212)	(0.211)	(0.211)	(0.211)	(0.212)
	[0.005]	[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.607]	[0.539]	[0.597]	[0.556]	[0.578]	[0.616]
ln(total sales)	−0.0663***	−0.0684***	−0.0651***	−0.0777***	−0.0713***	−0.0706***	−0.0432	−0.0478	−0.0444	−0.0477	−0.0471	−0.0452	−0.0250	−0.0312	−0.0242	−0.0313	−0.0325	−0.0249
	(0.0225)	(0.0226)	(0.0227)	(0.0224)	(0.0221)	(0.0229)	(0.0473)	(0.0469)	(0.0417)	(0.0465)	(0.0466)	(0.0473)	(0.0324)	(0.0325)	(0.0328)	(0.0321)	(0.0319)	(0.0329)
	[0.003]	[0.002]	[0.004]	[0.001]	[0.001]	[0.002]	[0.361]	[0.308]	[0.287]	[0.306]	[0.312]	[0.339]	[0.440]	[0.338]	[0.461]	[0.330]	[0.308]	[0.450]
Sales unchanged %	−0.0855	0.169	−0.0997	0.349	0.229	−0.152	0.241	0.630	0.258	0.634	0.570	0.246	0.388	1.067*	0.375	1.163**	0.987*	0.334
	(0.347)	(0.321)	(0.345)	(0.337)	(0.324)	(0.349)	(0.616)	(0.587)	(0.602)	(0.587)	(0.587)	(0.615)	(0.533)	(0.564)	(0.532)	(0.559)	(0.540)	(0.524)
	[0.805]	[0.598]	[0.773]	[0.300]	[0.480]	[0.663]	[0.696]	[0.283]	[0.668]	[0.280]	[0.331]	[0.689]	[0.466]	[0.058]	[0.481]	[0.038]	[0.067]	[0.524]
HHI	−0.0907	−0.0954	−0.0913	−0.103	−0.0891	−0.102	0.145	0.146	0.145	0.147	0.150	0.147	0.0518	0.0494	0.0513	0.0597	0.0700	0.0666
	(0.120)	(0.121)	(0.120)	(0.122)	(0.120)	(0.122)	(0.104)	(0.104)	(0.111)	(0.105)	(0.105)	(0.106)	(0.103)	(0.102)	(0.103)	(0.101)	(0.101)	(0.103)
	[0.450]	[0.429]	[0.447]	[0.399]	[0.459]	[0.403]	[0.164]	[0.162]	[0.193]	[0.161]	[0.152]	[0.163]	[0.615]	[0.629]	[0.619]	[0.555]	[0.490]	[0.517]
Haltiwanger ind.	0.393	0.429	0.400	0.423	0.422	0.409	0.0804	0.0911	0.0680	0.0891	0.0908	0.0688	0.241	0.266	0.248	0.252	0.273	0.269
	(0.409)	(0.409)	(0.409)	(0.409)	(0.409)	(0.409)	(0.576)	(0.580)	(0.593)	(0.577)	(0.576)	(0.579)	(0.514)	(0.512)	(0.513)	(0.513)	(0.509)	(0.511)
	[0.335]	[0.294]	[0.327]	[0.302]	[0.302]	[0.317]	[0.889]	[0.875]	[0.909]	[0.877]	[0.875]	[0.905]	[0.639]	[0.604]	[0.630]	[0.623]	[0.591]	[0.598]
Product inn.	−0.270*		−0.243			−0.278*	−0.272		−0.299			−0.284	−0.521***		−0.501**			−0.430**
	(0.147)		(0.155)			(0.163)	(0.219)		(0.233)			(0.232)	(0.187)		(0.197)			(0.198)
	[0.066]		[0.117]			[0.089]	[0.214]		[0.199]			[0.221]	[0.005]		[0.011]			[0.030]
Process inn.		−0.143	−0.0692			−0.155		−0.0127	0.0712			0.0746		−0.187	−0.0541			−0.0198
		(0.127)	(0.134)			(0.138)		(0.181)	(0.195)			(0.200)		(0.154)	(0.162)			(0.162)
		[0.259]	[0.605]			[0.262]		[0.944]	[0.715]			[0.709]		[0.224]	[0.738]			[0.903]
Organizational inn.				0.195		0.341***				−0.0159		0.0500				−0.158		0.0392
				(0.120)		(0.131)				(0.175)		(0.193)				(0.148)		(0.150)
				[0.104]		[0.009]				[0.928]		[0.796]				[0.284]		[0.794]
Marketing inn.					−0.103	−0.124					−0.136	−0.113					−0.458***	−0.379**
					(0.135)	(0.149)					(0.195)	(0.215)					(0.177)	(0.181)
					[0.445]	[0.405]					[0.485]	[0.601]					[0.010]	[0.036]
Sectoral dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Provincial dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N. observations	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908	2908
Chi-squared	152.9	151.7	152.7	156.5	152.1	160.4	79.59	72.86	67.83	73.33	75.07	80.08	138.5	122.9	138.1	122.7	131.8	144.4
p-value	0.000	0.000	0.000	0.000	0.000	0.000	2.26e-06	1.99e-05	0.000146	1.71e-05	9.84e-06	8.66e-06	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	−2548	−2549	−2548	−2548	−2549	−2545	−1176	−1176	−1176	−1176	−1176	−1175	−1744	−1748	−1744	−1748	−1745	−1742

