Firm Survival in Complex Value Chains and Global Innovation Systems: Evidence from Solar Photovoltaics

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ABSTRACT

Economic globalization and the modularization of value chains increasingly challenge long-held conceptual models explaining the spatial evolution of industries. This paper seeks to re-interpret early industry life cycle dynamics by disintegrating an industry's value chain into upstream, core and downstream parts and characterizing each part according to its underlying global innovation system (GIS) configuration. We distinguish between firms in parts of the value chain that depend on formalized, science-based innovation and cater for globally standardized mass markets ('footloose' GIS) and firms in parts of the value chain that rely on spatially more stable GIS structures, in which either the innovation activities or the valuation dynamics (or both) depend on spatial embedding in given territorial contexts. Our hypothesis is that firms which occupy parts of the value chain with footloose GIS characteristics will have shorter survival times than firms which operate in spatially more stable GIS types. Demand-side policies will accordingly produce stronger competitive advantages for firms operating in GIS with spatially stable valuation structures. The empirical context of our study is the solar photovoltaics (PV) industry. We analyze market entry and exit of 129 German and 127 Japanese PV firms from 1960 to 2016 using a Cox Proportional Hazards model. The results support the hypotheses that firm survival and policy effects depend on a value chain part's underlying GIS configuration.

KEYWORDS

Industry life cycle, value chain, global innovation system, firm survival, photovoltaics

JEL CLASSIFICATION CODES

O32, O38, L16

1. Introduction

Economic globalization, the modularization of value chains and outsourcing-based corporate strategies have increasingly interconnected production and innovation processes that are dispersed in space (Coe and Yeung, 2015). Many products are nowadays developed with inputs from a diverse set of supplying and demanding industries that are distributed worldwide, which significantly increases the complexity of their ‘sectoral configuration’ (Stephan et al., 2017). The factors influencing a firm’s entry, survival and exit in a given industry, as well as the spatial configuration of its innovation activities are thus increasingly multi-scalar and multi-sectoral. These trends challenge long-held conceptual models explaining the spatial evolution of firms and industries.

Industrial dynamics literature explains firms’ entry and exit patterns by e.g. a change in the minimum efficient scale of production (Fuss and Gupta, 1981), the emergence of a dominant design (Suárez and Utterback, 1995) or submarket dynamics (Bhaskarabhatla and Klepper, 2014). It provides an in-depth view of the driving forces behind industrial transformations on micro- and meso-levels (Dosi, 1982; Malerba and Orsenigo, 1991; Malerba, 2002). Yet, the strong focus on firm-specific and industry-internal factors (often assessed based on the development of a firm population in a single country) has come at the expense of a structured view on the wider political, economic and institutional embedding of industries in the globalizing knowledge economy (Malerba et al., 2016). In particular, the increasingly complex co-evolutionary dynamics between firms, countries and sectors in the same value chain need deeper elaboration (Huenteler et al., 2016b; Stephan et al., 2017; Lee and Malerba, 2017). This holds especially for newly emerging growth sectors like biotech, cleantech or artificial intelligence, where ambitious national policy support schemes are implemented to increase the competitiveness of firms and countries (Carlsson, 2016).

Recent evidence shows that early industry formation phases in these sectors are strongly influenced by demand-side or ‘deployment’ policy interventions, like Feed-in-tariffs (FiTs), renewable energy portfolio requirements or public procurement guidelines favoring the development and diffusion of ‘clean’ technologies (Edquist et al., 2005; Jenner et al., 2013; Rogge and Reichardt, 2016). Yet, while the literature has explored in detail the effects of R&D policies on firm survival and performance (Vanino et al., 2019; Hipp and Kalthaus, 2018; Hottenrott and Lopes-Bento, 2016), our understanding of the effects from demand-side policies on firm entry and exit in different parts of an industry’s value chain is still limited at best (Hoppmann, 2018).

These gaps are increasingly criticized (Forbes, 2017, 2016). Empirical evidence shows that many emerging industries experience surprisingly fast reconfigurations of their global actor structure, which are not explained by current theories and which may quickly undermine the competitive advantage of pioneering firms in developed economies (Binz et al., 2017; Dewald and Fromhold-Eisebith, 2015; Lee and Malerba, 2017). In many cases, industrial dynamics can furthermore not be separated from the sectoral configuration of the value chain anymore (Stephan et al., 2017; Huenteler et al., 2016a; Quitzow, 2015). Rather, a more internationalized and cross-sectoral perspective on industry dynamics would help policy makers in designing interventions that more efficiently achieve national/regional industrial development and innovation objectives (Beuse et al., 2018; Graf and Kalthaus, 2018; Grau et al., 2012).

This paper seeks to address these gaps by connecting the industry life cycle literature to recent approaches in innovation studies and in particular the global innovation systems (GIS) approach (Binz and Truffer, 2017). It aims at re-interpreting industry life cycle dynamics by disintegrating an industry's value chain into upstream, core and downstream parts and relating each part to a different type of supportive innovation system structure. We follow the GIS approach in distinguishing between firms in parts of the value chain that depend on a highly internationalized, 'footloose' innovation system structure and firms that operate in parts of the value chain with spatially more stable GIS types, in which either the creation of innovation or valuation processes (or both) depend on spatial embedding in given territorial contexts. Based on this distinction, we seek to answer two interrelated research questions. First, we ask *whether firms in parts of a value chain that depend on a 'footloose' GIS configuration have different survival chances than firms which evolve in spatially more stable GIS configurations?*

Second, and relatedly, we use this conceptualization to further explore the effects of demand-side policy interventions (Hoppmann et al., 2014, 2013; Peters et al., 2012; Wang et al., 2016) on the survival chances of firms in different parts of a value chain. We hypothesize that demand-side policies improve survival chances only for firms in parts of a value chain with markets that depend on spatially sticky interaction between producers and customers, i.e. related to product customization needs or highly specialized preference structures ('spatially sticky' / 'market-anchored' GIS). In contrast, they will create only short-lived competitive advantages due to larger competitive pressures and considerable spatial spillovers in parts of a value chain that depend on standardized and easily accessible global mass markets ('footloose' and 'production-anchored' GIS). The second research question accordingly asks *whether demand-side policy interventions have distinct effects on firms that operate in 'standardized' vs. 'customized‘ valuation systems?*

The empirical context of our study is the solar photovoltaics (PV) industry, a case in point for an emerging cleantech industry with a highly internationalized, multi-sectoral value chain architecture. We collected market entry and exit data on 129 German and 127 Japanese firms and added information from company websites, annual reports and public funding organizations from 1960 to 2016. In order to assess the drivers behind early industry life cycle dynamics, we disintegrated the value chain of crystalline PV into upstream (silicon and manufacturing machinery), core (ingots, wafers, cells and modules), and downstream parts (balance of systems/BoS, grid integration). Each part of the value chain is then attributed to a characteristic GIS configuration. Firm survival data is analyzed using a Cox Proportional Hazards model.

Our results support the basic hypothesis that firm survival depends on an actor's positioning in different parts of a value chain and the related GIS configurations. I.e. PV ingot/wafer/cell/module manufacturers (core part of the PV value chain) depend on a 'footloose' GIS configuration and thus have significantly shorter survival times than upstream silicon and machinery suppliers and downstream system integrators and inverter producers, which rely on spatially more 'sticky' GIS configurations. Demand-side policies are found to have negative effects on firm survival in parts of the value chain with standardized valuation systems, while they show no significant survival-enhancing effects for firms operating in customized valuation systems.

The remainder of the paper is structured as follows: Chapter 2 provides an overview of the literature on industry life cycles, the sectoral configuration of value chains, and the GIS concept. We then derive an integrated framework that explains the different firm survival rates and policy effects with the GIS configuration of the value chain part firms are operating in. Chapter 3 introduces the research case of the solar PV industry, while Chapter 4 gives information on the data used, the empirical approach and our results. Chapter 5 discusses our key findings and their implications for industrial dynamics and innovation system literature as well as innovation policy. Chapter 6 offers conclusions and avenues for further research.

2. Theory and hypotheses

2.1. Conventional industry life cycle models

The literature on industrial dynamics has a long tradition in analyzing the evolution of firms and industries in time and space (Carlsson, 2016). Its foundational models propose that firms enter an industry to develop capabilities and innovate, which drives technological progress (Dosi, 1982). While some firms exploit technological opportunities and grow, others cannot compete and eventually leave the industry (Nelson and Winter, 2002). Industries thus follow a dynamic pattern of firm entry and exit that got stylized into life cycle models (Abernathy and Utterback, 1978).

