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RESEARCH ARTICLE

Innovation and firm survival over the industry life cycle

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Abstract We analyze how patents, R&D subsidies, and subsidized R&D collaborations influence firm survival in the German photovoltaics industry. We collected data on 154 firms, covering the whole industry life cycle from the emergence of the industry in 1964 until 2016, including the industry's shakeout and decline. We utilize time-variant data for these measures for innovation activity and use discrete-time hazard models to estimate their relationship with firm survival. Our results show that patenting increases a firm's probability of survival. In contrast to previous findings, process patents do not increase survival, but product patents do. Furthermore, we do not find a relationship between public R&D subsidies or subsidized R&D collaboration and firm survival. Other factors, such as entry timing, the dynamics in the industry, and demand-side policies, show expected relationships. We provide recommendations for managers and policy makers who seek to engage in innovative activities to enhance firm survival.

Plain English Summary Our results show that firms that patent their inventions increase their probability of survival in the German photovoltaics industry. Contrary to our hypotheses, R&D subsidies and subsidized R&D collaborations do not increase the survival of firms over the industry life cycle. We obtain these results by studying 154 German firms that were active in the photovoltaics industry from the emergence of the industry in 1964 until 2016, when many firms left the industry. In our quantitative analysis, we provide detailed insights into how product patents in particular are important for firm survival, but process patents are not. Furthermore, we do not find survival-enhancing effects from receiving different kinds of R&D subsidies, despite their substantial amounts. Based on our findings, we recommend that managers engage in patenting, particularly that of product-related innovative activities. For policy makers, we suggest a reassessment of R&D subsidy strategies and point to the high fluctuation of subsidies over time as a potential problem.

Keywords Firm survival · Industry life cycle · Innovation · Discrete-time hazard model · Photovoltaics · Patent

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1 Introduction

Innovative activities and knowledge accumulation are core determinants of firm performance (Dabić et al., 2021). In particular, the probability of a firm's survival is an important measure of firm performance, and empirical evidence on numerous industries confirms the role of innovation as contributing to survival (e.g., Audretsch, 1995; Corbo et al., 2023; Peltoniemi, 2011). Although there is plenty of empirical evidence on the impact of innovative activities on firm dynamics for business cycles or a short period of 3–15 years (e.g., Cefis & Marsili, 2005, 2012; Ejermo & Xiao, 2014; Fontana & Nesta, 2009; Vanino et al., 2019; Velu, 2015), less is known about the role of innovative activity over a longer time horizon that spans several decades. In terms of the relationship between innovative activity and firm survival, research covering longer periods of time finds that the underlying life cycle of the industry provides a general pattern for firm survival. This life cycle pattern shows that the firm population evolves through several stages, and in each of these stages, firms have different probabilities of survival (Gort & Klepper, 1982; Klepper, 1996, 1997). However, it has not been determined how innovative activity can influence firm survival probabilities, particularly when the life cycle pattern is accounted for.

Understanding the relevance of engaging in innovative activities for firm survival is important, because it involves several externalities and uncertainty with respect to the outcome and implementation (e.g., Arrow, 1962; Griliches, 1992), and firms may refrain from engaging in innovative activities, despite their potential positive effect on the probability of survival. Policy makers have implemented various policy instruments to address these problems and to foster innovative activity and ultimately firm performance. Although there is substantial evidence on the positive effects of different policy instruments, particularly R&D subsidies, on innovation and firm performance over a short period of time (e.g., Almus & Czarnitzki, 2003; Dimos & Pugh, 2016; Vanino et al., 2019), it remains open if their impact on firm performance sustains over a longer time horizon such as the life cycle of an industry. Thus, it still remains unclear what types of innovative activities firms should engage in (and to what extent) to enhance their chances of survival over the course of the industry life cycle (ILC). Understanding these relationships could provide nuanced insights into the effect of innovative activities on firm performance and long-term survival.

We analyze the influence of three types of innovative activities, namely, patenting, engaging in publicly funded R&D, and subsidized cooperation on R&D, on a firm's survival probability within the context of the general life cycle pattern of the industry. We argue that firms can use the different kinds of innovative activity to increase their performance during the industry's development. We use the German photovoltaics (PV) industry as an empirical case, as the industry is highly dynamic and Germany has been world leader in PV production for several years. Moreover, the industry is characterized by high levels of patenting activity, strong political support for R&D, and intense collaboration (Dewald & Fromhold-Eisebith, 2015; Quitzow, 2015; Willeke & Räuber, 2012). Nonetheless, the industry experienced a shakeout after 2008, and since then, the industry has been in decline. The PV industry is therefore an ideal case for studying how different types of innovative activities influence a firm's probability of survival throughout the ILC. We collected a novel data set of 154 German PV firms from the industry's birth in 1964 until 2016, when the industry was in decline, including each firm's technological entry and exit year, the different types of innovative activities, and further firm and industry characteristics. We apply discrete-time survival methods to account for this firm- and time-variant data and estimate the effect of innovative activities on a firm's hazard rate throughout the ILC. Our results have several implications for managers and policy makers regarding the choice of innovative activities on firm survival.

The paper is structured as follows. In Section 2, we review the theoretical and empirical literature on the ILC and the impact of innovative activities on firm survival. Section 3 provides information on the PV industry, and Section 4 describes the data and the industry development. Section 5 explains the empirical approach and presents the results as well as robustness tests. Section 6 discusses the results and concludes.

2 Theoretical background

2.1 Industry life cycle, innovation, and firm survival

Efforts to understand the dynamics of industries, particularly the entry, exit, and survival of firms, have identified several stylized patterns (Carlsson, 2016). One prominent pattern derived from firm entry and exit is the ILC, which illustrates changes in the firm population, that can be separated into different phases of development over time. Gort and Klepper (1982) present a model in which the industry evolves through the five stages of emergence, growth, shakeout, decline, and stabilization. These stages are determined by the industry's net entry, that is the number of new entries in the industry in a given year minus the number of firms that exit from the industry in that given year. The net entry is positive in the first phases but becomes negative after a shakeout has occurred. Several refinements and deviations from these models and overarching ILC patterns have been proposed (e.g., Klepper, 1996, 1997; Klepper & Simons, 2000; Klepper & Sleeper, 2005).

Inherent in these models is the relationship between innovation and firm survival. Knowledge and competences translated into improved or new products provide firms with a competitive advantage, which in turn results in improved performance, for example, higher survival chances (Malerba & Orsenigo, 1996). Williamson (1975) explains that in the course of the ILC, fundamental innovations become fewer in favor of incremental improvements. Abernathy and Utterback (1978) show that the ILC is shaped by a shift from product to process innovation as a dominant design emerges. In line with this, Klepper (1996) demonstrates that firms switch from product innovations to process innovations due to increasing returns of process innovations.

Empirical evidence from various industries supports the theoretical pattern of the ILC. Most prominent are examples from the automobile industry in the USA (Klepper, 1997, 2002a, 2002b), Great Britain (Boschma & Wenting, 2007), and Germany (Cantner et al., 2009). However, Klepper (1997) shows that for a set of industries, such as petrochemicals and lasers, the general pattern does not always hold. The survival of firms in the industry, which constitutes the ILC pattern, is usually positively influenced by early entry (e.g., Klepper & Sleeper, 2005), pre-entry experience (e.g., Klepper & Simons, 2005; Klepper, 2002b), or innovative activity (e.g., Cantner et al., 2009; Klepper & Simons, 2005; McGahan & Silverman, 2001).

Whereas the entry timing and the pre-entry experience are static, innovative activity can change throughout the ILC, as proposed in the theoretical models. However, empirical evidence on the dynamics of a firm's innovative activity and survival throughout the ILC is scarce.[1] In the following, we consider three proxies that capture different dimensions of innovative activity and motivate their potential relationship with firm survival.

2.2 Patenting and firm survival

Innovative activity is costly and uncertain, and the nature of knowledge as a latent public good reduces its appropriability and a firm's incentives to engage in innovation (Arrow, 1962; Griliches, 1992). Patents incentivize innovative activity by providing a temporary monopoly right for the owner. Patents are the result from an organization's application-oriented R&D process (Archibugi & Planta, 1996) and thus document a firm's inventive activity and its generated knowledge (Griliches, 1990). Even though not all inventions lead to innovation and not all innovations are patented (Cohen et al., 2002), patent data serve as a good proxy for the deliberate search for new solutions and innovative activity in general (e.g., Artz et al., 2010). If this activity is successful, the firm should introduce new or improved products or technologies that increase its performance and provide a competitive advantage in the industry.

With respect to patenting and the ILC, Cantner et al. (2009) show survival-enhancing effects from

[1] For instance, Klepper and Simons (2000) demonstrate that more experienced firms have higher innovation rates that allow for a longer survival throughout the ILC of US firms producing television receiver. Klepper and Simons (2005) distinguish between firms as innovators and non-innovators and show that innovators, and early innovators in particular, have an increased survival probability among four different industries. Cantner et al. (2009) show that firms' engagement in patenting increases their survival probability in the German automobile industry. Closely related research looks at a short period of time across a larger set of industries to understand the relationship between innovative activity and firm survival, or the role of patenting, R&D subsidies, and R&D collaborations (for a literature survey, see Carlsson, 2016).

patenting in the German automobile industry. However, the results only hold if patents are measured by means of a binary indicator, which implies that it is the inventive activity per se which is important for survival, not the number of patents. A similar relationship is shown by Buenstorf and Heinisch (2018), who observe that firms in which the founder has patented their inventions survive longer in the German laser industry.

While patenting in general influences firm survival, patents can be further differentiated regarding the type of invention into product- or process-related patents. The emergence of an industry is usually connected with a product innovation, which is refined with follow-up innovations of lower importance and a shift towards process innovation over the course of the ILC (Abernathy & Utterback, 1978; Gort & Klepper, 1982). For instance, Buenstorf and Klepper (2010) observe a change from product- to process-related patents before the shakeout of the US tire industry. However, McGahan and Silverman (2001) find no shift from product- to process-related patents over the ILC.

With regard to firm survival, the importance of process innovations is immanent. In a sample of US manufacturing plants between 1987 and 1991, Doms et al. (1995) show that firms have a higher probability of survival when they implement new process technologies. Using the Community Innovation Survey between 1994 and 1996, Cefis and Marsili (2005) observe that manufacturing firms in the Netherlands increase their probability of survival by 25% with the introduction of a process innovation. In a later study, Cefis and Marsili (2012) find that process innovation reduces the probability of exit by radical restructuring, whereas product innovation increases the probability of exit by M&As. However, none of these studies so far provides a clear picture of how patents in general or a specific type of patent influences firm survival for a longer time period.

2.3 R&D subsidies and firm survival

In addition to the above-mentioned externalities in terms of the uncertainty and non-appropriability of the results of innovative activities (Arrow, 1962; Griliches, 1992), firms are often financially constrained and abstain from investments in R&D or a deeper exploration of technological opportunities (Musso & Schiavo, 2008). R&D subsidies are an opportunity to engage in R&D and are a frequently used policy instrument to reduce market failures and incentivize innovative activities (e.g., David et al., 2000). The received R&D subsidies are well suited to address market failures, and it has been shown that they neither crowd out nor complement a firm's internal R&D expenses (Dimos & Pugh, 2016). Furthermore, most governments support science-based industries such as biotechnology and the laser and semiconductor industries via R&D subsidies to foster technology development (for an overview, see Jugend et al., 2020). R&D subsidies have thus become a prominent part of a mix of policy instruments to support innovative activities, particularly in emerging industries (Cantner et al., 2016).