Notes: all coefficients are hazard ratios. Robust standard errors are reported in round brackets, p-values in square brackets.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

and M&A during the crisis, and for closure during the recovery), highlighting the dangers of such restructuring events (what we might call a "liability of organizational innovation"). Our results therefore do not support earlier studies identifying downturns as opportunities to 'clean-up', leveraging on the increased slack and decreased opportunity-costs of diverting resources (Caballero and Hammour, 1994; Geroski and Walters, 1995; Nickell et al., 2001). Similarly, the crisis and recovery prevent marketing innovation from having a survival premium (for closure and failure). During the crisis, the chances of failure linked to marketing innovation even appear to increase, possibly because of the perils of marketing innovation in fast-changing demand conditions (e.g. if demand drops and consumers become increasingly price-sensitive and risk-averse, thereby becoming less responsive to previous marketing strategies (Quelch and Jocz, 2009)). Optimal marketing strategy should carefully reduce, although not completely eliminate, marketing budgets during a crisis (Quelch and Jocz, 2009). Our results therefore support earlier findings that the effectiveness of a proactive marketing strategy is lower in times of crisis (Srinivasan et al., 2005). While marketing innovation can provide an affordable, immediate fix to support sales (Naidoo, 2010), it proved ineffective, if not counterproductive, during the 2008 financial crisis. Nevertheless, during both crisis and recovery we observe that marketing innovation reduces the chances of M&A, in some way supporting the findings of Grazzi et al. (2021) that observe that trademarks markedly reduce the likelihood of being acquired in the recovery period. In general, therefore, the crisis and recovery are times when non-technological forms of innovation appear to be risky.

Overall, this suggests that – apart from product innovation and marketing innovation only for exiting via M&A–the other types of innovative activity undertaken during the crisis are less appropriate in the recovery context. For example, if innovative activity during a crisis focuses on cost-reduction rather than novelty generation or quality improvements, then such efforts might be misguided and inappropriate for a recovery context.

Some interesting results can also be seen for our control variables. Young firms are more likely to exit (for all exit routes), confirming previous intuitions on the 'liability of newness' (Stinchcombe, 1965), according to which young firms are particularly vulnerable due to factors such as inexperience, lack of routines, lack of an accumulated customer base, being weakly embedded in the broader socio-economic network, etc. Small firms are more likely to exit via closure. Small firms are more likely to exit via M&A in normal times (perhaps because their small size makes them easier targets), but less likely to exit via M&A in crisis and recovery periods, highlighting how the meaning of M&A changes over the business cycle (from the acquisition of high-potential stars in booms, to the acquisition of fire-sale bargains in recessions). Finally, firms belonging to domestic groups are more likely to be sold (i.e. exit via M&A) in all the three periods, in line with notions that subsidiary firms face selection pressures in terms of economic viability in the broader market, as well as selection pressures in terms of internal relations to the parent company in the context of being a disposable part of the parent's portfolio (Bradley et al., 2011).