The canonical model proposed that products and industries evolve in generic patterns that move through several analytically distinct phases. In the earliest stage (‘era of ferment’), incumbents from related industries move into a new market with a product of a simple design (Klepper, 1996). Since large market opportunities exist, many new firms subsequently enter the market to develop a variety of products and enable an industry’s growth until a dominant product design emerges. As competition around this dominant design intensifies, production becomes more standardized. The industry growth may stagnate as the number of firms remains constant and only moves into a new life cycle stage, the shakeout, as more firms exit than enter (‘era of incremental change’). A small number of specialized firms that achieve economies of scale will survive while many others fail and leave the market (Klepper, 1997; Klepper and Graddy, 1990; Klepper and Simons, 2005). Eventually, the market may saturate and create an oligopolistic structure with a stable number of firms that may diversify into newly emerging markets as the industry declines.

This generic model proved helpful for explaining how and why industries in specific places and countries emerge, thrive and ultimately decline. Some studies broadened the view of industry structures and its evolution by focusing on diversification and vertical integration and referring to their embededdness in specific countries (Henderson et al., 1999; Malerba and Orsenigo, 1991; McKelvey et al., 2004). These dynamics were assigned to specific features of industry structures such as sectoral particularities that influence the probability of firm survival (Audretsch, 1991). The survival literature has identified several determinants that explain a firm’s hazard of industry exit due to e.g. its size, industry experience and vertical scope (e.g. Dunne et al., 1989; Utterback and Suárez, 1993; Buenstorf, 2007; Esteve-Pérez et al., 2018). Yet, studies that have assessed the effects of a firm’s embedding in wider socio-economic and sectoral structures on entry-exit patterns have remained somewhat more scant. Only recently, scholars have tried to systematize how early life cycle dynamics differ between industries with varying technology characteristics and value chain architectures (Castellacci, 2008; Huenteler et al., 2016a; b; Stephan et al., 2017).

2.2. Industry dynamics, technology characteristics and complex value chains

A first important qualification made by these authors is that industry life cycles fundamentally differ based on generic technology characteristics. Huenteler et al. (2016b) distinguish between industries that produce standardized, mass market goods (i.e. solar panels) and complex products and systems (i.e. wind turbines). While the former develop in life cycles that closely match the conventional Abernathy/Utterback model (1978), the latter evolve in patterns that are better explained with what Davies (1997) called complex product systems (CoPs). Here, the production process never gets fully standardized and instead of a dominant design, a dominant architecture eventually emerges, which is followed by a series of product innovations in the system's key components (Davies, 1997). Incremental learning, dense producer-user interaction and the co-location of different parts of the value chain in spatial clusters are a key feature of this industry type. However, how the different modes of innovation and the specific mix of sectors involved in parts of an industry's value chain influence early life cycle dynamics is not explored in this literature (Castellacci, 2008; Stephan et al., 2017).

Recent empirical evidence shows that firms in some parts of a value chain can influence the life cycle dynamics of firms in other value chain parts. For instance, Kapoor and Furr (2015) show that firms in the global PV industry enter into new parts of the value chain in hopes of sustaining their competitive advantage and survival. Malerba et al. (2016) trace the low concentration of firms in the personal computer industry back to the emergence of an upstream component industry into which core producers re-located over time. Hoppmann (2018) finds that knowledge spillovers in the upstream parts triggered firm exits in the core parts of the PV value chain in Germany.

A second important qualification relates to the sectoral complexity of an industry's value chain. Stephan et al. (2017) conceptualize the dynamics of an industry's entire value chain drawing on insights from the technological and sectoral innovation systems literature. They define an industry's innovation system based on the actors, networks and institutions that are involved in producing, diffusing and using a certain product, including all stages of the value chain. An industry's sectoral configuration then consists of a technology value chain and all actors that produce these technologies, often from different sectors that supply key inputs or intermediary goods. A sector is defined broadly as the sum of actors with similar resources and production outcomes (Malerba, 2002). Each step of the value chain is related to one or several sectors that provide key inputs (Stephan et al., 2017).

Figure 1 illustrates that disintegrating an industry's value chain into several distinct parts with their own sectoral configuration has deep implications for industry life cycle approaches. It becomes evident that the overall evolution of the industry (and the related entry-exit behavior of firms) will differ between parts of the value chain, since they draw on distinct knowledge bases, market structures and supporting sectors. Except for the (rare) case of an industry where the whole value chain is integrated in one specific sector or controlled by one vertically integrated firm, there will always be some discernible differences in the evolution of firms in upstream, core and downstream parts of the value chain. I.e. one can expect that some parts of a value chain depend on industry structures that follow the conventional Abernathy/Utterback model (1978), while others will depend on life cycles that follow the CoPs model by Davies (1997), or yet another, hitherto not conceptualized trajectory. Some parts of the value chain may accordingly depend on sectoral configurations and supportive innovation system structures in which standardized knowledge, international mass markets and fierce price-based competition play a key role, while others will evolve rather slowly, drawing on historically grown, place-based institutional structures. To further conceptualize the underlying innovation system structures in different parts of the value chain, a connection to recent advances in innovation system studies seems promising.

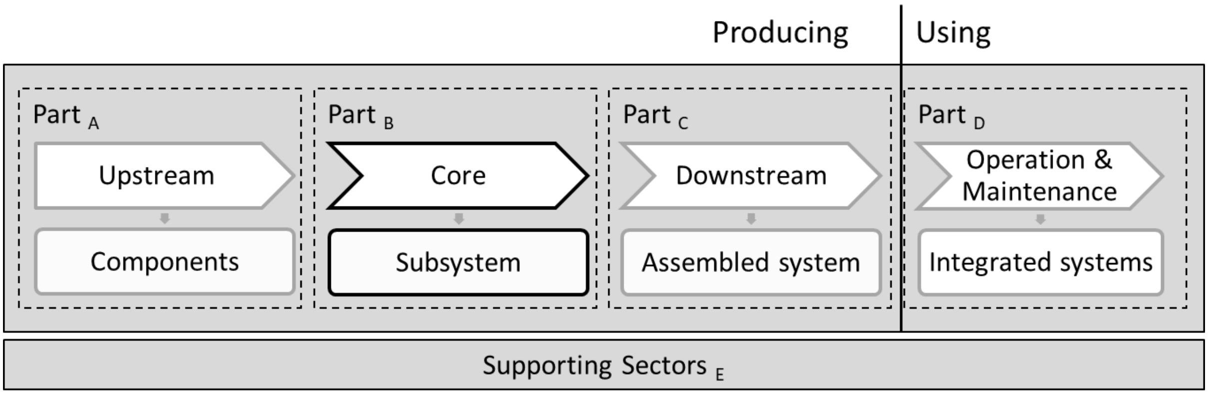


Figure 1: Sectoral configuration of an industry's value chain (adapted from Stephan et al., 2017).

2.3. Complex value chains in a global innovation system perspective

Among the various existing innovation system frameworks, in particular the global innovation system approach (GIS) is of interest here, since it explicitly conceptualizes the spatial configuration of an industry's innovation processes in the early life cycle stages (Binz and Truffer, 2017). It argues that in today's globalizing knowledge economy, innovation processes and industrial dynamics depend on complex multi-scalar networks that transcend traditional spatial and sectoral boundaries. The many potential multi-scalar GIS configurations were systematized into a four field industry typology.

The typology expands on Huenteler et al.'s (2016b) framework on mass produced and complex products by explicitly distinguishing between an industry's innovation mode and valuation system (Figure 2). The innovation mode relates to the dominant form of knowledge production and learning, which can be either based on a science-technology-innovation (STI) or a doing-using-interacting (DUI) mode. STI-based knowledge is highly analytical and depending upon formalized, lab-based R&D. Since this form of knowledge can be codified into patents, papers, blueprints, etc., it is relatively easily transferable in space. In contrast, DUI-based knowledge is synthetic, experience-based and tacit and thus typically developed in dense producer-user interaction in territorially delimited contexts (Huenteler et al., 2016a; Martin and Moodysson, 2013). Innovation processes in DUI-based industries thus typically show stronger spatial stability.

The valuation system, in turn, refers to the process by which a product is connected to (market or social) values (Jeannerat and Kebir, 2016). This social construction process can evolve in standardized or customized patterns (Binz et al., 2017). In the former, products and user preferences are highly standardized and structured in global mass markets (Jeannerat and Kebir, 2016). A product that is manufactured in one place can be sold relatively easily in distant places. In customized valuation systems, in contrast, products have to be tailored to highly specialized user needs in spatially diversified institutional contexts. In this case, market structures emerge from a complex social embedding process, are sticky in space and can only be accessed by firms with intimate knowledge of local contexts. Depending on the innovation mode and the valuation system, four ideal-type GIS configurations can be derived that have different implications for a firm's innovation processes, its entry and exit pattern, as well as the expected effects of policy measures.