With respect to firm survival, Karhunen and Huovari (2015) show that R&D subsidies increase employment and the survival of small and medium-sized enterprises in Finland during the period of 2000 to 2012. In a sample of entrepreneurial firms in China between 1998 and 2007, Howell (2015) observes that innovative firms that initially received comparatively more subsidies survive for a longer period of time. In contrast, Wang et al. (2017) find for China's Innofund program between 2004 and 2015 that, controlling for selection effects, R&D subsidies do not result in a higher probability of firm survival. However, as yet, the empirical evidence has only considered a rather short period of time and does not account for the underlying pattern of the ILC.

2.4 R&D collaboration and firm survival

Knowledge exchange and mutual learning are important for the innovation process, and innovative activities are increasingly performed in R&D collaborations (Becker & Dietz, 2004). Actors' motives to participate in collaborations are influenced by access to complementary knowledge (e.g., Sakakibara, 1997), risk and cost sharing (e.g., Baum et al., 2000), and the possibility to internalize knowledge spillovers (e.g., Griliches, 1992). However, such interactions are hampered by transaction costs and system failures, which reduce firms' incentives to engage in collaborative innovation activities. System failures result from a lack of complementarity, reciprocity, or intermediation (OECD, 1997). Policy makers can implement instruments to reduce such failures, provide incentives for R&D collaboration, and facilitate knowledge exchange and learning.

Subsidizing R&D collaboration is a tool that is frequently used to involve different actors in R&D projects and to improve firm performance (Smits & Kuhlmann, 2004). Empirical evidence shows that collaborative R&D subsidies increase inventive and innovative output. For example, Czarnitzki et al. (2007) and Hottenrott and Lopes-Bento (2014) find that subsidies for R&D collaborations in Germany, Finland, and Belgium enhance a firm's innovativeness. In a sample of German biotech firms, Fornahl et al. (2011) find that collaborative R&D subsidies create a higher inventive output compared to individual R&D subsidies. Additionally, Cantner et al. (2016) show that interaction structures in inventive activity increase via collaborative R&D subsidies, facilitating knowledge exchange in photovoltaics. However, there is no empirical evidence for whether and how subsidies for R&D collaboration influence firm survival, even though the enhancing effect of the exchange of knowledge, learning, and innovation should translate into an increased probability of survival.

3 The German photovoltaics industry

3.1 The photovoltaics system

PV is the conversion of sunlight into electric energy using the photovoltaic effect. The PV system consists of several components: first, a light-absorbing material that is usually based on silicon or other semiconductors. Second, this material is sliced into wafers to produce a PV cell. Third, the PV cells are joined together to form a PV module. The modules can be installed in different locations but must be connected to balance of system (BoS) components to either power off-grid applications or to feed electricity into the grid (Kalthaus, 2019). These steps represent the value chain of the final product.

The technological progress of PV with regard to decreasing module costs and a wider range of applications has increased substantially since the 1950s. Fraunhofer ISE (2019) estimates a 24% learning rate of enhancing a PV cell's efficiency over the last 38 years, which nowadays makes PV cost-competitive with other forms of electricity generation. By the end of 2017, PV had gained a substantial share of global electricity production with more than 40 GW installed capacity in Germany and approximately 400 GW installed capacity worldwide (Fraunhofer ISE, 2019). However, the electricity production based on PV in Germany accounted only for about 6% of electricity consumption in 2017. Fossil energy production had cost advantages compared to PV and remained the major source of electricity production in Germany.

To a large extent, this success was driven by innovative activities. Private and public actors engaged in R&D, and there was a manifold increase in patents and publications on PV (Binz et al., 2017; Graf & Kalthaus, 2018; Kalthaus, 2019). This included the creation of product-related patents for new PV modules, or process patents, which describe how the modules could be produced in a novel way, for example, through different coating mechanisms. Furthermore, the R&D subsidy amounts were substantial and increased over time (Bruns et al., 2009). In addition, collaboration became frequent in PV, as shown by Graf and Kalthaus (2018) regarding publications, Cantner et al. (2016) regarding patents, and Hipp (2021) regarding R&D collaboration.

3.2 The photovoltaics industry

The PV industry in Germany emerged during the 1960s, when a few major industrial players, such as AEG-Telefunken AG and Siemens AG, started developing PV cells and modules, and firms such as Wacker Chemie started the production of silicon (Bruns et al., 2009). In these early years of the PV industry, the focus was on developing small, off-grid applications, notably satellites (Dewald & Fromhold-Eisebith, 2015). Based on initial research funding during the 1980s, pioneers from Germany entered into basic research on materials and solar cells as well as cost reductions in production processes (Bruns et al., 2009). As a result, Germany, and also the USA and Japan, became leaders in solar PV patents from the 1970s onward, followed by China and other Asian countries, which were only able to catch up much later (Binz et al., 2017). However, the high costs of these PV applications hindered the stimulation of a large-scale market for PV (Jacobsson & Lauber, 2006). As the achieved cell efficiency of 10% was insufficient for cost competition, most firms went through a strategic reorientation, which mainly resulted in exiting the business segment or consolidating at a low level (Räuber, 2005). Bruns et al. (2009) consider this a pioneering phase that allowed for the exploration of technological possibilities and the emergence of major technological characteristics until 1985.

In 1991, political impetus drove the first wave of large-scale demand in Germany by means of the 1000 roofs program. This program allowed the large-scale production of cells and modules for the first time and led to a significant cost reduction (Dewald & Fromhold-Eisebith, 2015). As a result, many new firms entered the production of PV cells and modules (Quitzow, 2015). Firm strategies then shifted towards the increased production of PV, often by integrating other parts of the value chain (diversification strategy) (Bruns et al., 2009). BoS components, particularly inverters, became relevant, and German firms started producing them, particularly SMA Solar Technologies (Bruns et al., 2009). As the 1000 roofs program ended and international demand further increased, other programs on a smaller scale were implemented. In particular, the Renewable Energy Sources Act (EEG), which was introduced in 2000, and its subsequent amendments established a feed-in tariff that fostered the creation of a (niche) market, and firm entry and innovative activity flourished. The EEG also influenced firms from related industries, particularly machine producers, that provided machinery to automate production and help realize economies of scale (Bruns et al., 2009; Jacobsson & Lauber, 2006; Quitzow, 2015).

Based on substantial policy support and the growing international demand for PV from the 1990s onward, German PV firms increasingly invested in large-scale production. Before this, the US and Asian countries had been pioneers in terms of the global production of PV, but from 1999 onwards, Germany, Japan, and China caught up quickly. Particularly in countries with strong demand-side support, such as in Germany, firms aimed to access the domestic market by means of large-scale local production or focused on niches with distinct products of high quality and service (Haley & Schuler, 2011). At the same time, focus was placed on increasing cell efficiency and improving industrial processes, which was politically supported by the German high-tech strategy during the early 2000s (Bruns et al., 2009). Regarding global solar PV installation, Japan, Germany, and the EU had the largest shares during this period (Binz et al., 2017).

In 2009, Germany became the largest market for solar cells (Dewald & Fromhold-Eisebith, 2015) and 2 years later became the market leader for solar PV system installations in the world (Haley & Schuler, 2011). However, German firms faced three interrelated challenges in the mid-2000s. First, the supply of silicon could not keep pace with the rapid market developments and German PV producers suffered from high material costs (Willeke & Räuber, 2012). However, during that period, several silicon producers entered the industry (Quitzow, 2015).[2] Second, the introduction of the feed-in tariff led to a rapid increase in market size, and it made PV installations a profitable business. Subsequent cost reductions and performance improvements increased the margins for PV installations, and the German government had to reduce the tariff level substantially (Hoppmann et al., 2014). This reduced the market size drastically, and only low-cost PV modules, mainly produced in Asian countries, particularly China, were installed. At this time, the PV industry was already suffering from the global financial crisis (Huang et al., 2016), and the increased international competition placed further pressure on German cell and module manufacturers, and their margins decreased (Binz et al., 2017; Willeke & Räuber, 2012). Third, and related to this, Chinese industrial policy focused attention on PV by supporting firms financially and facilitating the rapid extension of production capacities and exports to Germany (Chen, 2016). German firms could not decrease their costs to the extent to which they would have been competitive with the cheaper Chinese PV products, and many firms had to leave the market (Hipp & Binz, 2020).[3]

3.3 Policy support in Germany

The PV industry in Germany has received a broad and diverse policy mix to support innovative activity and diffusion (Cantner et al., 2016). Since the 1970s,

[2] However, many firms had to close soon after silicon prices considerably dropped and production was no longer economically viable for most of them (Willeke & Räuber, 2012).

[3] The development in China was also not sustainable given that many firms had to exit the market as they were dependent on subsidies, and demand was not sufficiently high due to anti-dumping laws in the USA and the EU. See Chen (2016) for a thorough discussion.

R&D subsidies have been granted on a large scale to increase technological performance and reduce costs (Bruns et al., 2009). Policy makers prioritized PV support for several decades by investing more than one billion euro in R&D subsidies (Cantner et al., 2016). As a requirement for firms to receive the R&D subsidies, they needed to provide at least 50% of their own R&D funds. Since the 1980s, R&D policies have been targeted not only at individual firms, but policy makers have placed increasing focus on research consortia in terms of increasing collaborations between different actors (Dewald & Fromhold-Eisebith, 2015). This has resulted in a dense knowledge network of heterogeneous actors (Jacobsson & Lauber, 2006). In addition to German R&D subsidies, the EU Framework programs have offered R&D subsidies to incentivize engagement with European actors.

Complementarily to R&D subsidies, other systemic instruments were implemented. For example, during the 1980s and at the beginning of the 1990s, the German government established public research institutes such as the Fraunhofer ISE, ZSW Stuttgart, ISET Kassel, and ZAE Bayern (Dewald & Fromhold-Eisebith, 2015). These institutes were important for providing additional research and for connecting and interacting with firms in the industry. Additionally, in Eastern Germany, the PV cluster Solarvalley Mitteldeutschland emerged in 2009 and was funded by the Leading-Edge Cluster Competition; other efforts to increase R&D and collaboration in PV included the Innovationsallianz Photovoltaik funded by the Federal Ministry for Research and Education (Quitzow, 2015).