For sake of comparison with the previous results in the literature, our complete model (Model 7) is re-estimated using different econometric methodologies (in particular, the piecewise exponential hazard model, the Cox proportional hazard model for the entire period, and Cloglog models). Appendix B discusses and compares these results with the ones from the landmark analysis.

7. Conclusion

This exploratory paper investigates the influence of innovative activities on firms' modes of exit, during three time periods ranging from pre-crisis normal times to the onset of the crisis and subsequent recovery, using novel statistical techniques that we transfer into economics from the epidemiology literature: i.e. landmark analysis and CIF plots. Several interesting results are obtained.

First and foremost, our results highlight that each type of innovation, comparing across normal times, crisis and recovery, affects, in a substantial different way, the likelihood to exit the market through different modes of exit. Our analysis emphasised the evolution over time of each relationship between innovation types and exit routes and, in general, no common pattern appears between the evolution of such relationships.

We begin by investigating the links between innovation types and exit routes in normal times. Technological innovation bestows a survival premium: process innovators have lower exit chances for all three exit routes (closure, failure, and M&A), and product innovators are less likely to exit via closure, in normal times. However, non-technological innovation (organizational and marketing innovation) confers no survival advantage for any of the exit routes in normal times.

We then discuss how the relationships between innovation types and exit routes vary for crisis and recovery phases. After the crisis hits, the survival premium of product innovation is appreciable. Conditional on having survived the onset of the crisis, the weakest firms are perhaps already dead, hence the survival benefits conferred by product innovation are all the more important, if the surviving firms are more resilient and competitive.

The survival premium for process innovation seems lower once the onset of the crisis has passed, however. Process innovators are less likely to exit by closure at the onset of the crisis, but process innovators have no survival advantages for any of the exit routes in the recovery period.

In each period, the survival premium for innovation appears stronger for technological innovations than for non-technological types of innovation. In fact, organizational innovation never bestows a survival premium, and actually is significantly *positively* associated with exit via closure in both the crisis and recovery periods. Marketing innovation grows negatively related to exit via M&A in the crisis and recovery, and marketing innovators become more likely to fail during the crisis. A likely interpretation is that marketing innovation is particularly risky in times of crisis, due to rapid changes in demand (with consumers growing price-sensitive and risk-averse). Another more complex explanation could be that these firms are in an advanced stage of the innovation process (i.e. with newly-developed marketable products) when the crisis hits. These firms had probably already invested in researching, developing, and manufacturing a new good/service and hence are already financially exposed. If the burden of investing in marketing innovation coincides with the onset of the crisis, this could lead to failure. Further research could better investigate this conjecture, if data were available to compare how innovation projects at different stages (from research to development to production to the commercialization of a final product) are differentially affected by exogenous negative shocks such as the 2008 financial crisis.

In our sample, innovators are less likely to be acquired, which is different from some previous work, and may be due to the financial crisis (i.e. if successful firms are acquired at a premium during times of plenty, whereas unsuccessful firms are sold off at a discount during times of difficulty). Instead, innovators are shielded from selling since they have the competences and the capabilities to react to the crisis in a more effective way.

Our landmark analysis reveals results that otherwise would not be discernible. For example, our landmark analysis reveals different results across sub-periods, that otherwise would not be detectable in a standard approach that calculates an average effect for the entire period.

We expect that landmark analysis will be increasingly useful in many contexts of merged datasets, where each dataset has different time intervals. In our application, we used monthly survival data merged with biennial innovation survey data. Other applications could include, for example, high-frequency survival data (some data can be relatively costless to collect at high frequency) merged with episodic questionnaire data (which is expensive to collect, and hence lower-frequency, but providing valuable new statistical information).

Our analysis is not without limitations. First, while Community Innovation Surveys provide high-quality data on firms' innovative activities, they do not allow to punctually locate them over time, but only within the time frame defined by their biennial distribution. Further research is required to precisely investigate how the temporality of firms' innovative activities affect different forms of exit, particularly around recessions. Second, our unit of observation is the firm (or enterprise), not the whole company (or group). While we control for whether firms are part of either a domestic or foreign group, we cannot account for how groups are structured, or react to the financial crisis. Future studies could pursue this research avenue, focusing on how managers can strategically readjust innovation projects undertaken within large corporations, by either involving different subsidiaries or shifting resources among them.