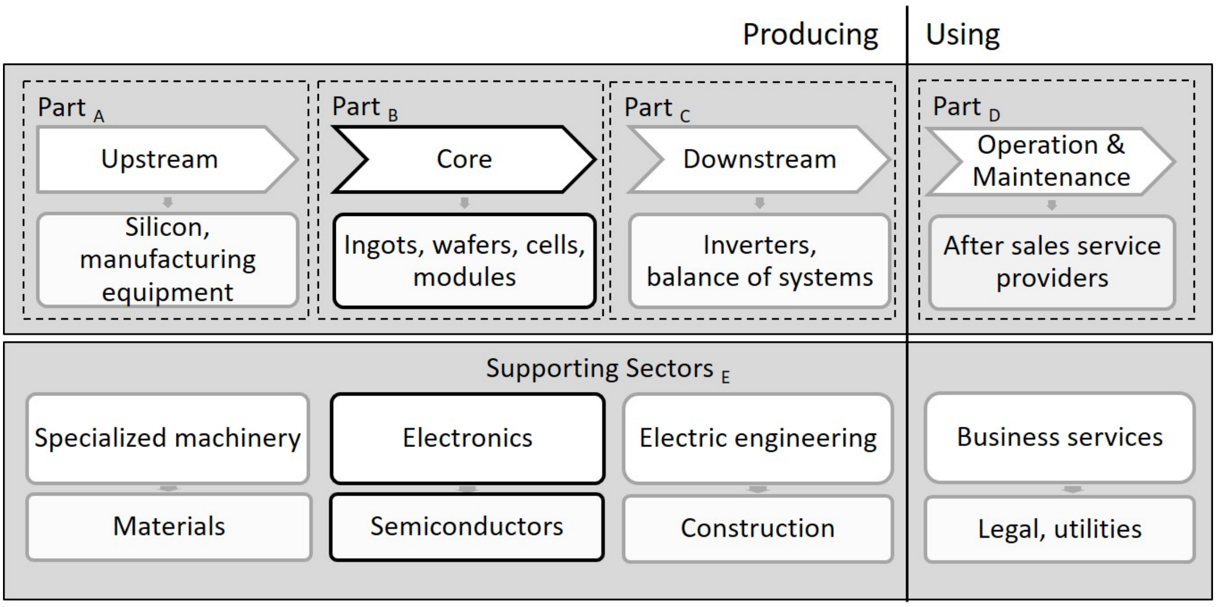


Figure 2: GIS configuration in different industry types (based on Binz and Truffer, 2017).

First, industries with an STI-based innovation mode and a standardized valuation system ('footloose GIS') will show the highest spatial dynamics and shortest average firm survival times: Since in this GIS type the relevant knowledge and market structures are easily accessible and mobile, no region will retain extensive first-mover advantages. Lead firms will emerge in one place, but then get replaced by new entrants that draw on the same globally available knowledge stocks and market structures, but are able to produce at lower costs (Holm et al., 1996). Firm exits in this case will thus be driven by fierce price-based competition in international markets and by considerable knowledge spillovers that undermine any first-mover advantage. Demand-side policy support can accordingly be expected to support firm entries in general (Hoppmann, 2018), but they create significant spillovers and increased supply-side competition globally that may subsequently trigger quick exits, as well.

Production-anchored GIS describe industries with a DUI-based innovation mode and a standardized valuation system. Here, the innovation mode provides protection against global competitive forces. I.e. the relevant knowledge relates to craftsman skills and practical experience about how the different components of a complex product interact (Jeannerat and Crevoisier, 2013). This type of knowledge is embodied in skilled people's brains and often embedded in regional clusters with a distinct industrial culture (Bergeron et al., 1998; Jeannerat and Crevoisier, 2013; Martin and Moodysson, 2013). Firms may be driven out of business only if a comparable manufacturing cluster emerges elsewhere that is able to reach the same quality standards at a lower price or if the underlying knowledge base becomes more science-driven (i.e. be turned into an STI-based innovation mode). Also in this situation, demand-side policies will have only marginal or even negative effects on firm survival, i.e. by supporting the industry's overall global market potentials, which may however also lead to the same spatial spillover effects and competitive pressures as described above.

Third, in market-anchored GIS, a firm's spatial proximity to relevant customers and a deep knowledge of their specialized, culturally mediated preferences (i.e. related to regulations, investment patterns, cultural norms, etc.) create spatial stability. Markets that require intense product customization will be hardly accessible to outside actors that lack spatial and cultural embedding. Pioneering firms in market-anchored GIS are thus likely to experience market-related first mover advantages that reduce their likelihood of exit, especially in early life cycle stages. Here, shakeouts may occur if the local demand diminishes, if the valuation system gets more standardized (as it is often the case when industries move to more mature life cycle stages), or if outside actors invest heavily in getting embedded in a given market place. Since spatial stickiness may turn into a disadvantage here if local market structures saturate, demand-side policies can be expected to have positive effects on the local industry's survival rates, since they artificially increase the market volume for firms that depend on the local market while being somewhat protected from outside competitors.

Finally, industries operating in 'spatially sticky' GIS experience the strongest spatial stability in the innovation and valuation dimensions. Here, innovation and market success directly depend on each other and are only achievable if technology providers, specialized customers and various intermediary actors are co-located in the same place. We thus expect such industries to show the most stable life cycle patterns of all four cases, with entry and exit patterns that are slower than in the other three GIS types. Here, knowledge spillovers and market access by outside actors are only possible with extensive learning efforts, so the most plausible explanation for firm exits are generic market downturns, as well as mergers and acquisitions (M&As) by foreign competitors. Demand-side policies can accordingly be expected to have even stronger positive effects on the innovation and market deployment activities of local firms than in market-anchored GIS.

2.4. Integrated framework and hypotheses

Figure 3 synthesizes the above discussion into a conceptual framework. Similar to the work by Stephan et al. (2017), we define industries as including all actors, networks and institutions that are involved in creating and diffusing a product, including all steps of the technology value chain. Yet, in contrast to their work, we characterize each part of the value chain not only based on its sectoral configuration, but also by its characteristic GIS configuration.[1] Assigning different GIS types to each part of the value chain then allows us hypothesizing about the different entry-exit dynamics along the value chain.

First, if the sectoral configuration of a certain part of a value chain is characterized by a 'footloose' GIS configuration, we expect dynamic entry-exit patterns with relatively short firm survival times. Firms will quickly enter the industry in a specific place, but also quickly exit, when parts of the activities move to a new place. In the three other GIS types, either the innovation mode or valuation system (or both) provide spatial stickiness, leading to slower firm exits and spatial mobility, most so in the bottom left quadrant of 'spatially sticky' GIS.

We thus hypothesize that **H1: Firms in parts of a value chain with a footloose GIS configuration have shorter survival rates than firms in parts of a value chain with spatially more stable GIS configurations (production-anchored / market-anchored / spatially sticky GIS).**

[1] Note that this is a subtle, but important adaptation, since an industry's GIS configuration is influenced by 'supply' side and 'demand' side factors, whilst the sectoral configuration is characterized predominantly based on a sector's knowledge structure (i.e. the supply side).

Second, the above considerations allow us hypothesizing about the effects of demand-side policies on firm survival chances and how they differ between GIS configurations in different parts of the value chain. Demand-side policies are instruments that create a niche market for an emergent industry and support the entry and innovativeness of new firms (Cantner et al., 2016). Different types include FiTs, public procurement, fiscal incentives or soft instruments such as product labels (Edler, 2010). In particular for environmental or 'green' technologies, a protected niche market is often required initially because of their 'double externality problem' and cost disadvantages in the competition with traditional sectors that could mobilize economies of scale in the past (Kemp et al., 1998). Demand-side policy support in early industry lifecycle stages may ensure a firm's revenues to achieve economies of scale and to re-invest in production facilities and R&D (Peters et al., 2012; Hoppmann et al., 2013; Nemet, 2009).

Existing empirical evidence on the effects of demand-side policies on innovation patterns and firm survival is rather contradictory. Recent studies on the one hand show that demand-side policies result in the growth of a market as investments and installed capacity increase and prices for end-consumers fall (Grau et al., 2012; Quitzow, 2015; Hoppmann, 2015). They were also shown to have positive effects on the 'supply side', i.e. to increase innovation, firm profits and technical change (Peters et al., 2012; Cantner et al., 2016; Böhringer et al., 2017). I.e. Wang et al. (2016) found that the introduction of a FiT in China's PV industry increased the profitability of listed firms in downstream parts of the value chain. On the other hand, authors found demand-side policies to limit market opportunities for non-incremental technical innovations (Nemet, 2009) and to create unintended spillovers to foreign firms (Peters et al., 2012), technological lock-ins (Hoppmann et al., 2013) or demand spikes in markets that face an undersupply of products, incentivizing new firms to enter the market and replace existing ones (Hoppmann et al., 2014). Also, Rammer et al. (2017) indicate that demand-side policies have a negative impact on firms' international competitiveness.