Furthermore, several demand-side instruments were introduced to support the diffusion of PV (Bruns et al., 2009). In the 1970s and 1980s, no systematic demand-inducing policies were in place, and only bilateral agreements between municipality utilities and the installation owner existed (Jacobsson & Lauber, 2006). After the 1000 roofs program, a general feed-in tariff system (Stromeinspeisegesetz) was implemented during the 1990s, which covered only a small fraction of actual PV system costs but guaranteed grid access for PV installations (Jacobsson & Lauber, 2006). This feed-in tariff law was replaced in 2000 by the EEG, which provided more favorable remuneration. In 1999, the 100,000 rooftops program followed to support the large-scale deployment of PV. In 2004, this program was integrated into a revised EEG (Bruns et al., 2009). Since then, the EEG has been amended several times, and support has been adjusted to keep abreast with technological progress (Hoppmann et al., 2014). Particularly at the end of the 2000s, subsidy levels were substantially reduced to account for the increase in technological progress and to reduce windfall profits (Hoppmann et al., 2014). In addition to these national efforts to foster innovation and the diffusion of PV, the ratification of the Kyoto Protocol increased attention to renewable energies, and PV in particular, to reduce greenhouse gas emissions and spurred subsequent innovative activity (Bruns et al., 2009). Overall, the German demand-pull programs increased the incentive to install PV and the number of new installations, making Germany the world leader in installed PV capacity for several years (Binz et al., 2017).

4 Data

To analyze the influence of innovative activity on firm survival in the German PV industry, we combined data from various sources to construct three types of variables. First, we collected the entry and exit data of PV firms in Germany to reconstruct the life cycle of the industry. Second, we collected data on three sets of firms' innovative activities, namely, patenting, received R&D subsidies, and R&D collaboration subsidies. Third, we collected a set of control variables with respect to firms' entry characteristics, acquisitions, their position in the value chain, and their geographical location. We further collected data describing the market demand for PV in Germany. Table 1 provides the descriptive statistics, and Table 3 in Appendix 1 depicts correlations.

4.1 The industry life cycle of the German photovoltaics industry

We identified 154 German firms operating in the PV industry from 1964 until 2016. These firms represent the whole population in the industry from its emergence to its current state in Germany. We built a novel database in which we included entry and exit information from the German common register portal Handelsregister. Handelsregister is a public company register portal of the German Federal States that stores details on the legal status of firms; the commercial registers are maintained locally by district courts. The primary purpose of the register portal is to provide information about firms. We used a set of keywords to identify PV firms in Handelsregister.[4] Although Handelsregister is a reliable data source for active firms, data on inactive firms could have been changed or deleted over time. We therefore additionally searched for firms on websites and in industry journals (e.g., Photon), newspapers, and other publicly available sources.

In the database, only firms that have a substantial share of their business in PV are included, and we excluded firms that provide services with respect to installation, maintenance, or operation. As some firms diversify in PV, we considered the year of technological entry as the entry date. We collected the entry date for all firms and did not have left censoring. If a firm changed ownership without changing its operation, we consider this as a continuation. If a firm retreats from the market, it exits from the industry, which in most cases is due to bankruptcy or closure. If a firm was acquired by another firm, we treat this as an exit, as most mergers and acquisitions in the German PV industry occurred because firms suffered financial turmoil, particularly from the mid-2000s onward.[5] Similar to technological entry, we accounted for technological exit from the industry, as some firms end their activities in PV but continue in another line of business. All firms which were still in operation at the end of 2016 are right censored and have no exit event.

Figure 1 depicts the entry and exit pattern of the 154 PV firms. The evolution of the number of active firms resembles the typical shape of an ILC. However, the emerging stage is fairly long, and only a few firms enter in the first 30 years, which is unusual for an ILC (Agarwal & Tripsas, 2008), but not an exception. Lamberg and Peltoniemi (2020) show a similar development in the paper and pulp industry.[6] From the mid-1990s onward, the number of entrants increases substantially and peaks in 2008 with 123 active firms. After this, a shakeout occurs and the number of firms declines. At the end of 2016, 64 firms are active in the German PV industry. The median lifetime of all firms is around 12 years. The non-parametric survival function and the hazard rate show a typical pattern. The only remarkable aspect is the few firms that survive for a fairly long time, and most of them are still active (see Appendix 2).

In our empirical analysis, the ILC is operationalized by the *Net Entry Rate*, that is the number of new entries in the industry in a given year minus the number of firm exits in that year divided by the overall number of active firms in that year. The *Net Entry Rate* captures the dynamics in the industry as a relative change of the firm population and is usually positive until the industry's shakeout, after which it turns negative (see Fig. 1). The *Net Entry Rate* has an advantage over fixed ILC periods in that it accounts for nuances in the industry dynamics which are not captured otherwise.[7] To estimate how the ILC influences firm survival, we use the *Net Entry Rate* of the previous period to avoid potential simultaneity issues. Via controlling for the *Net Entry Rate*, all ILC phase-specific factors are accounted for, such as the higher survival rate in the early phases of the industry.

4.2 Innovative activities: patents, R&D subsidies, and subsidized R&D collaboration

Patent applications are an indicator of successful inventive activities (Griliches, 1990). Even though patent applications have several shortcomings, they are frequently used as a proxy for innovative activity in assessing firm survival and ILC (Buenstorf & Klepper, 2010; Cantner et al., 2009; McGahan & Silverman, 2001). We collected priority patent applications based on the search strategy described in Kalthaus (2019), using a combination of classifications and keywords from PATSTAT 2017 Autumn Edition (EPO,

[4] We searched for keywords that relate to PV in general, such as "solar" or "PV", and keywords that relate to the value chain such as "silicon", "cell", "module", and "system".

[5] In total, 34 firms were acquired. At the time of acquisition, most of these firms were on the brink of going bankrupt. The acquirer was usually interested in gathering the production machinery or intellectual property.

[6] The low number of firms can be also attributed to the information available during this time period, since no trade journals, industry registers, or associations existed that systematically gathered data. This phenomenon is referred to as survival bias. We apply a robustness test in Section 5.3 and exclude the entries before 1990 to account for such a bias.

[7] Other ways to operationalize the ILC include, for example, the use of pre-defined time periods. We discuss an estimation with specific ILC phases in the robustness section. The net entry can be alternatively operationalized by the total number of entries and exits from the industry (e.g., Fontana & Nesta, 2009).

Table 1 Descriptive statistics

	Description	Min.	Mean	Median	Max.	S.D.	Unique Obs.
Firm-variant and time-variant variables							
$Exit_{it}$	Exit from the industry	0	0.05	0	1	0.22	1842
$Patents_{it}$	Number of patents	0	0.70	0	30	2.29	1842
$Product\ Patents_{it}$	Number of product-related patents	0	0.44	0	23	1.46	1842
$Process\ Patents_{it}$	Number of process-related patents	0	0.26	0	21	1.10	1842
$Overall\ R\&D\ Subsidies_{i,t\text{-}1}$	Amount of overall R&D subsidies	0	150,956.26	0	7,276,996	562,405.44	1842
$Individual\ R\&D\ Subsidies_{i,t\text{-}1}$	Amount of individual R&D subsidies	0	85,871.26	0	7,276,996	483,404.85	1842
$Collaborative\ R\&D\ Subsidies_{i,t\text{-}1}$	Amount of collaborative R&D subsidies	0	65,085.00	0	4,777,248	268,477.31	1842
$Acquisitions_{it}$	Number of acquisitions	0	0.18	0	6	0.65	1842
Firm-variant and time-invariant variables							
$Tech\ Silicon_i$	1 if a firm produces PV silicon	0	0.10	0	1	0.30	154
$Tech\ Cell_i$	1 if a firm produces PV cells	0	0.32	0	1	0.47	154
$Tech\ Module_i$	1 if a firm produces PV modules	0	0.33	0	1	0.47	154
$Tech\ BoS_i$	1 if a firm produces BoS components	0	0.10	0	1	0.30	154
$Tech\ Others_i$	1 if a firm operates in niches	0	0.15	0	1	0.36	154
$Primary\ PV_i$	1 if a firm mainly engages in PV	0	0.81	1	1	0.40	154
$Entry\ Lateral_i$	1 if a firm is a subsidiary, joint venture, or spin-off	0	0.41	0	1	0.49	154
$East_i$	1 if a firm has its headquarter in East Germany	0	0.46	0	1	0.50	154
$Entry\ Cohort\ 1964\text{–}1999_i$	1 if a firm is in the first entry cohort (emergence)	0	0.26	0	1	0.44	154
$Entry\ Cohort\ 2000\text{–}2008_i$	1 if a firm is in the second entry cohort (growth)	0	0.62	1	1	0.49	154
$Entry\ Cohort\ 2009\text{–}2016_i$	1 if a firm is in the third entry cohort (shakeout)	0	0.12	0	1	0.33	154
Firm-invariant and time-variant variables							
$Net\ Entry\ Rate_{t\text{-}1}$	Number of firm entries in a year minus the number of firm exits in that year divided by the overall number of active firms in that year	−0.13	0.09	0	1	0.17	53
$Newly\ Installed\ Capacity_{t\text{-}1}$	Annually newly installed PV capacity in Germany	0	740.08	0.5	8161	1925.96	53

2017).[8] We counted patent applications at the patent family level. We manually matched applicant names to our firm data. Overall, 82 out of 154 firms filed at least one patent, and there are 1289 patents in total. Furthermore, we divided patents into product- and process-related patents based on the abstract of the patent document. We independently coded the patents and

[8] We extend the search strategy by Kalthaus (2019) to account for patents related to the production of silicon for PV cells. See Appendix 3 (Table 4) for details.

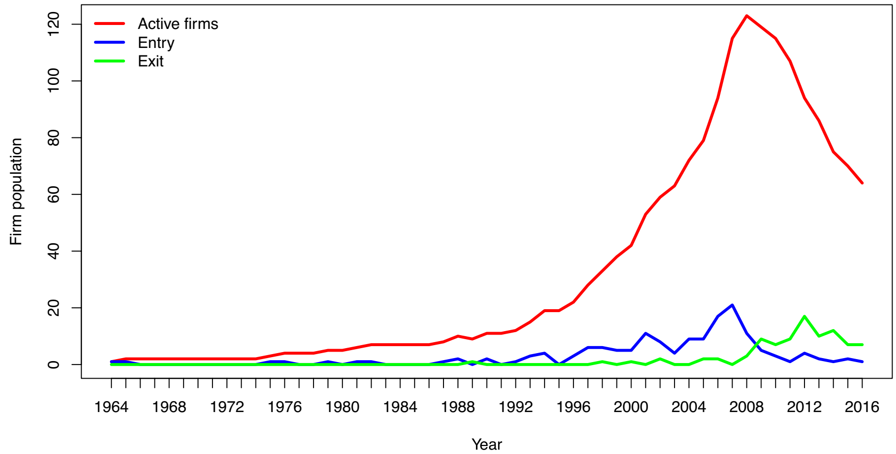

Fig. 1 Population dynamics of the German PV industry

performed intercoder reliability checks.[9] Figure 2 depicts the development of the overall number of patents as well as product- and process-related patents over time. In the PV industry, firms applied for more product patents (814) than process patents (475), and over time, the share of product patents in all patents increased, which is contrary to previous theoretical and empirical observations (Abernathy & Utterback, 1978; Gort and Klepper, 1982; Buenstorf & Klepper, 2010; Peltoniemi, 2011). In our empirical specification, we included the yearly number of applications by each firm for *Patents*, *Process Patents* and *Product Patents* in logs to dampen the effect of heterogeneity.