In many cases we find that innovation variables do not influence significantly firms' exit rates and sometimes their significance is at the 10 % level, indicating that selection mechanisms do not strongly favour the survival of innovators. In the midst of the recession, the grim reaper of failure takes swipes at innovators and non-innovators alike, without discriminating. This could suggest a novel rationale for public policy to provide support for innovators during a recession and a recovery: besides motives of correcting for the pro-cyclical nature of R&D investment (Barlevy, 2007) and correcting for the tendency for firms to respond to the crisis by cutting back on longer-term investments such as R&D (Garicano and Steinwender, 2016), our results suggest that innovative firms enjoy significantly different survival premiums according to the different types of innovations they introduce and to the timing of their introduction. Therefore, innovation policy instruments, that seek a decisive role in helping firms stay afloat during crisis and restart during recovery, could be tailored with regard to the specific phase of the business cycle and to the specific characteristics of the innovators.

CRediT authorship contribution statement

All authors have contributed equally to the development of the paper.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The empirical part of this research was carried out at Microdata – Centraal Bureau voor Statistiek (CBS), the Netherlands. The authors do not have any data but only the results of the elaborations.

Appendix A. Literature table on firms' innovation and exit routes/survival

Authors	Year	Journal	Innovation indicator	Exit variable(s)	Data	Recession/Recovery	Main method	Key results
Cefis, Marsili	2005	ICC	Product (CIS) Process (CIS)	Pooled exit (including M&A)	3275 manufacturing Dutch firms 1996-2003	n	AFT	Survival premium for innovators Process innovation key driver
Cefis, Marsili	2006	RP	Innovation (product + process, CIS)	Pooled exit (unspecified)	3275 manufacturing Dutch firms 1996-2000	n	Transition Probability Matrices	Survival premium for innovators Highest for young and small firms
Levitas, McFadyen, Loree	2006	JETM	Patents Patent citations Patent references	Industry participation	295 US integrated circuit manufacturing firms 1975-1994	n	Logit	Non-innovators face highest risk of exit. Introducing multiple, valuable innovations based on older technologies increases survival when technological turbulence is high. Introducing new technology increases exit when technological turbulence is low.
Esteve-Perez, Manez-Castillejo	2008	SBE	R&D (survey)	Pooled exit (incl. shift to non-manufacturing)	2028 Spanish manufacturing firms 1990-2000	n	Cox & parametric survival model	R&D increases survival. In high-tech environments internal R&D is more effective than purely external R&D.
Fontana, Nesta	2009	RIO	Distance from technological frontier (product quality) R&D expenditures	Closure (liquidation) M&A	121 high-tech firms (LAN industry) 1990-2005	n	Cloglog (CR)	Distance from the frontier increases risk of exit. Firms closer to frontier are more likely to be acquired than to close. R&D expenditures reduce exit via closure & M&A.
Naidoo	2010	IMM	Marketing innovation as 7 items scale (survey)	Survival, as composite performance measure	184 Chinese manufacturing SMEs, in textile industry Survey distributed in 2008-2009	2008 crisis	Structural Equation Modelling	Marketing innovation develops competitive advantage, which increases survival.
Buddelmeyer, Jensen, Webster	2010	OEP	Innovation investment, function of patent, trademark, and design applications (IP data) Innovation capital, function of n. years IPs were in-force (IP data)	Pooled exit (de-registration)	299'038 Australian firms (mostly SMEs) 1997-2003	n	Piecewise	Overall, heterogeneous results. Patent capital reduces the risk of exit, but patent investment increases it. Both trademark capital and investment reduce exit.