The GIS-based typology may help to structure some of this seemingly contradictory evidence. As outlined above, we expect demand-side policies to create a significant positive effect on firm survival particularly in parts of the value chain with a customized valuation system, say with 'market-anchored' or 'spatially sticky' GIS types. In contrast, their effect on firms in parts of the value chain catering for standardized mass markets might be only marginal, if not negative. Since standardized valuation systems (in 'production anchored' and 'footloose' GIS types) are easily accessible for external competitors, firms do not achieve a competitive advantage from serving a local customer base. Quite to the contrary, since demand-side policies assure a certain amount of local firm's sales and profits, they may lower their incentives to remain cost-competitive in global mass markets. The competitiveness of domestic firms may accordingly quickly dwindle if firms from low-cost areas enter the market with products of the same quality at lower prices. Introducing demand-side policies in footloose / production anchored GIS might thus increase price-based competition in global markets with detrimental effects to the local industry.

Based on these considerations, we hypothesize that **H2: Demand-side policies have positive effects on firm survival in parts of a value chain with a customized valuation system (market-anchored / spatially sticky GIS), while they have marginal or negative effects on survival rates in parts of a value chain with standardized valuation systems (production-anchored / footloose GIS).**

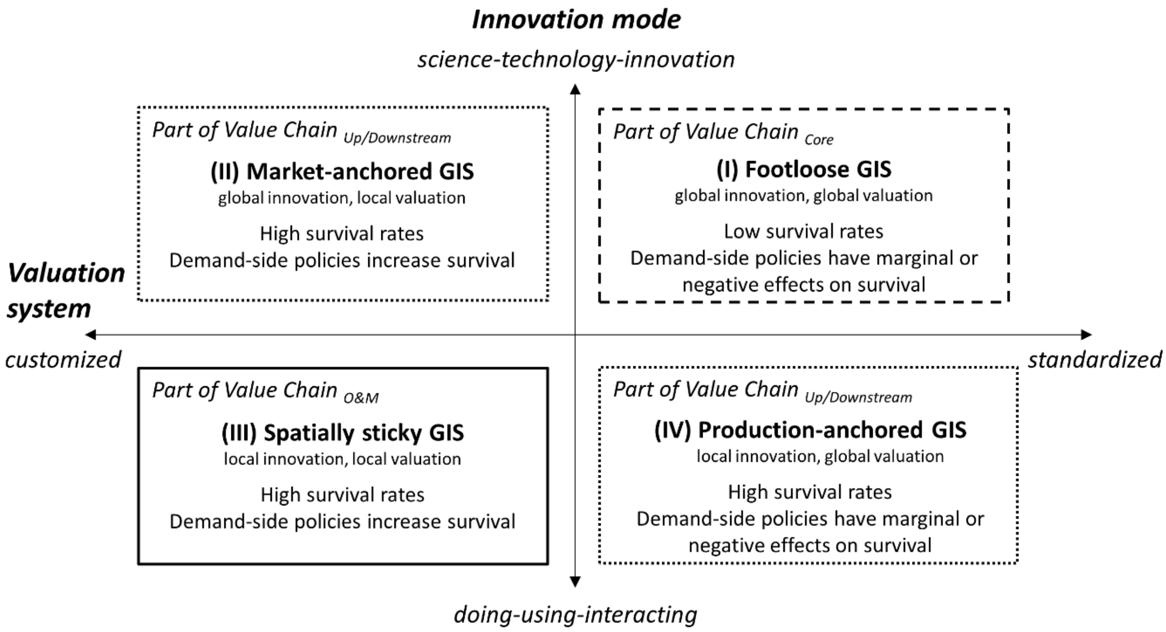


Figure 3: Integrated framework on firm survival and policy effects in different GIS configurations.

3. Empirical case study: The solar PV industry

The crystalline solar PV industry was chosen for testing our hypotheses because it represents an emblematic example of a booming cleantech industry with a complex multi-scalar and multi-sectoral value chain architecture (cf. section 3.2). The focus in our empirical analysis is laid on firms that operate in the producing part of the silicon-based, crystalline solar PV value chain, thus excluding thin-film and other 3rd generation technologies, that are based on qualitatively different technology and value chain structures. Prior studies provide anecdotal evidence that innovation and firm dynamics in the crystalline PV industry considerably vary for different parts of the value chain (Binz et al., 2017; Dewald and Fromhold-Eisebith, 2015). Furthermore, the industry experienced for a long time a relatively clear segmentation of firms in different parts of the value chain (Hoppmann, 2018), which allows us to assess the early life cycle dynamics in each part as being relatively independent from each other. Finally, since the industry has received wide interest by policy makers and innovation scholars, rich secondary data is available that helps us to contextualize these studies' findings (Dewald and Truffer, 2011; Jacobsson and Bergek, 2011; Markard et al., 2012).

3.1. General overview and history of the crystalline solar PV industry

The roots of the solar PV industry can be traced back to an invention in the USA in the mid-1950s (Varadi, 2014). Until the 1990s, US and Japanese firms were the frontrunner in global PV production and consumption, before Germany took the lead in the early 2000s (Binz et al., 2017). In the industry's long 'era of ferment', firms had to customize their products to local user contexts and niche markets (Dewald and Fromhold-Eisebith, 2015; Huenteler et al., 2016b). Since the 1990s, however, federal policies triggered considerable dynamics in the PV market and the firm population (Hipp and Kalthaus, 2018). The German FiT was of crucial importance, since it created the first mass market for PV systems in 2001, followed by similar policies in various European countries and Japan (Hoppmann et al., 2014; Ayoub and Yuji, 2012).

The FiT provided guaranteed tariffs for electricity fed into the power grid from renewable energy plants (Hoppmann et al., 2014). From the mid-2000s on, a dominant design for crystalline silicon cells and modules emerged and production shifted to cater for an increasingly standardized mass market (Huenteler et al., 2016b). Module prices declined exponentially, price-based competition intensified and Chinese manufacturers swiftly took over a leading position in the core part of the value chain (ingots, wafers, cells and modules). Even though policy makers in Japan and Germany tried to defend their PV firms' competitive advantage, they were ultimately successful only in the upstream (silicon and manufacturing machinery) and downstream part of the value chain (BoS, grid integration) (Binz et al., 2017; Hoppmann et al., 2014; Quitzow, 2015). Examining the sectoral configuration of the PV value chain in the following section allows us to identify the GIS characteristics that explain these diverging development patterns in different parts of the value chain.

3.2. Characterizing the PV industry's technology value chain

The value chain of crystalline PV systems consists of three main parts, which can be roughly characterized as an upstream (silicon, manufacturing equipment), core (ingot, wafer, cell and module manufacturing) and downstream part (BoS components, grid integration) (Malhotra et al., 2019; Hoppmann, 2018). Upstream parts rely on knowledge-intensive R&D on basic PV cell materials and technologies, as well as the development of automated production lines that are used to manufacture ingots, wafers, cells and modules. Activities in the core parts include etching and polishing wafers to create PV cells, adding anti-reflective coating and combining them into the final product, PV modules. The downstream parts include all elements beyond the PV module that are needed to connect a PV system to the electricity grid and operate it, comprising electrical wires, charge controllers, mounting equipment, etc. PV system design, installation, as well as operation and maintenance can be allocated to the 'using' part of the value chain, which is however excluded from our analysis.[2]

Figure 4 summarizes the different parts of the PV value chain and their supportive sectors. The upstream parts depend on highly standardized raw materials developed within chemical process industries as well as on R&D intensive, specialized automation/machinery manufacturing and robotics sectors. Activities comprise the conversion of metallurgical-grade silicon to highly purified silicon and casting it into ingots. The core part is in turn an electronics mass-manufacturing industry, while the downstream part relies more strongly on electric engineering and construction sectors. The PV industry furthermore depends on various supportive industries that provide generic inputs like glass, metal frames, electric cables, etc.

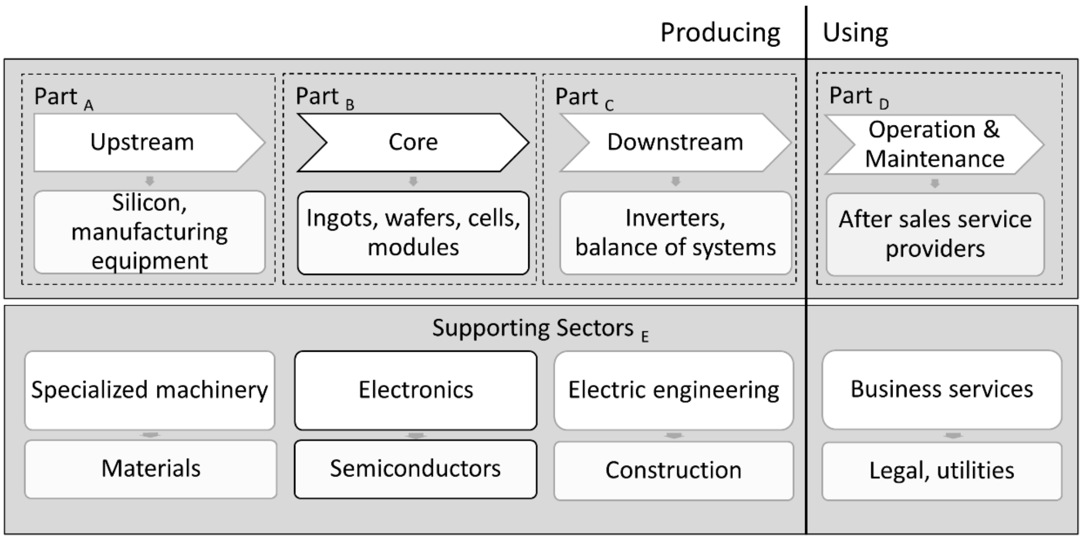


Figure 4: The value chain of the solar PV industry.