We collected R&D subsidies from the German Federal Government's funding database Förderkatalog, which includes over 100,000 completed and running projects funded by the German Government from 1960 until today (see Broekel & Graf, 2012, for a detailed description). The Förderkatalog allows for a search of funded projects via technology classifications as well as keywords. Moreover, it allows for a separation of individual and collaborative R&D subsidies. We queried all projects for PV-related technology fields and used "photovoltaic" and "solar" as keywords to search the whole database. Manual cleaning based on project title and abstract was conducted to remove unrelated projects.[10] Another source of R&D subsidies is the Community Research and Development Information Service (CORDIS), which contains all EU-funded research projects. The Publications Office of the EU has administrated the service since 1990. We used the same search procedure for PV-related projects as above and conducted manual cleaning.

[9] A patent is coded as a process patent if the title or abstract contains a description of a process, a method, a production process of an input material, or similar. These patents focus in most cases on a new method of manufacturing a PV cell, as indicated in patent titles such as "Method for manufacturing wafer to manufacture e.g. photovoltaic cell…" or "Method for producing contact metallization structure i.e. linear contact finger, on emitter-side surface of solar cell…." These patents have the potential to reduce the production cost, increase the cell efficiency, or cell quality. A product patent is identified if the title or abstract contains a description of a device, apparatus, component, new material, machinery, arrangement, system, or similar. In most cases, it describes a new module with a specific feature, as illustrated by this title: "Photovoltaic module i.e. thin-film photovoltaic module, for use in e.g. photovoltaic power plant, has integrated energy storage, and front substrate comprising active layer system bonded with rear substrate through lamination layer." In most cases, these patents result in new products with slightly different product specifications (i.e., rather incremental improvements), but can also contain substantial new ways to produce a PV, as the invention of the dye-sensitized solar cell. Furthermore, complementary products are considered, such as a "Support system for fixing solar modules at flat roof," which can be important for opening up new areas of application. If a patent contains both, it is coded as a product patent because we assume that the underlying process relates to the production of the new product. Examples are indicated in titles such as "Hetero-junction solar cell with edge isolation and method of manufacturing same".

[10] We removed projects which, for example, relate to concentrated solar power or projects that are not relevant for innovative activities, such as information and education programs.

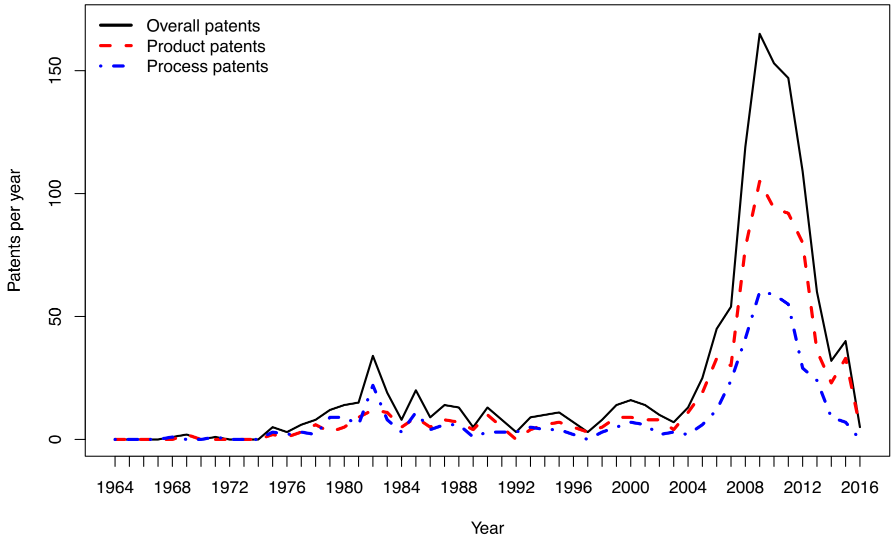

Fig. 2 Aggregated patent applications by German PV firms

We matched the subsidy recipients with the firms in our sample and distributed a firm's received subsidies over the subsidy duration.[11] We use *Overall R&D Subsidies* as the total amount of funding that each firm receives. R&D subsidies can be disaggregated into subsidies that only one firm receives, that is *Individual R&D Subsidies*, and subsidies that are granted to conduct R&D in collaboration, that is *Collaborative R&D Subsidies*. Figure 3 depicts the development of the received amounts of subsidies by all German PV firms over time.[12] The subsidy data shows a peak in the early 1980s, which marks the efforts to search for alternative electricity sources motivated by the oil crises. Another peak occurs in the 2000s, when the industry was flourishing and the German Government supported many firms with R&D subsidies. Thereby, the distribution of *Overall R&D Subsidies* over time is highly turbulent. After the oil crisis, huge amounts of subsidies were allocated to only a few firms (e.g., one firm was allocated up to 7.5 million euro in 1977). In contrast, from the mid-1980s onwards, the average subsidy per firm declined substantially to as low as 34,000 euro on average per firm. From the end of the 2000s onwards, the amount of *Overall R&D Subsidies* increased along with the number of firms, which received on average between 130,000 and 210,000 euro per year. Moreover, a shift in the type of R&D subsidies is observable. *Collaborative R&D Subsidies* outweighed *Individual R&D Subsidies* from the 2000s onward. Overall, 78 firms received 278 million euro of *Overall R&D Subsidies*, of which 119 million euro were attributed to *Collaborative R&D Subsidies*.

For the empirical analysis, we logged and lagged all R&D subsidy-related variables by 1 year, as we assume that there would not be an instantaneous effect, and research takes time to translate into performance. Lagging also reduces possible endogeneity concerns in our estimation.

4.3 Control variables

To control for firm-specific and industry-related factors, we collected several variables on the firm and industry levels. With respect to time-invariant firm variables, first, we distinguished between firms that had their main business in PV and those that diversified into PV and had a business in other activities (*Primary PV*), as diversifying entrants are more likely to survive (Buenstorf et al., 2022). Second, we distinguished between firms that are founded without any attachment to other firms and firms that had pre-entry experience because they were subsidiaries, spin-offs, or joint ventures (*Entry Lateral*) (Klepper & Sleeper, 2005). Third, we controlled for firms that had their headquarters

[11] For EU subsidies, a direct attribution of received subsidies to firms is not possible. The database provides only aggregated subsidies for all project partners. We assume that each firm receives the same amounts and divided the total amounts of subsidies in a given year by the number of project partners.

[12] Subsidy data is price adjusted and presented in prices of 1991.

in East Germany (*East*), as firms in East Germany received more attention from policy makers, which might have influenced their entry and exit behavior (Brachert et al., 2013). Fourth, we distinguished firms by their position in the PV value chain in terms of firms that produced silicon for the PV industry (*Tech Silicon*), firms that produced wafers and cells (*Tech Cell*), firms that produced modules (*Tech Module*)[13], firms that provided BoS components (*Tech BoS*), and firms that cannot be attributed to these groups, but which are important players in the industry and usually operate in niches, such as producers of machines for coating (*Tech Others*). Last, we controlled for different entry cohorts. Firms which enter an industry early usually show higher survival rates than late entrants (Klepper & Simons, 2005; Klepper, 2002a). We defined the first entry cohort as firms that entered the PV industry in its emergence stage from 1964 to 1999 (*Entry Cohort 1964–1999*), during which 40 firms entered the industry. The second stage covers the industry's growth phase to the shakeout from 2000 to 2008, with 95 entries (*Entry Cohort 2000–2008*). The third entry cohort includes 19 firms that entered the industry during its shakeout and decline from 2009 to 2016 (*Entry Cohort 2009–2016*). With respect to time-variant firm variables, we accounted for mergers and acquisitions in the industry (Kato et al., 2022). We counted and added up the number of *Acquisitions* a firm had made over time (Klepper & Simons, 2005; Klepper, 2002a).

To account for the policy-induced market and its underlying demand-pull policies and their changes, we used the annual newly installed PV capacity in Germany as a catch-all proxy (Cantner et al., 2016). We collected data on the annually installed PV capacity from Jacobsson et al. (2004) before 1990, and from then onward from BMWi (2018).[14] We logged and lagged the *Newly Installed Capacity* by 1 year to avoid simultaneity issues.

[13] Firms that produce thin-film or organic PV modules are attributed to this group, since they need no wafers or silicon cells. If firms are active in multiple value chain positions, we use the one in which the major activities are conducted, or, if this information in not available, the higher level in the value chain.

[14] Jacobsson et al. (2004) collected data from 1983 onward and account only for larger installations. However, these larger installations in 1983 are 0.3 MW, which are marginal in size. We set the installed capacity to 0 before 1983.

5 Empirical analysis

5.1 Estimation approach and model specification

We use survival analysis, which estimates the probability of an event occurrence conditional on the event having not yet occurred. In the current analysis, the event occurrence is the exit of a firm from the industry. Standard methods for such duration analysis include Cox proportional hazard models for continuous time (Cox, 1972). However, in the current case, the assumptions for the Cox models are not fulfilled. First, we cannot observe firms in continuous time but have discrete data on a yearly basis. Second, as we have time-variant co-variates on a yearly basis, the spell length is equal to one, and we have a large number of ties in our data, which distorts proportional hazard models (Cox & Oakes, 1984). We therefore use logistic regressions in the form of a discrete-time hazard model to estimate the hazard function and the effects of co-variates, as is frequently done in ILC studies (e.g., Buenstorf et al., 2022). For detailed discussions on discrete-time hazard models, see, among others, Allison (1982) and Singer and Willett (2003).

We are interested in the effects of the co-variates $\boldsymbol{X}_{it}$ on the hazard function $h_{it}(t)$ as the probability of a firm i's exit from the industry in period t given no earlier exit. Given that T_i is the event time, $h_{it}(t) = \Pr(T_i = t|T_i \geq t; \boldsymbol{X}_{it})$. To estimate the hazard function and the influence of the co-variates, we start by modeling the baseline hazard function (for more details, see Appendix 4). The baseline hazard function describes a firm's hazard rate only dependent upon time periods, which represents a firm's age in the industry, that is the years in which the firm has been active in PV. In a fully specified form, the baseline hazard rate can be estimated with a dummy for each time period. However, such an approach is computationally intensive, and the hazard function would not be specified for all periods. We therefore approximate the baseline hazard by a polynomial of the firm's age (Mantel & Hankey, 1978). We estimated several baseline specifications, and based on the AIC and model convergence, we choose the third order polynomial of the time period as an approximation of the baseline hazard function. We assume a complementary log–log link function, whose hazard probability is asymmetric and more closely resembles

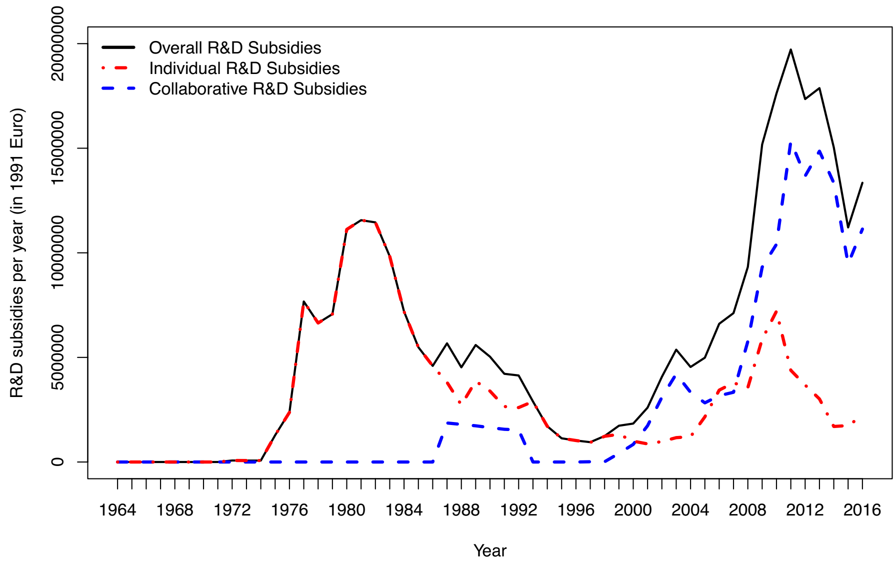

Fig. 3 Aggregated R&D subsidies for German PV firms

the properties of a continuous process (Singer & Willett, 2003).