Esteve-Perez, Sanchis-Llopis, Sanchis-Llopis	2010	EE	R&D activities (survey)	Closure (as voluntary liquidation, bankruptcy, or shift to non-manufacturing) M&A	2998 Spanish manufacturing firms 1990-2000	n	Cox (pooled & CR)	R&D and advertising decrease closure No significant effect on M&A
Wagner, Cockburn	2010	RP	Patents	Delisting, due to bankruptcy or market value below minimum Delisting, due to merger	356 Internet-related firms, NASDAQ IPOs 1998-2005	1990s dot.com bubble	Cox (pooled & CR)	Patents enhance survival, both against failure and M&A (excluding business-method patents) Highly cited patents are attractive assets
Helmers, Rogers	2010	RIO	Patents (Patents offices) Trademarks (Patents offices)	Pooled exit (minor M&A incidence, kept as survivors)	161'857 limited-liability British startups (entry cohort 2001) 2001-2005	n	Probit	Both patents and trademark increase survival
Cefis, Marsili	2011	JEE	Product (CIS) Process (CIS)	Closure M&A	3257 manufacturing Dutch firms 1996-2003	n	Multinomial logit (CR)	For entrepreneurial firms, product innovation reduces exit via closure, but increase exit via M&A. Process innovation critical in low-tech industries. The survival innovation premium is observed in low-tech rather than high-tech industries.
Cefis, Marsili	2012	RP	Product (CIS) Process (CIS)	Closure (including failure) M&A Radical restructuring	3257 manufacturing Dutch firms 1996-2003	n	Multinomial logit (CR)	Both produce and process innovations reduce exit via closure. Process innovation reduces exit via restructuring. Product innovation increases exit via M&A.
Colombelli, Krafft, Quatraro	2013	TFSC	Knowledge stock (patent applications) Knowledge variety, coherence, and dissimilarity (patents' technological classes)	Pooled exit (including M&A)	74'862 French manufacturing firms 2001-2011	period of 2008 crisis	AFT	Innovation enhances survival Knowledge coherence and variety increase survival, while distance decreases it
Boyer, Blazy	2014	SBE	Innovative if new process of fabrication, product, service, or commercial activity (dummy, survey)	Legal liquidation	12'771 French micro-enterprises (<10 emp) 1998-2003	n	Cox	Innovation lowers survival
Hyytinen, Pajarinen, Rouvinen	2015	JBV	Plan to employ a process new to the market (in 3 years) Plan to introduce a product new to the market (in 3 years) Active pursue of innovations	Pooled exit (the DV is 'survival')	1165 Finnish start-ups Create in 2003 and 2005, and followed for 3 years	n	Probit	Pursuing innovation reduces survival Effect amplified by risk-taking attitude
Authors	**Year**	**Journal**	**Innovation indicator**	**Exit variable(s)**	**Data**	**Recession/Recovery**	**Main method**	**Key results**
Børing	2015	EE	Patents (R&D Survey) Product (R&D Survey) Process (R&D Survey)	Closure (including failure) M&A	985 Norwegian firms 2002-2006	n	Parametric CR	Product innovation increases M&A (if new to the market) Process innovation increases M&A in the manufacturing sector No significant effect on closure
Fernandes, Paunov	2015	REStat	Product, as new 7-digit products sold (secondary data)	Pooled exit (unspecified)	Manufacturing Chilean plants, 19439 plant-year observations 1996-2003	n	Cloglog, probit, and logit hazard models	Product innovation reduces exit for multi-product or more cautious innovators (in terms of diversification or market risk) Single-product innovators face higher exit
Howell	2015	RP	Sales from new products and processes (secondary data)	Closure	195'427 Chinese private startups 1998-2007	n	AFT	Risky innovators are prone to exit, while cautious innovators enjoy higher survival (risk is accounted for by debt ratio, revenue diversification, and market and geographical risk)