[2] The reason to exclude firms active in the planning, installation, operation and maintenance of PV systems are issues of data availability and consistency. Hundreds of small to medium-sized firms occupy this space in most countries, most of which are not specialized to PV systems alone, but active in all sorts of building equipment services.

3.3. Assigning the parts of the PV value chain to GIS configurations

Based on the explanations above we can now relate each of the three main parts of the value chain to a characteristic GIS configuration (cf. Figure 5). The following characterization was based on existing literature (Malhotra et al., 2019; Stephan et al., 2017; Zhang and Gallagher, 2016; Dewald and Fromhold-Eisebith, 2015) and 12 interviews with firm representatives at an international PV trade fair[3] and in personal meetings.

Firms in the upstream parts operate in 'market-anchored' and 'production-anchored' GIS types. The manufacturers of turnkey production lines innovate based on the most recent advances in the basic science for PV technology (e.g. related to new materials, cell architectures, wafer slicing techniques, etc.) as well as through feedbacks from large module manufacturers (Hoppmann, 2018). As Malhotra et al. (2019) underline, PV manufacturing lines consist of highly complex machinery that has to be adapted to each customer's specific needs. Innovation on turnkey manufacturing lines can thus be characterized as depending on a 'market-anchored' GIS type. In contrast, innovation in the production of raw silicon as well as casting and drawing it into high-purity ingots requires profound (DUI-based) engineering knowledge about complex chemical processes and various interlinked parameters that need to be delicately controlled. The produced silicon materials are in turn highly standardized across different regions, so we would characterize this step as a 'production-anchored' GIS (Malhotra et al., 2019).

Firms in the core part of the PV value chain, in contrast, depend on a 'footloose' GIS configuration. Manufacturers of ingots, wafers, cells and modules cater for a highly standardized, global mass market (Binz and Truffer, 2017; Huenteler et al., 2016b; Quitzow et al., 2017). PV modules are produced to the same specifications worldwide and tested according to globally established quality criteria. Continued innovation and cost cutting was achieved by sourcing the basic materials (glass, metal frames, welding materials, etc.) from low-cost suppliers, but also by constantly reducing the material use in cell manufacturing and increasing cell efficiencies in close interaction with the suppliers of turnkey manufacturing lines (Malhotra et al., 2019). While these iterative process improvements nowadays possess characteristics of a DUI-based innovation mode, in earlier life cycle phases (which are mostly in focus here), the key capabilities to innovate were more strongly STI-related. I.e. many large cell and module manufacturers sustained dense knowledge pipelines to leading universities (Quitzow, 2015) and in-house R&D labs to keep connected to the state of the art in the STI-based knowledge space

[3] 12th SNEC (2018) International Photovoltaic Power Generation and Smart Energy Exhibition & Conference in Shanghai, China.

(Zhang and Gallagher, 2016). For this study, we thus characterize the innovation mode of firms in the core part of the PV value chain as being STI driven, with important DUI-related elements.

Firms in the downstream part, finally, can be characterized as depending on a 'production-anchored' GIS configuration with DUI-based innovation and standardized valuation systems. The manufacturers of inverters and BoS equipment cater for a highly standardized product to global electronic equipment markets. Innovation requires experience-based engineering and the incremental adaption of solutions to new technological opportunities on global mass markets. Similar dynamics can be expected for firms that produce PV panel mounting systems, junction boxes, sun tracking devices or grid integration solutions.

When relating this characterization to our hypotheses, we expect a lower survival rate of ingot/wafer/cell/module manufacturers - which depend on a footloose GIS - than upstream and downstream actors - which depend on spatially more stable GIS structures (Hypothesis 1). The introduction of a FiT is in turn expected to produce positive effects on the survival of upstream manufacturing equipment suppliers operating in a customized valuation system, but only marginal or negative effects for producers of silicon, modules, inverters and BoS, which operate in standardized valuation systems (Hypothesis 2).

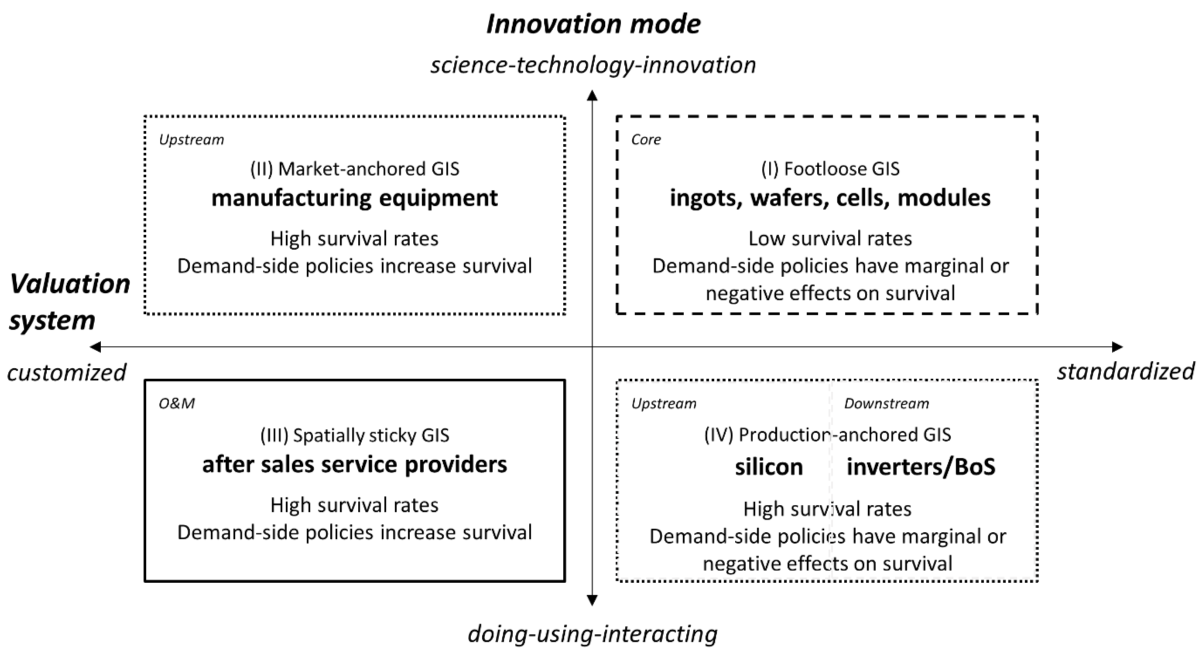


Figure 5: Integrated framework and hypotheses on PV firm survival in four GIS configurations.

4. Data and methods

4.1. Sample

To test our hypotheses, we constructed a database that includes information on the full population of PV firms in Germany and Japan. We consider firms' entire development history to gain a long-term perspective of the early movers' determinants of survival or exit (e.g. Bayus and Agarwal, 2007; Buenstorf, 2007; Kudic et al., 2016). Japan and Germany are high-cost countries that achieved significant early-mover advantages in the PV industry and their domestic firms have consistently played a key role in all parts of the industry's value chain. This stands in contrast to China, the US or other European countries, that only hosted considerable firm populations in some lifecycle stages or in some parts of the PV value chain. We thus decided to focus our study on Japanese and German firm populations.

Our balanced panel contains yearly observations from 1960 to 2016 on each firm's founding year, its position in the PV value chain, size (i.e. small and medium-sized enterprises/SMEs vs. large conglomerates), vertical integration, as well as the year and type of entry and exit in the industry. We build on an existing database of Hipp and Kalthaus (2018) that includes a large set of firm-level information from the German Commercial Registry ('Handelsregister'), but refined the available information on the 154 PV firms in Germany according to two main criteria. First, we categorized each firm according to its position in the upstream, core and/or downstream part of the value chain. We focus on that part of the value chain in which a firm has started to operate, but controlled later for its shifts into other parts or vertical integration. Given that a firm is still active in the industry, we aggregated its subsidiaries and M&As from the same part of the value chain into one parent company, which reduced the sample to 129 firms. A firm spining off its activities to engage in other parts of the value chain is treated as an independent firm with a later date of entry but an affiliation to its parent company. Firm data was then complemented with information from industrial organizations, public funding organizations or company homepages and annual reports. Regarding the Japanese PV industry, we applied the same data collection procedure using the databases of the International Energy Agency (IEA), the New Energy and Industrial Technology Development Organization (NEDO) and ORBIS, resulting in a sample of 127 firms (for a detailed description of the databases and the search strategy, cf. Appendix A).