We estimate a regression with the following stylized form:

$$\log\left(-\log\left(1-h_{it}\right)\right)=\alpha_0+\sum_{k=1}^{3}\alpha_k(t)^k+\beta_1 Patent_{it}+\beta_2 R\&D\ Subsidy_{i,t-1}+\beta_3 Collaboration_{i,t-1}+\boldsymbol{\beta} Control_{it}$$

Patent is a set of variables capturing the overall number of patents a firm has applied for as well as the number of product- and process-related patents. *R&D Subsidy* is a variable for the R&D subsidy amounts. *Collaboration* measures the collaborative R&D subsidy amounts. *Control* is a set of variables for the time and firm-variant and invariant co-variates.

We estimate eight model specifications. Model 1 includes only the baseline hazard. Model 2 adds the time-invariant control variables, and Model 3 includes the time-variant variables. The next models are used to assess the influence of the different proxies for innovation activity on firm survival. Model 4 adds the overall number of *Patents*. In Model 5, the patents are separated into *Product Patents* and *Process Patents*. Model 6 includes the *Overall R&D Subsidies* a firm received. Model 7 splits the *Overall R&D Subsidies* into *Individual R&D Subsidies* and *Collaborative R&D Subsidies*. Model 8 is the full specification and includes *Product Patents* and *Process Patents*, *Individual R&D Subsidies,* and *Collaborative R&D Subsidies*.

5.2 Results

Table 2 shows the regression results regarding the impact of different innovative activities on a firm's probability of survival. Models 1–3 include the control variables for the firm- and industry-specific factors. Model 1 shows the coefficients of the third-order polynomial, that is the baseline hazard function based on the time periods. A clear non-linear effect of firm age on survival is present in the industry. Model 2 introduces the time-invariant variables. First, there is no distinct difference in a firm's survival rate depending on its value chain position in the PV system; only a significantly lower hazard rate for *Tech Others* compared to the baseline of *Tech Module* is observable. These firms operate in niches, which gives them an advantage compared to firms in the core value chain. There is no significant difference in the hazard rates between firms that were located in the East of Germany (*East*) and firms that entered the industry as a subsidiary, joint venture, or spin-off (*Entry Lateral*). However, firms that focused on PV (*Primary PV*) had a higher hazard rate and exited the industry earlier than firms that were also active in other industries. The different *Entry Cohorts* show the anticipated pattern; firms that entered the industry later had a higher hazard rate compared to firms that entered early. Model 3 includes the time-variant variables. The pattern of the ILC, measured by the lagged *Net Entry Rate*, has a negative and significant effect. This indicates that the dynamics in the industry substantially influence firm survival. If there is a positive *Net Entry Rate*, firms have a lower hazard rate, and if the *Net Entry Rate* becomes negative, firms have a higher hazard rate, thus reinforcing the dynamics in the industry. This pattern resembles the core logic of the ILC and highlights the importance of accounting for the ILC when assessing firm survival. After including the *Net Entry Rate*, parts of the baseline hazard rate were not significant anymore, indicating that the hazard rate is predominantly driven by the ILC and is only linear with firm age. The *Acquisitions* a firm has made do not influence the hazard rate. The lagged *Newly Installed Capacity,* a proxy for market development and the respective demand-side policies, has a positive and significant effect on the hazard rate, which is in line with general industrial dynamics theory.

The next models introduce the different proxies for innovative activity.[15] In Model 4, the effect of *Patents* exerts a negative and significant influence on the hazard rate, indicating that patenting in general increases the probability of survival. Thereby, the size of the effect is remarkable: anti-logging the coefficient leads to a hazard ratio of 0.585 that means that a one unit increase in log *Patents* leads to a reduction of the hazard rate by 41.5%, given that the firm has survived until this time. A separation of *Patents* into *Product Patents* and *Process Patents* in Model 5 shows no significant coefficient for *Process Patents*. However, there is a negative and significant coefficient of *Product Patents*. The coefficient translates into a hazard ratio of 0.433 and a corresponding 57% reduction of the hazard rate for a one unit increase in log *Product Patents*, which is even larger than the effect size for *Patents* in the previous model.

Model 6 and Model 7 focus on the different R&D subsidies and firm survival. The coefficient of *Overall R&D Subsidies* is insignificant, indicating that a firm's received R&D subsidy amounts do not influence its survival. Model 7 categorizes *Overall R&D Subsidies* into subsidies that were given to support R&D collaborations (*Collaborative R&D Subsidies*) and the subsidies that were given to an individual firm (*Individual R&D Subsidies*). Both coefficients are statistically insignificant, indicating that particularly *Collaborative R&D Subsidies* do not influence firm survival.

Model 8 integrates the different types of innovative activities, namely *Product Patents* and *Process Patents*, *Individual R&D Subsidies,* and *Collaborative R&D Subsidies*. The results of the full model do not change any of the previous relationships of our variables of interest.

5.3 Robustness check

In a first set of robustness tests, we address the issue that our estimation might suffer from unobserved heterogeneity, as we lack several firm-specific variables. Even though Manjón-Antolín and Arauzo-Carod (2008) point out that unobserved heterogeneity can usually be neglected in firm survival contexts, we account for it via two approaches. Table 6 in Appendix 5 contains the results of these robustness tests for Models 4 to 8. First, we include a frailty term, which is a firm-specific random variable, in our regression. Given the increased complexity in the model, the estimation does not converge in all specifications, and we have to discard the time-invariant firm variables, which, however, would be captured by the frailty term. Compared to the main regressions, there are no structural changes in the direction and significance level of the coefficients of interest. However, in Model 7, *Individual R&D Subsidies* has a negative and significant coefficient. The estimated variance of

[15] In the empirical estimations, concerns of endogeneity can arise. Omitted variables can exist, selection into innovative activity can take place and firms can change their behavior if they sense a potential exit threat. By following previous studies (e.g., Klepper & Miller, 1995), we claim no causal relationships here, but correlation between innovative activities and survival. To reduce any potential bias, we employ three approaches. First, we utilize frailty and firm fixed effects regressions to reduce omitted variable bias and other potentially disturbing influences due to firm heterogeneity, such as different firm strategies. Second, we use t-tests to compare the innovative activities of firms in the year of exit and in the previous year. The tests show that there is no statistically significant difference between the innovative activities in the year of exit and in the year prior to exit, and a behavioral change seems not to take place. Third, R&D subsidies could be used to finance operational expenses in times of crisis. We lag the R&D subsidies by one year to address this potential issue. We lag several other variables as well to address simultaneity issues.

the frailty term in all models is very small and converges to 0. The AIC, as well as the deviance of the models that include the frailty term, are inferior compared to the models presented in the main specification. Likelihood ratio tests between the models with and without frailty show that the difference in the model fits is statistically significant. Overall, including frailty does not improve the model fit and does not change the results substantially.

Second, as accounting for unobserved heterogeneity via firm fixed effects, as an alternative solution to frailty, biases estimates in logistic regressions, we use a linear probability model (i.e., an ordinary least squares regression with a binary dependent variable) with firm fixed effects (Allison, 1982). As with the models that include the frailty term, we cannot estimate the time-invariant firm variables, as they are captured by the firm fixed effects. The results of our variables of interest are by and large the same, and we can rule out large effects of unobserved heterogeneity. Interestingly, the coefficient of *Newly Installed Capacity* becomes negative and significant. One interpretation of this effect is that there are firm-specific factors that allow some firms to better cope with the growing market than others and that these factors are not captured via the firm-specific variables in our main regressions. Again, in Model 7, *Individual R&D Subsidies* has a negative and significant coefficient.

Based on the two robustness tests, we can rule out a substantial effect from unobserved heterogeneity. The time-invariant firm variables in our main specification seem to be able to capture unobserved heterogeneity even better than a frailty term or fixed effects. Furthermore, these models are not able to account for ILC-specific characteristics, which have been deemed important for studying firm dynamics, particularly the differences between the entry mode and entry cohorts.

In a second set of robustness tests, we test our model assumptions and different operationalizations of our variables in the full Model 8. The results are presented in Appendix 5 in Tables 7 and 8.

First, we use time lags of 1 year for *R&D Subsidies*, as we assume that the subsidies need time to translate into innovative outcomes (Cantner et al., 2016). We estimate the model without these time lags to check whether there are contemporaneous effects (Model R1 in Table 7). The results of the full Model 8 do not show any qualitative changes. However, in Model 6 (not reported), *Overall R&D Subsidies* has a negative and significant coefficient. We also apply a different lag structure by lagging patents by 1 year and R&D subsidies by 2 years, but the results do not change qualitatively.[16]

Second, we test whether the different proxies for innovative activity have a distinct relationship with firm survival before and after the shakeout. We estimate a regression with all firms active in the emergence and growth stage (Model R2 in Table 7) and all active firms in the decline stage (Model R3 in Table 7). The survival-enhancing effect of *Product Patents* only remains significant in the declining stage.

Third, we use two alternative approaches to assess the inherent dynamics in the industry and to replace the *Net Entry Rate:* first, by using *ILC Phases* to account for the different life cycle stages of the industry (Model R4 in Table 7). We create three dummy variables for the different life cycle phases covering the same years as the entry cohorts: an emerging phase from 1964 to 1999, a growth phase from 2000 to 2008, and a shakeout phase from 2009 to 2016. The results of the variables of interest do not change. The second approach uses the number of active firms in a given year instead of the *Net Entry Rate*. Again, the results of the survival-related effects of innovative activities do not change (Model R5 in Table 8).

Fourth, we estimate the models with a reduced sample of 144 firms, excluding firms that entered the industry before 1990 (Model R6 in Table 8). The conditions for firms that entered the PV industry in the first 30 years of the emergence phase changed drastically, particularly the application space of PV, which changed from small-scale off-grid applications to large-scale grid-connected mass products. The type and availability of R&D funding also changed drastically. Furthermore, the data collection for the early years of the industry may suffer from a survival bias in which some information about firms that left the industry early is unavailable. The same is true for missing funding data from the EU Framework projects before 1990. The results for this reduced sample differ only for *Process Patents*, which has a positive and significant coefficient. One interpretation of this could be that process patents in the more recent years of the industry are in fact harmful for firm survival,

[16] Results are available upon request.