Jung, Hwang, Kim	2016	TFSC	R&D investment (survey)	Pooled exit (bankruptcy, closure, M&A, or shift to non-manufacturing)	588 Korean manufacturing SMEs 2008-2014	2008 crisis	Cox	R&D increases exit But turns positive for firms with patent applications or in high-tech sectors
Ugur, Trushin, Solomon	2016	RP	R&D expenditures (secondary data)	Liquidation or bankruptcy (excluding M&A)	37'930 UK firms 1998-2012	1998 Asian crisis, 2001 dot.com crisis, and 2008 financial crisis	Log-normal	Inverted U-shaped relationship
Ortiz-Villajos, Sotoca	2018	RP	5 Schumpeterian innovations (compiled by the authors) New products or services New processes or methods of production, New ways of organization New markets, new sources of supply New marketing methods Plus: patented vs non-patented, domestic vs imported	Pooled exit (liquidation, bankruptcy, or M&A)	200 "top" British firms 1816-2013	n	Log-normal and gamma duration models	Significant innovations (in particularly new processes, non-patented and domestic ones) increase survival. Patents only matter for manufacturing firms.
Cotei, Farhat	2018	SBE	Patents (survey) Trademarks (survey)	M&A Ceased operations	3140 US start-ups 2005-2011	period of 2008 crisis	Multinomial logit (CR)	Innovators face higher risk of M&A High-quality innovators most attractive targets
Cefis, Marsili	2019	ICC	Product (CIS) Process (CIS) Organizational (CIS) Marketing (CIS)	General exit Robustness on Closure and M&A	2329 Dutch start-ups 2001-2015	2008 crisis & recovery	Piecewise	Overall, product and process are superior to organisational and marketing innovations. Product is the only innovation enhancing survival both in crisis and recovery. Process innovation decreases exit during the crisis, while marketing increases it. Organisational innovation increases exit pre-crisis, but reduces it during the crisis.
Bartoloni, Arrighetti, Landini	2020	SBE	Skills and knowledge investments (profiled thourgh capital intensity, wages, and internationalization)	Pooled exit ("real death" + liquidation processes)	193'000 manufacturing firms period 2001-2013 Italy	2008 crisis & recovery	Cloglog	Skills and knowledge accumulation is more effective in supporting survival than cutting costs. Efficiency only partially supports survival. Firms must be able to cope with rising environmental complexity.
Landini, Arrighetti, Lasagni	2020	I&I	intangible assets (balance sheet)	Pooled exit (excluding M&A)	4746 Italian firms 2008–2014	2008 crisis	ML probability of exit & multinomial logit	Different selection model during and after the crisis. In 2008-2010, intangible assets directly reduce the probability of exit. In 2011-2014, they still reduce it only if paired with solid finances.
Cefis, Bartoloni, Bonati	2020	SCED	Product inno (CIS) Process inno (CIS)	Pooled exit (no distinction)	6542 manufacturing Italian firms 2006-2013	2008 crisis	Cox	General & Process inno always negative significant Product inno not consistently negatively significant Joint product & process not significant Higher survival premium for young & small firms
Guerzoni, Nava, Nuccio	2020	EINT	New indicator, via Machine Learning	Pooled exit	Two samples of Italian start-ups; 39'295 established in 2008 and 45'576 in 2013	2008 crisis	Cox	Survival premium for innovators, but geographically localised
Kato, Onishi, Honjo	2021	SBE	Patents	banrkuptcy, merger, voluntary liquidation	5270 Japanese manufacturing startups 2003-2013	2008 crisis	IV probit	Patents increase bankruptcy Patents increase M&A Patents (only if granted) increase closures
Grazzi, Piccardo, Vergari	2021	SBE	Patents Trademarks	Involuntary exit (e.g. forced due to bankruptcy) M&A	Panel of Italian firms over 2010-2014 (around 600'000 each year)	recovery after 2008 crisis	cloglog	Innovation increases survival Patents have a stronger shielding effect against involuntary exit, while trademarks against M&As