4.2. Operationalization

4.2.1. Dependent variable

Our dependent variable is a firm's probability of failure provided that it has not left the industry in the years before (De Vaan, 2014; Lin and Wei, 1989). The *Hazard rate* is a dummy variable that is set equal to 1 if the firm exits the industry in a particular year during its lifetime, 0 if it has survived until the last year of our observation period.[4] A total of 88 firm exits from the industry occurred between 1960 and 2016, 31 of which are a result of a M&A and not bankruptcy. We treated a M&A as exit given that the firm subsequently left the industry and test for model robustness (cf. section 4.4) when including different exit types.

4.2.2. Independent variables

In order to test hypothesis 1, we set *Footloose* as equal to 1 if the firm produces in the core parts of the value chain with a 'footloose' GIS configuration (here: ingot/wafer/cell/module manufacturers), 0 if it engages in upstream or downstream activities, which are characterized by spatially more stable GIS types. For hypothesis 2, we measure the variable *FiT* as the difference between the average amount of each country's FiT per year (as reported in IEA (2019) databases) and its levelized costs of electricity production (LCOE) (in Cent/kWh, as reported by the International Renewable Energy Agency (IRENA, 2018)).[5] This differential provides firms with a small additional premium as an incentive to invest in renewable energy technologies. Since we expect that the FiT has opposing effects on the hazard rate in different GIS configurations, we calculate a *Standardized* dummy that is set equal to 1 if a firm develops products in a 'footloose' or 'production-anchored' GIS configuration (in the PV case: silicon, ingot/wafer/cell/module manufacturers, BoS and grid integration). In addition, *Customized* takes 1 if a firm engages in a 'market-anchored' or 'sticky' GIS configuration (in the PV case: manufacturing equipment suppliers).

4.2.3. Control variables

Our models include several firm-specific and industry-related control variables to account for a possible correlation with the dependent or independent variables. First, we control for potential distortions that relate to a firm's characteristics such as its time of industry entry. The literature suggests that earlier entries tend to survive longer (Klepper and Simons, 2005).

[4] Note that a firm's failure is not based on its relocation in space, but on its exit from the industry, defined as bankruptcy or M&A. In case a firm relocates to another place but is still active on the market, it is classified as survivor.

[5] The calculation of the LCOE provided by IRENA accounts for each country's differences in irradiation conditions and the national cost of PV systems.

Therefore, we set the variable *Tech entry* as equal to 1 if the firm entered the industry in a specific year. We also account for *Firm Size* by differentiating between SMEs and large firms (Klepper, 1997). It is set equal to 1 if the firm has developed to a large conglomerate. Furthermore, we set *New firm* as equal to 1 if an organization entered the industry without an affiliation to another firm. Particularly in emerging high-tech industries, new firms are highly specialized and might undermine the competitive advantage of incumbents (Huenteler et al., 2016a; Lee and Malerba, 2017). *Mainly PV* describes the strategy of a firm to either specialize in PV technologies or to engage in other business areas as well. It is set equal to 1 if the firm predominantly develops PV products. Related to that, we add *Diversify* to the analysis as equal to 1 when a firm diversifies into other parts of the value chain, increasing its survival chances (Wang et al., 2016). Due to differences between the distinct innovation systems of Germany and Japan, we include *German* as a dummy variable that is set equal to 1 if the firm is active in the German PV industry. We expect that Japanese PV firms survive longer because of more stable industry structures in Japan that are based on highly diversified conglomerates (IEA, 2019).

Furthermore, industry-level characteristics determine a firm's survival probability (Klepper, 1997). One key factor is the size of the market that influences the development of an industry (Hoppmann et al., 2014). We therefore include *Capacity* as the cumulative installed global capacity of PV in a given year. We further control for a firm's survival chances during different stages of the industry life cycle (Buenstorf, 2007). The variable *Incremental change* (indicating the beginning of the mature life cycle stages in Klepper's model) was accordingly set equal to 1 for all years after which the shakeout has occurred and the number of active firms in the PV industry started to decrease (i.e. from 2010 onward). In addition, international competition played a crucial role in the dynamics of the PV industry (Quitzow, 2015). Recent studies investigate global industry dynamics by using data on international technical conferences and exhibitions (e.g., Kapoor and Furr, 2015). We accordingly proxy the level of global competition by including *Competition* as the average number of international exhibitors in each year in two of the largest international solar PV conferences and exhibitions (Intersolar Europe, Munich, and SNEC, Shanghai). Moreover, 'supply-side' policy measures like R&D subsidies that aim to support the competitiveness of firms in technology innovation and commercialization can influence an industry's development (Cantner et al., 2016). We thus used data on the Energy Technology RD&D Budget for renewables from the IEA to control for *R&D support*. To further control for 'supply-side' policy measures, we set *Invest support* and *Demo* *support* as equal to 1 for the years in which the respective country has established significant investment and/or demonstration programs.

4.3. Empirical approach

For testing the first hypothesis, we estimated a Cox Proportional Hazards model as a semi-parametric approach by assuming a proportional hazard rate (De Vaan, 2014; Lin and Wei, 1989). The hazard rate of firms (i.e. the probability of a firm exiting the PV industry) is seen as a function of the covariates and the baseline hazard. We measure the hazard rate at the age t when the firm leaves the industry (provided that it survived up to age t as a conditional rate at which the event occurs). Thus, the hazard rate is operationalized as a function of the firms' age and the independent variables. We estimate the parameters as follows:

(1) $h(t, X(t), \beta) = h_0(t)exp(\beta X(t))$,

where $h(t, X(t), \beta)$ is the hazard for a firm of age t and $h_0(t)$ is the non-parametric baseline hazard. The independent variables $x_1(t)$, $x_2(t)$ …, $x_n(t)$ are time-dependent and calculated as matrix $X(t)$. The β parameters are measured by a maximum partial likelihood function that refers to the order of industry exits rather than the time scale (De Vaan, 2014). The hazard rate is right censored and corresponds to the latest observable year in which the firm is active in the industry or the number of years till the firm's exit from the industry, respectively. The covariates are annually adapted to follow a balanced panel structure of the data. Our empirical approach includes a total of 256 firms with a minimum observation of one year and a maximum of 57 years, producing 14,592 observations. We have complete information on all firms in every year of the observation period.

The second hypothesis relates to the mechanism of how a FiT influences the survival chances of firms in value chain parts with standardized or customized valuation systems (Figure 5). We apply a moderation analysis to investigate the mechanism affecting the relation between an independent and dependent variable at a certain point in time (Baron and Kenny, 1986). We treat the FiT as an independent variable whose influence on the hazard of exit is moderated by a firm's position in the value chain and its characteristic GIS configuration. For firms in value chain parts with a 'footloose' or 'production-anchored' GIS (i.e. standardized valuation) we expect positive or insignificant moderation effects in the relation between a FiT and the *Hazard rate*. In contrast, we expect that firms in parts of a value chain with a 'sticky' and 'market-anchored' GIS (i.e. customized valuation system) negatively moderate the link between a FiT and the *Hazard rate*. Figure 6 summarizes the relationships outlined above.

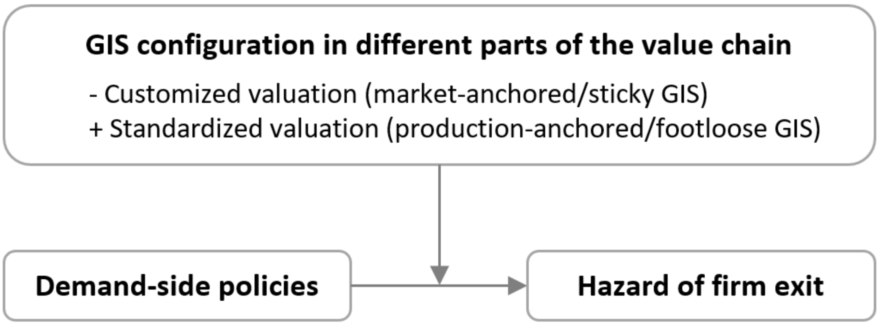
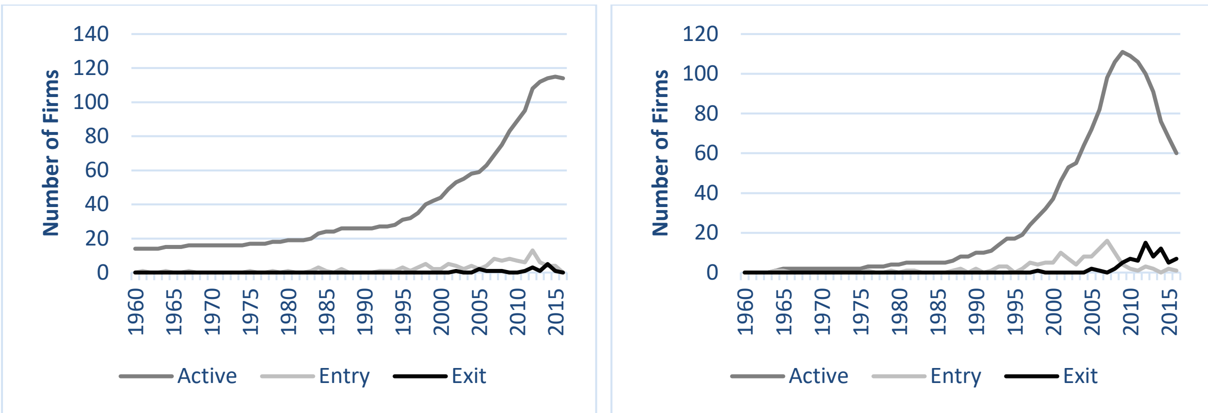