Table 2 Regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
(Intercept)	−4.157 ***	−6.934 ***	−6.631 ***	−6.566 ***	−6.493 ***	−6.644 ***	−6.494 ***	−6.396 ***
	(0.365)	(0.649)	(0.987)	(0.999)	(0.987)	(0.994)	(1.001)	(0.997)
$Period_{it}$	0.305 ***	0.364 ***	0.198 **	0.202 **	0.197 **	0.210 **	0.214 **	0.207 **
	(0.083)	(0.085)	(0.101)	(0.100)	(0.100)	(0.101)	(0.101)	(0.100)
$Period_{it}^{2}$	−0.017 ***	−0.013 **	−0.006	−0.007	−0.007	−0.007	−0.008	−0.008
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$Period_{it}^{3}$	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)
$Tech\ BoS_i$		−0.530	−0.624	−0.580	−0.596	−0.608	−0.601	−0.575
		(0.511)	(0.508)	(0.505)	(0.505)	(0.509)	(0.508)	(0.505)
$Tech\ Cell_i$		0.010	0.118	0.196	0.178	0.179	0.153	0.190
		(0.252)	(0.259)	(0.261)	(0.261)	(0.266)	(0.267)	(0.267)
$Tech\ Others_i$		−0.679 *	−0.856 **	−0.847 **	−0.887 **	−0.840 **	−0.873 **	−0.898 **
		(0.403)	(0.407)	(0.406)	(0.408)	(0.407)	(0.407)	(0.409)
$Tech\ Silicon_i$		−0.580	−0.531	−0.479	−0.523	−0.509	−0.512	−0.516
		(0.437)	(0.436)	(0.436)	(0.436)	(0.436)	(0.436)	(0.437)
$East_i$		0.099	−0.057	−0.054	−0.063	−0.034	−0.047	−0.059
		(0.226)	(0.233)	(0.234)	(0.233)	(0.235)	(0.235)	(0.234)
$Primary\ PV_i$		0.695 **	0.556	0.459	0.483	0.505	0.496	0.456
		(0.343)	(0.339)	(0.341)	(0.342)	(0.344)	(0.342)	(0.344)
$Entry\ Lateral_i$		0.262	0.196	0.169	0.149	0.220	0.220	0.169
		(0.232)	(0.237)	(0.238)	(0.238)	(0.238)	(0.239)	(0.24)
Entry Cohort $2000–2008_i$		1.988 ***	1.225 ***	1.161 ***	1.139 ***	1.197 ***	1.099 **	1.056 **
		(0.362)	(0.419)	(0.420)	(0.42)	(0.418)	(0.425)	(0.426)
Entry Cohort $2009–2016_i$		2.645 ***	1.261 *	1.197 *	1.145 *	1.216 *	1.100	1.038
		(0.549)	(0.675)	(0.679)	(0.678)	(0.678)	(0.684)	(0.685)
$Acquisitions_{it}$			−0.168	−0.105	−0.128	−0.145	−0.136	−0.123
			(0.169)	(0.174)	(0.176)	(0.172)	(0.173)	(0.177)
$Net\ Entry\ Rate_{t-1}$			−3.487 **	−3.171 *	−3.446 **	−3.487 **	−3.529 **	−3.523 **
			(1.702)	(1.724)	(1.731)	(1.707)	(1.707)	(1.735)
Newly Installed $Capacity_{t-1}$			0.194 **	0.211 **	0.209 **	0.200 **	0.197 **	0.209 **
			(0.089)	(0.092)	(0.091)	(0.090)	(0.091)	(0.092)
$Patents_{it}$				−0.536 *				
				(0.286)				
$Product\ Patents_{it}$					−0.836 **			−0.771 *
					(0.414)			(0.417)
$Process\ Patents_{it}$					0.312			0.368
					(0.467)			(0.472)
Overall R&D $Subsidies_{i,t-1}$						−0.021		
						(0.021)		
Individual R&D $Subsidies_{i,t-1}$							−0.065	−0.052
							(0.053)	(0.054)

Table 2 (continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Collaborative R&D							−0.015	−0.009
Subsidies$_{i,t-1}$							(0.022)	(0.023)
Deviance	703.095	629.285	611.845	607.467	606.295	610.843	609.218	604.977
AIC	711.095	655.285	643.845	641.467	642.295	644.843	645.218	644.977
McFadden R^2	0.022	0.125	0.149	0.155	0.157	0.150	0.153	0.158
No. of firms	154	154	154	154	154	154	154	154
Degrees of freedom	1838	1829	1826	1825	1824	1825	1824	1822
Observations	1842	1842	1842	1842	1842	1842	1842	1842

Asymptotic standard errors in parentheses. Sig. at *** 0.01. ** 0.05. * 0.1 level.

as the focus could have been too much on smaller improvements rather than novel ways of developing PV applications.

Fifth, we treat firms that were acquired by other firms as exits. As the reasons for types of exit due to bankruptcy or M&A can differ, we remove the 34 acquired firms from our sample (Model R7 in Table 8). Again, *Process Patents* is positive and significant.

Lastly, from 2005 onwards, the German PV industry was in strong competition with international firms, particularly from China (Chen, 2016). To account for the competition from China, we collected trade statistics from the COMTRADE database to estimate this influence. However, the data has two caveats: first, there is no clear separation of PV from other electronic products; only a broader product group ("854140, i.e., Electrical apparatus; photosensitive, including photovoltaic cells, whether assembled in modules or made up into panels, light-emitting diodes (LED)") is available. Second, the time series starts in 1991, thus omitting the first 30 years of the industry. We include *Chinese Imports* in our regression, but we have to exclude *Newly Installed Capacity* due to high correlation with the trade data (Model R8 in Table 8). The results barely change, and the coefficient for *Chinese Imports* is positive and significant.

6 Conclusion and implications

We investigate the influence of different types of innovative activities on a firm's probability of survival in the German photovoltaics (PV) industry from its birth in 1964 until 2016, the period after the shakeout. We use time-variant data on product- and process-related patenting, R&D subsidies, and R&D collaboration as proxies for innovative activity. We built a novel data set of 154 German PV firms spanning the whole industry life cycle and estimate discrete-time hazard models to investigate the influences on firm survival.

First, we assess the relationship between innovative activity in terms of patenting and firm survival in the German PV industry. The econometric results show that patenting reduces the hazard rate of firm exit, which is consistent with previous findings (Buenstorf & Heinisch, 2018; Cantner et al., 2009). In addition to these studies, we find that the survival-enhancing effect not only exists for patenting per se, but that the extent of patenting also plays an important role, given the large effect size. Contrary to the literature (e.g., Buenstorf & Klepper, 2010; Gort & Klepper, 1982; Klepper, 1996), we do not find empirical evidence for an increased probability of survival from process patents. However, our results show that product patents are of particular relevance, as they reduce the hazard of exit from the industry. This is in line with previous findings by McGahan and Silverman (2001), who do not find a shift from product to process patents with industry maturity. A more detailed examination of the product patent documents indicates that the PV products described in the patent applications are of an incremental nature. This means that the German PV firms that were able to survive, particularly during industry decline, reacted to Chinese cost-based competition with product improvements. Incremental product improvements, which cannibalize previous products, can lead to higher survival rates, as shown by Audretsch (1995) regarding manufacturing sectors between 1976 and 1986, Banbury and Mitchell (1995) regarding the US pacemaker industry, and Velu (2015) regarding the business model innovation of 129 new firms in the US bond market. Radical innovation, in contrast, might not necessarily be beneficial for firms and endanger their survival (Ebert et al., 2019). Previous theoretical models therefore need some adjustments to incorporate product improvements, which, at least for the PV industry, are decisive for survival, in contrast to process innovations.

Second, an increasing stream of literature shows that public R&D support, which mitigates market failures in innovative activity, increases firm performance (e.g., Dimos & Pugh, 2016; Howell, 2015). However, we do not find that such R&D support translates into higher survival rates in the German PV industry. This is surprising given that the PV industry supposedly received large amounts of financial support over its life cycle and that other studies find that R&D subsidies increase inventive output in PV (e.g., Cantner et al., 2016). However, the effect of R&D subsidies may be too small to be precisely estimated. Alternatively, it is possible that the subsidy amounts per firm were not large enough. If the overall amount of the subsidies is divided by the number of firms that received subsidies, each firm received on average no more than 265,000 euro per year (or approximately 163,000 euro per year if all firms in the industry are taken into account). Furthermore, R&D subsidies per firm in the early stage of the PV industry were considerably larger compared to the later stages. This unstable support over time could have discouraged firms from engaging more intensively in R&D or resulted in the loss of competences when support decreased. This is in line with the findings by Rogge and Schleich (2018), who show that the consistency and credibility of policy support are important for innovative activity and, potentially, also for survival. The claim that R&D subsidies were insufficient, particularly in the later years of increasing international competition, has already been discussed by, for example, Breyer et al. (2013).

Lastly, we pursued the notion that firm performance is increased by subsidized collaborative R&D activity and the underlying knowledge exchange and spillover. We find no empirical support for such an effect on firm survival. This challenges related findings that innovative activities in collaborations increase a firm's innovativeness (e.g., Hottenrott & Lopes-Bento, 2014). The general shift in German policy towards collaborative R&D subsidies, which includes several programs for the PV industry such as the Leading-Edge Cluster Solarvalley Mitteldeutschland or the Innovationsallianz Photovoltaik, was not translated into higher firm performance.[17] Reasons for the absence of an effect could be attributed to insufficient subsidy amounts, insufficient exploitation of knowledge acquired from collaboration (Hung & Chou, 2013), or no strategic fit between the partners (Corbo et al., 2023).

In addition to the results on innovative activities, the analysis provides further interesting findings. First, the life cycle dynamics in the industry, operationalized by the net entry rate, are core determinants of firm survival, which underlines the relevance of evolutionary forces for changes in the firm population (Gort & Klepper, 1982). Second, the pattern that early entry into the industry increases the probability of survival is also confirmed in the PV industry (Klepper, 2002b). Third, in the PV industry, firm survival is independent of a firm's pre-entry experience, contrary to previous findings in other industries (e.g., Klepper & Sleeper, 2005). Moreover, our results show that an increase in market size results in a decrease in firm survival. This result is counterintuitive when contrasted with policy makers' increasing use of demand-side policies as instruments to enhance a firm's innovativeness. Recent empirical evidence supports the survival-decreasing effects of demand-side policies in the context of the ILC (Hipp & Binz, 2020).

Our results contribute to a better understanding of innovative activity as the core determinant of firm survival. Our distinction between three forms of innovative activity captures different mechanisms of knowledge generation and shows heterogeneous results, which have been barely explored in previous literature. First, we extend previous findings on the role of patenting for firm survival (Buenstorf & Heinisch, 2018; Cantner et al., 2009) by showing that the magnitude of patenting inventions matters. Second, the results on the different effects of product and process patents challenge existing theoretical models which highlight the importance of process innovations. The empirical relevance of incremental product innovations in the PV industry calls for a better theoretical understanding of product and process innovations, as already pointed out by Audretsch (1995), Banbury

[17] These findings do not mean that the policies itself were not effective in improving the overall industry performance. Innovative outcomes could have been spilled over to other firms and lead to imitation or follow-up innovations.

and Mitchell (1995), and McGahan and Silverman (2001). Third, policy interventions to incentivize innovative activity or collaboration do not influence the dynamics in the PV industry. The data indicate that the amount of each subsidy might not be sufficient to enhance the firm's probability of survival, but a more detailed analysis is needed to enable further assessment.