Notes: 'CR' refers to competing risks; 'AFT' refers to Accelerated Failure Time

List of Journal acronyms used: ICC - Industrial and Corporate Change; RP - Research Policy; JETM - Journal of Engineering and Technology Management; SBE - Small Business Economics; RIO - Review of Industrial Organization; IMM - Industrial Marketing Management; OEP - Oxford Economic Papers; EE - Empirical Economics; JEE - Journal of Evolutionary Economics; TFSC - Technological Forecasting & Social Change; JBV - Journal of Business Venturing; REStat - The Review of Economics and Statistics; WB policy - World Bank Policy Research Working Paper; I&I - Industry and Innovation; SCED - Structural Change and Economic Dynamics; EINT - Economics of Innovation and New Technology; EBR - Eurasian Business Review; WB policy - Policy Research Working Paper, World Bank.

Appendix B. Comparison with other methodologies already used in the literature

B.1. The piecewise exponential hazard model

Table B1 reports the results of a piecewise exponential hazard (PEH) model with 3 periods (normal times, crisis, recovery) using the 4 types of innovation and the 3 modes of exit. The PEH model has been used recently in the economic literature to measure the effects of an independent variable on survival during different time periods (Bradley et al., 2011; Cefis and Marsili, 2019) In fact, this model allows to interact the innovation variables with the time dummies allowing to capture the effects of those time dummies on survival, something that the Cox model cannot perform. The relevant difference with our methodology is that the PEH model takes into consideration the innovation variable measured only at the beginning of the first period and it is maintained fixed throughout the periods, while with the landmark analysis we are able to input, for each time period, the current innovation variables. To compare PEH models with landmark analysis, we have estimated the PEH using the innovation variables registered in the CIS 2006 on our representative sample of the firms' population. The estimates were produced for the model 7 only for comparative purposes.

As Table B1 shows, there are significant differences in the signs and in the magnitude of several coefficients. We regard to product innovation, the PEH shows no significant coefficient during the recovery phase for closure as opposed to Landmark, while magnitude of the coefficient for exit via M&A during the crisis and recovery changes drastically from those observed with Landmark analysis. Process innovation decreases the probability of exit (all modes) during the crisis with both methodologies even if the magnitude is slightly different. The difference is striking for the likelihood to decrease closure during the crisis that is strongly significant and with a large coefficient in landmark analysis while it has a non-significant effect in the PEH model. In addition, process innovation seems to decrease the probability to exit via closure during recovery with PEH models, but not in our analysis. The non-technological innovations are those that show the more salient differences among the two methodologies. Organizational innovations have no effect on survival during normal times while they increase the likelihood to exit via closure during both the crisis and the recovery and via M&A during the crisis with landmark analysis. On the contrary, with PEH models, they increase the probability of exit (all modes) in normal times and reduce it during the crisis. For marketing innovation, in the PEH models, there is not a single coefficient significant throughout the 3 periods, while with landmark analysis we see that this type of innovation increases the probability of failure during the crisis but decrease the likelihood to exit via M&A during the crisis and recovery.

B.2. A “single” Cox model for the entire period

Table OSM3.2 (Online Supplementary Materials - Appendix OSM3) reports the results of a unique Cox model estimated over the whole period, with the values of the variables are fixed at 2006. The estimates were produced for the model 7 only for comparative purposes. The results present substantial differences from the ones obtained with the landmark estimates. In model 7, product innovation reduces the likelihood of exit through both closure and M&A, but is non-significant for failure. Process innovation grants the same survival premium against closure and failure, but does not influence exit via M&A. Finally, non-technological innovations are not significant at all. Therefore, a unique Cox model does not detect at all the local significance of the other innovation variables.

B.3. The Cloglog Model

We repeat our analysis using complementary log-log (cloglog) models with frailty. This methodology has been widely employed in the survival literature (Bayus and Agarwal, 2007; Cefis and Marsili, 2012; Fernandes and Paunov, 2015). Cloglog models are designed for discrete time analyses, and to not require corrections for tied events. Moreover, they can account for unobserved heterogeneity through frailty. As a drawback, when a frailty term is included, cloglog models cannot be estimated including left-censored spells (Jenkins, 2005). Moreover, compared to Cox models, they are computationally onerous. Results are reported in Tables OSM4.1 to OSM4.3 in the Online Supplementary Materials (Appendix OSM4) and remain extremely consistent with the ones obtained using Cox Models, in every specification and at each landmark. All coefficients remain significant and comparable in magnitude, with minor changes regarding decimals.

Table B1
Piecewise exponential model with 3 periods (2006–07 Normal times; 2008–09 Crisis; 2010–2015 Recovery) versus Landmark analysis with landmarks in 2006, 2008, and 2010.