Figure 6: Moderation effects in the relation between a FiT and firm exits

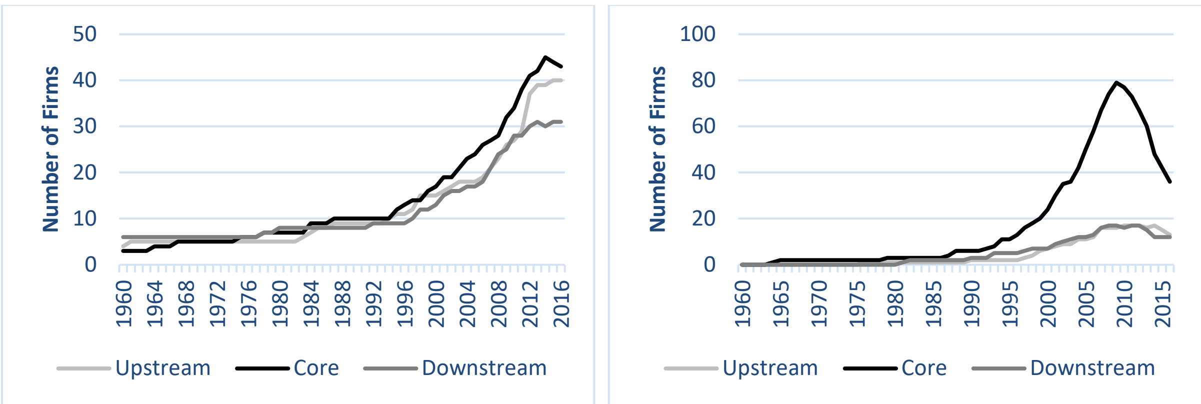
4.4. Results

Figure 7 depicts the evolution of the number of entries, active firms and exits in the Japanese and German PV industry. Figure 8 shows the development of these firms in the upstream, core and downstream parts of the value chain. Table 1 provides the descriptive statistics and the correlation matrix for the variables in our models.



(a) (b)

Figure 7: Evolution of the number of entries, active firms and exits in the (a) Japanese and (b) German PV industry.



(a) (b)

Figure 8: Evolution of the number of firms in upstream, core and downstream parts in the (a) Japanese and (b) German PV industry.

Table 1: Descriptive statistics and correlation matrix.

	Min	Max	Mean	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*
Hazard rate	0	1	.01	1																	
Age	0	109	4.56	.128**	1																
Footloose	0	1	.14	.144**	.659**	1															
FiT	0	57.40	4.19	.137**	.416**	.335**	1														
Standardized	0	1	.03	.027**	.310**	-.072**	.095**	1													
Customized	0	1	.07	.016	.455**	-.112**	.160**	.644**	1												
Tech entry	0	1	.02	-.003	.146**	.144**	.106**	.062**	.101**	1											
Firm size	0	1	.36	-.016	.274**	.098**	-.069**	.163**	.197**	.023**	1										
New firm	0	1	.16	.080**	.415**	.286**	.314**	.011	.082**	.118**	-.015	1									
Mainly PV	0	1	.12	.154**	.502**	.557**	.443**	.000	.040**	.162**	-.083**	.504**	1								
Diversify	0	1	.11	.036**	.378**	.466**	.142**	-.019*	.028**	.048**	.235**	.122**	.285**	1							
German	0	1	.50	.047**	-.108**	.014	.271**	-.109**	-.149**	.007	-.559**	.009	.157**	-.099**	1						
Capacity	0	303000	18253.81	.119**	.501**	.337**	.665**	.160**	.255**	.123**	.107**	.316**	.363**	.168**	.000	1					
Incr. change	0	1	.11	.155**	.360**	.199**	.571**	.124**	.211**	.028**	.055**	.168**	.207**	.087**	.000	.575**	1				
Competition	0	2124	249.82	.129**	.506**	.346**	.691**	.162**	.257**	.122**	.102**	.314**	.372**	.168**	.000	.929**	.591**	1			
R&D support	0	741.09	114.69	.104**	.380**	.235**	.412**	.128**	.203**	.069**	.122**	.224**	.240**	.117**	-.049**	.656**	.535**	.633**	1		
Invest support	0	1	.17	.146**	.462**	.327**	.750**	.150**	.230**	.105**	.039**	.274**	.368**	.136**	.071**	.658**	.612**	.710**	.497**	1	
Demo support	0	1	.19	.029**	.361**	.199**	.332**	.154**	.232**	.105**	.162**	.162**	.140**	.110**	-.178**	.618**	.337**	.658**	.420**	.436**	1

Sign.: ** p < .05; * p < .01

Table 2 presents the results of the Cox Proportional Hazards models. Model 1 only includes the control variables. We sequentially add the independent and/or moderating variables to models 2-4. The impact of *Tech entry* on the firm's hazard rate is positive and significant, which means that a later entry date into the industry has a negative influence on the survival probability of firms. *Firm Size* has a negative and significant impact on the hazard of exit, relating to higher survival chances of larger firms. *New firm* has a negative and significant impact on the hazard rate, which implies that new entries survive longer in the industry than firms entering with an affiliation to others. *Mainly PV* has a positive and significant impact on the hazard rate, implying that firms that specialize in the PV sector are less likely to survive compared to firms with a more diversified activity portfolio. The influence of *Diversify* is negative and significant, meaning that a firm's vertical integration into other parts of the value chain increases its survival probability. *German* has a positive and significant influence on the hazard rate, implying that German firms have smaller survival chances than Japanese firms. *Incremental Change* only has a positive and significant influence on the hazard rate in model 1, indicating that the beginning of the mature life cycle stage negatively affects a PV firm's survival probability when its position in the value chain and the FiT are not considered. *Capacity, Competition, R&D support and Demo support* have no significant impact on the hazard rate, which indicates that in the PV industry's strongly internationalized industry structures, market size, the degree of global competition and supply-side policy support schemes do not significantly influence a firm's survival probability. Only *Invest support* has a positive and significant impact on the hazard rate, which relates to negative consequences for a firm's survival chances due to a country's provision of investment programs. This effect is likely explainable with the fact that many investment support programs in the PV industry got implemented only after firm exit rates had already started to increase.

We first hypothesized that firms in a 'footloose' GIS have lower survival rates than firms operating in spatially more sticky (production-anchored, market-anchored, spatially sticky) GIS types. Therefore, we added *Footloose* in model 2, which has a positive and significant impact on the hazard rate, supporting Hypothesis 1. This result indicates that firms operating in a 'footloose' GIS configuration (i.e. ingot, wafer, cell and module manufacturers in core parts of the value chain) are indeed less likely to survive compared to firms in spatially more stable GIS configurations in the upstream and downstream parts of the value chain.

Table 2: Coefficient estimates of the Cox Proportional Hazards model.