Based on our results, we have several recommendations for managers and policy makers. First, managers should engage in patenting activities to increase their firm's probability of survival throughout the ILC. A higher number of patent applications decreases the probability of firm exit. In particular, product-related patents are important for firms to protect product improvements, withstand fierce price-based competition, and survive. Moreover, policy makers need to provide consistent and sufficient public subsidies for innovative activities so that firms can generate innovative output and translate it into higher firm performance. An increase in R&D or collaboration subsidies, particularly in times of fierce competition, seems appropriate to allow firms to stay at the technological frontier. However, firms should critically assess the costs and benefits of engaging in public R&D activities to be able to reduce the uncertainties of their innovative activities. They can also shift their focus to other means of support, such as counseling on business and marketing plans or financial strategies, that have been shown to increase survival rates (Solomon et al., 2013). Firms with substantial financial constraints could shift their focus to niche markets with high subsidy rates to ensure high survival rates before the industry grows and competitive pressures increase.

The analysis reveals potential for further theoretical and empirical research. The heterogeneous results for different kinds of innovative activity require a more thorough theoretical understanding, particularly the relevance of incremental product innovations in future theoretical models. Furthermore, the relevance of innovative activity could differ between the stages of the ILC. Analyzing such phase-specific effects of different innovative activities in theoretical and empirical research could provide a more fine-grained picture of the heterogeneous effects of innovative activities.

The limitations of our analysis are particularly related to the data and methodology. We lack detailed, time-variant firm-level data such as size, market share, and internal R&D activities and expenses. The non-availability of such firm-level data over long periods is, however, a general caveat of ILC studies (e.g., Bhaskarabhatla & Klepper, 2014; Klepper, 1997, 2002a). Incorporating such time-variant data would provide a much clearer understanding of the dynamics in the industry and potential relationships to innovative activity. Methodologically, several sources of endogeneity could bias our estimations. We applied several tests to assess and reduce potential biases and do not claim any causal relationships. Although causal claims about innovation and survival have to date been linked to explanations regarding specific phases, future research needs to return to this issue by considering the whole ILC.

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Author contributions All authors contributed equally to the study conception and design. Material preparation and data collection were performed by Ann Hipp. Martin Kalthaus conducted the analysis. The first draft of the manuscript was written by Ann Hipp and Martin Kalthaus commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability Data will be made available upon request.

Declarations

Competing interests The authors declare no competing interests.

Appendix 1: Correlations

Table 3 Correlation table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	*$Exit_{it}$*	1																				
2	*$Patents_{it}$*	-0.036	1																			
3	*Product $Patents_{it}$*	-0.041	0.923	1																		
4	*Process $Patents_{it}$*	-0.021	0.858	0.593	1																	
5	*Overall R&D $Subsidies_{i,t-1}$*	-0.041	0.314	0.264	0.304	1																
6	*Individual R&D $Subsidies_{i,t-1}$*	-0.037	0.249	0.182	0.277	0.879	1															
7	*Collaborative R&D $Subsidies_{i,t-1}$*	-0.020	0.210	0.225	0.138	0.512	0.041	1														
8	*$Acquisitions_{it}$*	0.013	0.299	0.265	0.271	0.252	0.019	0.495	1													
9	*Tech $Silicon_i$*	0.007	-0.044	-0.049	-0.026	-0.028	-0.037	0.008	-0.029	1												
10	*Tech $Cell_i$*	0.047	0.174	0.159	0.151	0.173	0.175	0.047	0.061	-0.186	1											
11	*Tech $Module_i$*	0.033	-0.140	-0.088	-0.100	-0.054	-0.064	0.003	0.007	-0.180	-0.445	1										
12	*Tech BoS_i*	-0.049	0.021	0.030	0.005	-0.050	-0.044	-0.025	0.086	-0.150	-0.260	-0.251	1									
13	*Tech $Others_i$*	-0.057	-0.075	-0.080	-0.050	-0.082	-0.071	-0.043	-0.136	-0.131	-0.325	-0.313	-0.183	1								
14	*Primary PV_i*	0.071	-0.122	-0.095	-0.128	-0.170	-0.095	-0.054	-0.008	0.020	0.180	0.154	-0.363	-0.098	1							
15	*Entry $Lateral_i$*	0.057	0.082	0.066	0.083	0.135	0.150	0.012	-0.048	0.120	0.281	-0.036	-0.184	-0.202	-0.052	1						
16	*$East_i$*	0.054	0.038	0.019	0.054	-0.029	-0.007	-0.050	-0.083	0.131	0.185	-0.019	-0.135	-0.168	0.073	0.098	1					
17	*Entry Cohort $1964–1999_i$*	-0.131	0.083	0.059	0.093	0.174	0.172	0.055	0.093	-0.237	-0.034	-0.029	0.121	0.126	-0.177	-0.216	-0.317	1				
18	*Entry Cohort $2000–2008_i$*	0.117	-0.086	-0.071	-0.084	-0.153	-0.155	-0.041	-0.081	0.246	0.036	-0.010	-0.091	-0.114	0.146	0.192	0.295	-0.909	1			
19	*Entry Cohort $2009–2016_i$*	0.032	0.007	0.026	-0.020	-0.050	-0.040	-0.033	-0.028	-0.022	-0.004	0.092	-0.071	-0.029	0.074	0.056	0.053	-0.214	-0.213	1		
20	*Net Entry $Rate_{t-1}$*	-0.161	-0.034	-0.047	-0.009	-0.059	0.016	-0.153	-0.168	-0.035	0.041	-0.001	0.006	-0.030	-0.029	-0.025	-0.062	0.209	-0.150	-0.244	1	
21	*Newly Installed $Capacity_{t-1}$*	0.166	0.079	0.089	0.046	-0.014	-0.075	0.150	0.124	0.031	-0.040	0.027	-0.017	0.009	0.080	0.044	0.110	-0.293	0.217	0.178	-0.627	1

Appendix 2: Non-parametric survival and hazard function

We use non-parametric hazard and survival functions to visualize the rate of firm exits from the industry based on a life table (Fig. 4). The hazard rate provides the probability that a firm will exit dependent on its age in the industry. It is calculated by the share of firms leaving in a specific period from all firms in this period at risk of exit. The high exit rates in later periods result from a very small set of active firms that stayed so long alive in the industry. The survival rate analogously represents the probability of surviving until a specific period. The non-parametric display of the survival rate is commonly referred to as Kaplan-Meier estimator. For details see, for example, Singer and Willett (2003).

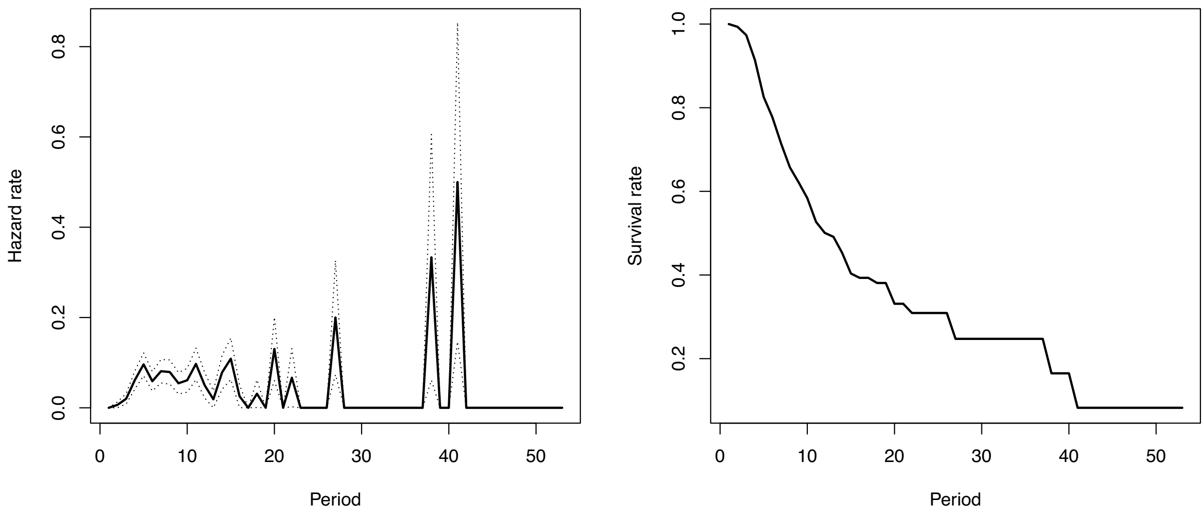

Fig. 4 Hazard and survival function

Appendix 3: Patent search strategy for silicon patents

We extend the patent search strategy developed in Kalthaus (2019) to include PV silicon patents (see Table 4). Silicon used for PV cells requires less purity compared to silicon used for microchips, and specific processes were developed to produce lower quality silicon. We apply the same procedure described in Kalthaus (2019) to derive the relevant set of IPCs and keywords.

Table 4 PV silicon patent search strategy

IPC Symbol	Keywords
C01B 33%	%SoG_Si% | %siemens_method% | %siemens_process% | ((%silicon% | %high_purity% | %semiconductor%) + (%photovoltai% | %solar%'))
C25B 1%	
C30B 9%	
C30B 13%	
C30B 15%	
C30B 25%	
C30B 28%	
C30B 29%	
C30B 33%	

Appendix 4: Baseline hazard specification

We approximate the baseline hazard function via a polynomial of firm age in the industry. Table 5 presents several operationalizations, where Model 1 contains a fully parametrized baseline hazard. We choose the third order polynomial of Model 5 as our baseline specification because it shows a good tradeoff between model fit and convergence. Even though Model 6-8 show better model fits, they do not converge anymore and cannot be reliably estimated.

Table 5 Baseline Hazard

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Period dummies	included							
(Intercept)		-2.994 ***	-3.064 ***	-3.508 ***	-4.157 ***	-5.659 ***	-6.202 ***	-9.360 ***
		(0.105)	(0.161)	(0.263)	(0.365)	(0.634)	(0.849)	(1.756)
$Period_{it}$			0.007	0.102 **	0.305 ***	0.908 ***	1.187 ***	3.136 ***
			(0.012)	(0.044)	(0.083)	(0.205)	(0.338)	(0.918)
$Period_{it}^2$				-0.003 **	-0.017 ***	-0.082 ***	-0.126 ***	-0.524 ***
				(0.002)	(0.005)	(0.021)	(0.045)	(0.174)
$Period_{it}^3$					0.000 ***	0.003 ***	0.005 **	0.041 ***
					(0.000)	(0.001)	(0.003)	(0.015)
$Period_{it}^4$						0.000 ***	0.000	-0.002 **
						(0.000)	(0.000)	(0.001)
$Period_{it}^5$							0.000	0.000 **
							(0.000)	(0.000)
$Period_{it}^6$								0.000 **
								(0.000)
Deviance	642.053	718.910	718.572	712.469	703.095	688.056	686.974	679.013
AIC	748.053	720.910	722.572	718.469	711.095	698.056	698.974	693.013
McFadden R^2	0.107	0.000	0.000	0.009	0.022	0.043	0.044	0.055
No of Firms	154	154	154	154	154	154	154	154
Degrees of Freedom	1789	1841	1840	1839	1838	1837	1836	1835
Observations	1842	1842	1842	1842	1842	1842	1842	1842

Asymptotic standard errors in parentheses. Sig. at *** 0.01. ** 0.05. * 0.1 level.