Competing risks piecewise mode, 2006				Competing risks Cox model, landmarks			
	Closure	Failure	M&A		Closure	Failure	M&A
	(6)	(6)	(6)		(6)	(6)	(6)
Product inn. x Period 1	−0.327**	0.0706	−0.0929	Product inn. - Landmark 2006	−0.299*	−0.0604	−0.296
	(0.150)	(0.136)	(0.172)		(0.162)	(0.154)	(0.204)
	[0.029]	[0.604]	[0.590]		[0.065]	[0.694]	[0.148]
Product inn. X Period 2	−0.146	0.112	−0.632***	Product inn. - Landmark 2008	0.0304	−0.0488	−0.274***
	(0.142)	(0.224)	(0.199)		(0.139)	(0.226)	(0.0965)
	[0.306]	[0.617]	[0.001]		[0.827]	[0.829]	[0.005]
Product inn. x Period 3	−0.122	0.172	−0.292***	Product inn. - Landmark 2010	−0.278*	−0.284	−0.430**
	(0.133)	(0.202)	(0.0978)		(0.163)	(0.232)	(0.198)
	[0.357]	[0.396]	[0.003]		[0.089]	[0.221]	[0.030]
Process inn. x Period 1	−0.360**	−0.338***	−0.296*	Process inn. - Landmark 2006	−0.421***	−0.340***	−0.464***
	(0.146)	(0.129)	(0.171)		(0.147)	(0.132)	(0.173)
	[0.014]	[0.009]	[0.083]		[0.004]	[0.010]	[0.007]
Process inn. x Period 2	−0.00650	−0.0558	0.199	Process inn. - Landmark 2008	−0.462***	−0.189	−0.130
	(0.140)	(0.220)	(0.172)		(0.137)	(0.197)	(0.0889)
	[0.963]	[0.800]	[0.246]		[0.001]	[0.339]	[0.145]
Process inn. x Period 3	−0.274**	−0.0918	−0.0689	Process inn. - Landmark 2010	−0.155	0.0746	−0.0198
	(0.130)	(0.192)	(0.0849)		(0.138)	(0.200)	(0.162)
	[0.035]	[0.633]	[0.417]		[0.262]	[0.709]	[0.903]
Organizational inn. x Period 1	0.221**	0.174*	0.441***	Organizational inn. - Landmark 2006	0.0935	0.121	0.153
	(0.107)	(0.102)	(0.127)		(0.109)	(0.104)	(0.130)
	[0.040]	[0.089]	[0.001]		[0.390]	[0.245]	[0.241]
Organizational inn. x Period 2	−0.225*	−0.0229	0.135	Organizational inn. - Landmark 2008	0.319***	0.0802	0.198***
	(0.129)	(0.189)	(0.152)		(0.112)	(0.186)	(0.0766)
	[0.081]	[0.904]	[0.374]		[0.004]	[0.667]	[0.010]
Organizational inn. x Period 3	0.136	−0.0918	−0.101	Organizational inn. - Landmark 2010	0.341***	0.0500	0.0392
	(0.102)	(0.169)	(0.0737)		(0.131)	(0.193)	(0.150)
	[0.182]	[0.588]	[0.172]		[0.009]	[0.796]	[0.794]
Marketing inn. x Period 1	−0.139	−0.100	−0.0901	Marketing inn. - Landmark 2006	−0.115	−0.107	−0.130
	(0.172)	(0.150)	(0.200)		(0.175)	(0.151)	(0.201)
	[0.416]	[0.503]	[0.653]		[0.508]	[0.479]	[0.516]
Marketing inn. x Period 2	0.0192	−0.0165	−0.0454	Marketing inn. - Landmark 2008	−0.199	0.359*	−0.213**
	(0.182)	(0.275)	(0.232)		(0.141)	(0.193)	(0.0960)
	[0.916]	[0.952]	[0.845]		[0.159]	[0.062]	[0.026]
Marketing inn. x Period 3	0.0690	0.110	−0.0112	Marketing inn. - Landmark 2010	−0.124	−0.113	−0.379**
	(0.148)	(0.230)	(0.107)		(0.149)	(0.215)	(0.181)
	[0.642]	[0.632]	[0.917]		[0.405]	[0.601]	[0.036]

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2023.104778.

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