Appendix 5: Further robustness tests

Table 6 Robustness tests for unobserved heterogeneity

	Frailty					Linear Probability				
	Model 4	Model 5	Model 6	Model 7	Model 8	Model 4	Model 5	Model 6	Model 7	Model 8
(Intercept)	-5.374 ***	-5.348 ***	-5.282 ***	-5.282 ***	-5.313 ***	-0.033	-0.032	-0.024	-0.023	-0.019
	(0.741)	(0.736)	(0.720)	(0.734)	(0.720)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Period	0.159 *	0.155 *	0.160 *	0.165 *	0.159 *	0.026 ***	0.026 ***	0.026 ***	0.026 ***	0.026 ***
	(0.088)	(0.088)	(0.089)	(0.088)	(0.089)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Period²	-0.011 **	-0.010 **	-0.010 **	-0.011 **	-0.010 **	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Period³	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)	(0.000)	(0.000)
Acquisitions$_{it}$	0.047	0.027	-0.041	-0.012	-0.034	0.015	0.014	0.007	0.004	0.006
	(0.160)	(0.163)	(0.158)	(0.159)	(0.160)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Net Entry Rate$_{t-1}$	-4.349 ***	-4.467 ***	-4.849 ***	-4.656 ***	-4.841 ***	-0.229 ***	-0.231 ***	-0.251 ***	-0.247 ***	-0.247 ***
	(1.516)	(1.518)	(1.500)	(1.504)	(1.500)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Newly Installed Capacity$_{t-1}$	0.288 ***	0.287 ***	0.269 ***	0.267 ***	0.273 ***	-0.010 **	-0.010 **	-0.011 **	-0.012 **	-0.012 **
	(0.085)	(0.084)	(0.082)	(0.084)	(0.082)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Patents$_{it}$	-0.655 **					-0.042 ***				
	(0.287)					(0.011)				
Product Patents$_{it}$		-0.891 **					-0.048 ***			
		(0.403)					(0.015)			
Process Patents$_{it}$		0.159					-0.004			
		(0.452)					(0.018)			
Overall R&D Subsidies$_{i,t-1}$			-0.018					-0.001		
			(0.020)					(0.001)		
Individual R&D Subsidies$_{i,t-1}$				-0.092 *					-0.004 **	
				(0.055)					(0.002)	
Collaborative R&D Subsidies$_{i,t-1}$				-0.009					0.000	
				(0.021)					(0.002)	
R&D Collaboration Partner$_{i,t-1}$					-0.079					0.000
					(0.094)					(0.007)
Random effect variance	0.000	0.000	0.000	0.000	0.000					

Table 6 (continued)

	Frailty					Linear Probability				
	Model 4	Model 5	Model 6	Model 7	Model 8	Model 4	Model 5	Model 6	Model 7	Model 8
Firm fixed effects						included	included	included	included	included
Deviance	635.232	634.605	641.346	637.637	641.378					
AIC	653.232	654.605	659.346	657.637	659.378					
Adj. R^2						0.090	0.090	0.083	0.085	0.083
No of Firms	154	154	154	154	154	154	154	154	154	154
Degrees of Freedom	1833	1832	1833	1832	1833	1681	1680	1681	1680	1681
Observations	1842	1842	1842	1842	1842	1842	1842	1842	1842	1842

Robust standard errors in parentheses. Sig. at *** 0.01. ** 0.05. * 0.1 level.

Table 7 Robustness tests R1-R4

	Model R1: No Time Lags	Model R2: Stage Growth	Model R3: Stage Decline	Model R4: ILC Dummies
(Intercept)	-6.352 ***	-10.486 ***	-3.927 **	-6.288 ***
	(0.998)	(2.449)	(1.801)	(0.951)
Period$_{it}$	0.218 **	0.876 **	-0.022	0.192 **
	(0.100)	(0.357)	(0.124)	(0.096)
Period$_{it}^{2}$	-0.009	-0.041 **	0.002	-0.007
	(0.006)	(0.020)	(0.007)	(0.006)
Period$_{it}^{3}$	0.000	0.001 *	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tech BoS$_{i}$	-0.541	-16.789	-0.398	-0.580
	(0.506)	(2115.725)	(0.509)	(0.505)
Tech Cell$_{i}$	0.228	1.544 *	0.031	0.200
	(0.268)	(0.905)	(0.284)	(0.268)
Tech Others$_{i}$	-0.880 **	-0.424	-1.012 **	-0.889 **
	(0.409)	(1.274)	(0.437)	(0.407)
Tech Silicon$_{i}$	-0.508	4.119 ***	-1.144 **	-0.505
	(0.437)	(1.326)	(0.545)	(0.436)
East$_{i}$	-0.034	-0.481	-0.101	-0.064
	(0.235)	(0.816)	(0.249)	(0.234)
Primary PV$_{i}$	0.414	-0.908	0.787 *	0.437
	(0.344)	(0.743)	(0.407)	(0.343)
Entry Lateral$_{i}$	0.188	0.585	-0.049	0.145
	(0.240)	(0.640)	(0.260)	(0.240)
Entry Cohort 2000–2008$_{i}$	1.029 **	-0.091	1.271 **	1.025 **
	(0.420)	(1.228)	(0.606)	(0.432)
Entry Cohort 2009–2016$_{i}$	1.019		0.414	0.975
	(0.682)		(0.859)	(0.652)
Acquisitions$_{it}$	-0.122	0.116	-0.092	-0.120
	(0.179)	(0.717)	(0.186)	(0.178)
ILC Phase 2000–2008$_{i}$				-0.140
				(1.037)
ILC Phase 2009–2016$_{i}$				1.233
				(1.220)
Net Entry Rate$_{t-1}$	-3.495 **	5.505 *	-5.051 *	
	(1.738)	(2.803)	(2.654)	
Newly Installed Capacity$_{t-1}$	0.207 **	0.168	0.033	0.095
	(0.092)	(0.171)	(0.164)	(0.133)
Product Patents$_{it}$	-0.748 *	0.592	-1.299 **	-0.785 *
	(0.416)	(0.789)	(0.524)	(0.417)
Process Patents$_{it}$	0.455	-1.433	0.843	0.320
	(0.476)	(1.338)	(0.525)	(0.466)
Individual R&D Subsidies$_{i,t-1}$	-0.096	-1.574	-0.019	-0.053
	(0.070)	(155.181)	(0.053)	(0.054)
Collaborative R&D Subsidies$_{i,t-1}$	-0.026	0.008	0.000	-0.009
	(0.023)	(0.092)	(0.024)	(0.023)
Deviance	602.121	93.424	461.379	599.379

Table 7 (continued)

	Model R1: No Time Lags	Model R2: Stage Growth	Model R3: Stage Decline	Model R4: ILC Dummies
AIC	642.121	131.424	501.379	641.379
McFadden R^2	0.162	0.285	0.100	0.166
No of Firms	154	135	142	154
Degrees of Freedom	1822	1015	788	1821
Observations	1842	1034	808	1842

Asymptotic standard errors in parentheses. Sig. at *** 0.01. ** 0.05. * 0.1 level.

Table 8 Robustness tests R5-R8

	Model R5: Firm Number	Model R6: Entry since 1990	Model R7: Exit by Bankruptcy	Model R8: Chinese Imports
(Intercept)	-7.107 ***	-7.499 ***	-9.261 ***	-7.589 ***
	(0.845)	(1.313)	(1.906)	(1.805)
$Period_{it}$	0.222 **	0.596 ***	0.264	0.186 *
	(0.098)	(0.225)	(0.200)	(0.101)
$Period_{it}^2$	-0.009	-0.049 **	-0.012	-0.007
	(0.005)	(0.020)	(0.013)	(0.006)
$Period_{it}^3$	0.000	0.001 **	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
$Tech\ BoS_i$	-0.570	-0.426	-0.181	-0.516
	(0.505)	(0.508)	(0.569)	(0.507)
$Tech\ Cell_i$	0.189	0.143	0.171	0.223
	(0.267)	(0.277)	(0.334)	(0.269)
$Tech\ Others_i$	-0.890 **	-0.907 **	-1.095 **	-0.865 **
	(0.409)	(0.417)	(0.521)	(0.410)
$Tech\ Silicon_i$	-0.524	-0.497	-1.550 **	-0.495
	(0.438)	(0.438)	(0.755)	(0.437)
$East_i$	-0.051	-0.141	-0.129	-0.057
	(0.234)	(0.241)	(0.304)	(0.236)
$Primary\ PV_i$	0.461	0.853 **	1.273 **	0.543
	(0.344)	(0.406)	(0.552)	(0.356)
$Entry\ Lateral_i$	0.190	-0.001	-0.151	0.122
	(0.239)	(0.25)	(0.305)	(0.242)
$Entry\ Cohort\ 2000–2008_i$	1.087 **	0.810	1.399 **	1.085 **
	(0.42)	(0.494)	(0.691)	(0.434)
$Entry\ Cohort\ 2009–2016_i$	1.124 *	0.729	1.397	0.993
	(0.672)	(0.739)	(0.965)	(0.693)
$Acquisitions_{it}$	-0.121	-0.199	-0.260	-0.126
	(0.177)	(0.213)	(0.230)	(0.177)
$Net\ Entry\ Rate_{t-1}$		-5.181 **	-11.268 ***	-5.515 ***
		(1.999)	(3.121)	(1.654)
Firm Number	-0.015 *			
	(0.008)			

Table 8 (continued)

	Model R5: Firm Number	Model R6: Entry since 1990	Model R7: Exit by Bankruptcy	Model R8: Chinese Imports
Chinese Imports				0.131 *
				(0.079)
Newly Installed Capacity$_{t-1}$	0.485 ***	0.237 *	0.354 **	
	(0.131)	(0.122)	(0.166)	
Product Patents$_{it}$	-0.753 *	-1.316 **	-1.107 *	-0.781 *
	(0.418)	(0.520)	(0.575)	(0.420)
Process Patents$_{it}$	0.377	0.920 *	1.154 *	0.424
	(0.475)	(0.496)	(0.606)	(0.480)
Individual R&D Subsidies$_{i,t-1}$	-0.049	-0.022	0.015	-0.043
	(0.054)	(0.051)	(0.055)	(0.054)
Collaborative R&D Subsidies$_{i,t-1}$	-0.009	-0.011	-0.012	-0.009
	(0.023)	(0.024)	(0.029)	(0.023)
Deviance	605.282	535.200	344.657	595.038
AIC	645.282	575.200	384.657	635.038
McFadden R^2	0.158	0.177	0.275	0.149
No of Firms	154	144	120	154
Degrees of Freedom	1822	1509	1450	1696
Observations	1842	1529	1470	1716

Asymptotic standard errors in parentheses. Sig. at *** 0.01. ** 0.05. * 0.1 level.

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