Dependent variable: Hazard Rate	Model 1	Model 2	Model 3	Model 4
Footloose		.587**		
FiT		-.007	-.009	-.008
FiTxStandardized			.110**	
FiTxCustomized				.062
Tech entry	2.007*	1.761*	1.937*	1.961*
Firm size	-1.293***	-1.187***	-1.298***	-1.306***
New firm	-.855***	-.674***	-.865***	-.869***
Mainly PV	.931***	.749**	.959***	.935***
Diversify	-.798***	-.881***	-.803***	-.793***
German	1.962***	1.961***	2.075***	2.078***
Capacity	-.188	-.174	-.193	-.190
Incremental change	.888*	.830	.822	.822
Competition	.164	.120	.118	.117
R&D support	.143	.144	.150	.151
Invest support	.306**	.357**	.350**	.351**
Demo support	-.076	-.058	-.057	-.055
Log-likelihood	1086.870	1082.374	1083.444	1085.855
Chi-square	305.779***	318.549***	311.501***	308.507***

Sign.: *** p < .01, ** p < .05; * p < .1

We further hypothesized that a FiT enhances the survival chances of firms in parts of the value chain with a customized valuation system (i.e. ‘sticky‘ and ‘market-anchored‘ GIS), while it has only marginal or negative effects on firms operating in parts of the value chain with a standardized valuation system (‘footloose‘ and ‘production-anchored‘ GIS) (Hypothesis 2). We consider the FiT and the moderating variables in model 3 and 4. The results show that the introduction of a FiT in general has a negative but insignificant impact on a firm’s hazard rate. As expected, the moderation effect of firms in a standardized valuation system (‘footloose‘ or ‘production-anchored‘ GIS) becomes positive and significant in the relation between the FiT and the hazard rate. However, firms in ‘sticky’ and ‘market-anchored’ GIS (i.e. customized valuation) do not significantly moderate the link between the FiT and the hazard rate. In sum, the implementation of a FiT lowers the survival rate of firms in a ‘footloose’ and ‘production-anchored’ GIS (in the PV case: silicon, ingots/wafer/cell/module manufacturers, BoS and grid integration). However, we cannot confirm a survival-enhancing effect from the introduction of a FiT in parts of the value chain with a customized valuation system since a moderation effect is missing here. Overall, the moderation analysis thus only partly supports Hypothesis 2 (Figure 9).

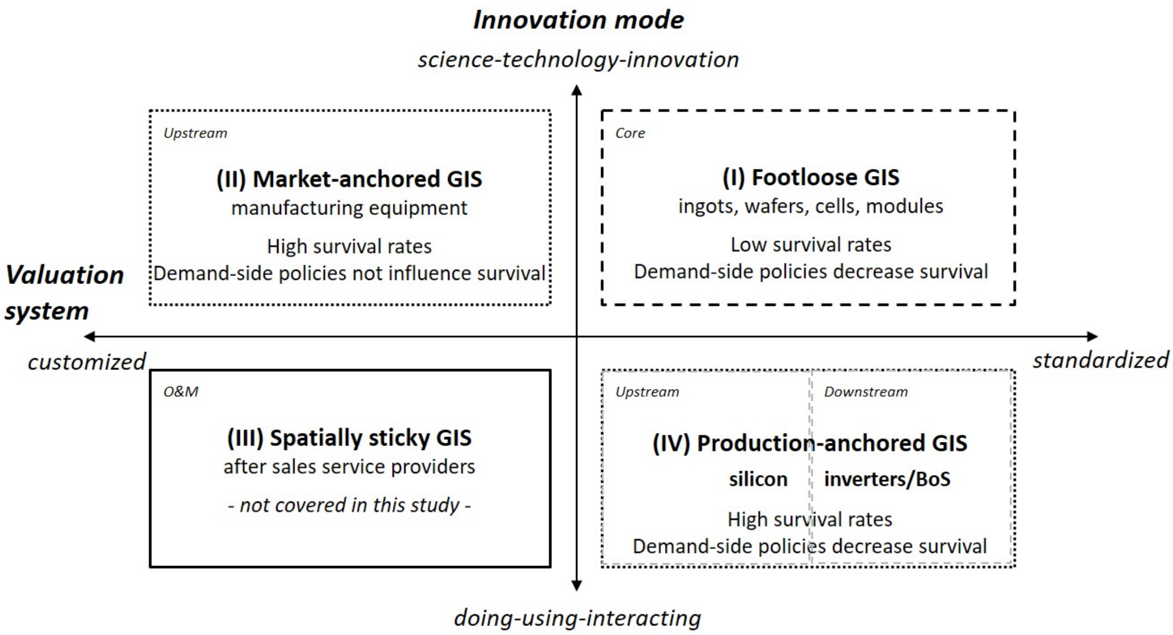


Figure 9: Results on PV firm survival in GIS configurations.

4.5. Robustness tests

Various robustness tests were performed to confirm the above results. We collected data on further factors that only indirectly influence a firm's hazard rate such as each country's yearly amount of CO2 emissions, energy commodity prices and macroeconomic conditions (Talay et al., 2014). After testing for the effects of CO2 emissions, commodity prices and the GDP, the coefficients remain similar. Moreover, we controlled for a value chain's interdependencies by adding the focal firm's respective upstream producer to the model (e.g. upstream parts are added to core parts). Even though we observe a varying significance level when including both upstream and core parts in the analysis, the coefficients do not change qualitatively (cf. Table A.1).

One could further argue that the hazards of industry exit vary between different intervals of an industry's development, requiring a discrete treatment of time with a relaxed proportional hazards assumption. Even though we here seek to find time-invariant patterns, we checked our results for robustness using a discrete-time model (Singer and Willett, 2003). Moreover, we treated a M&A as exit and distinguished between exit from the industry by M&A and exit by bankruptcy by applying a competing risk model (Fine and Gray, 1999). The coefficients remain similar when taking discrete times and both types of exit into account (Table A.2).

As a last test for robustness, we re-run the analyses by only considering the early life cycle stages and excluding the years after which technologies became standardized (i.e. 2005) (Binz et al., 2017). Interestingly, the results show a stronger negative influence of the FiT on the hazard rate in the PV industry, now also including for firms in parts of the value chain with customized valuation systems. Yet, also here the relevant positive relation between a FiT and firm survival particularly in parts of a value chain with customized valuation systems is not significant (Table A.3).

5. Discussion

Our results have important implications for the literatures on industrial dynamics, innovation policies and innovation system studies. First, we could show that firms acting in a 'footloose' GIS configuration generally have shorter survival rates than firms in parts of the value chain with spatially more stable GIS configurations (Hypothesis 1 supported). This is an important finding in the context of recent studies exploring the innovation dynamics in industries with complex value chains (Huenteler et al., 2016b; Stephan et al., 2017; Lee and Malerba, 2017). Our key contribution to industrial dynamics literature lies in widening the explanatory focus beyond firm- and industry-level factors to a multi-scalar innovation system context (Malerba et al., 2016). Globalization and multi-sectoral interaction indeed seem to shape industry life cycle dynamics in spatially and sectorally segregated ways that ask for improved explanatory models (Carlsson, 2016).

Future work could expand on these findings as follows. First, like other recent papers in the field (e.g. Stephan et al., 2017), we present a single-industry case study. Future studies should provide cross-comparisons between industries with differing value chain configurations. I.e. qualitatively different value chain architectures and life cycle dynamics can be expected in other cleantech industries like wind power, biomass gasification or water recycling (Huenteler et al., 2016a; Quitzow et al., 2017; Malhotra et al., 2019). Comparative analyses may help to derive more generic industry typologies e.g. for typical GIS configurations in upstream, core and downstream parts of the value chain. Our database and analysis furthermore mostly covers the early industry life cycle phase. A deeper exploration of the shifts in the entry/exit patterns after a dominant design emerged and the industry moved to the era of incremental change would be highly interesting.

Our second key contribution relates to the literature on demand-side policies' effects on industrial dynamics. The moderation analysis in section 4.4 shows that – in the case of the PV industry - the introduction of FiTs produces surprisingly negative effects on firms' survival chances. First, it reduces the survival chances of firms in parts of the value chain with highly standardized valuation systems. This finding is in line with recent studies that explain this pattern with an indirect substitution effect: Firms operating in global mass markets need to become price-competitive by the time competition intensifies. Demand-side policies like the FiT in Germany enabled the growth of a considerable niche market for PV products, which allowed them to become competitive with traditional energy sources (Reichelstein and Yorston, 2013). At the same time, they also seem to have 'blinded' local actors to the growing global competition and have enabled international knowledge spillovers that incentivized firms from latecomer countries to enter the industry and push incumbents out of business (Peters et al., 2012; Hoppmann et al., 2014; Lee and Malerba, 2017).

Second, our findings somewhat surprisingly indicate that demand-side policies do not increase the survival chances of firms that operate in customized valuation systems (i.e. 'market-anchored' or 'spatially sticky' GIS types). Also a robustness check with an exclusive focus on the early life cycle stages only indicates a non-significant positive influence on firm survival. This finding somewhat contrasts former policy studies, which found that demand-side policies increased a firm's innovation capability and the technological progress in PV and other clean energy sectors (e.g. Cantner et al., 2016; Hoppmann, 2015; Veugelers, 2012).

A possible explanation relates to the particular technology characteristics and sectoral configuration of the PV industry, where most firms with customized valuation systems operate in the upstream parts of the value chain. They thus experience only indirect benefits from the FiT since they depend strongly on firms operating in the core part of the value chain with a footloose GIS configuration. The competitive pressure from global market structures may thus be transposed into their sticky valuation systems. This pattern may differ substantially in other industries with different technology architectures and/or a stronger focus on a product's customization like wind power or lithium batteries (Malhotra et al. 2018), so more cross-comparative research is needed to further systematize demand-side policies' complex industry- and value chain-specific effects (Norberg-Bohm, 2000; Quitzow, 2015; Wilson, 2012). Finally, while we assumed a positive effect of spatial stickiness on firm survival, future work should more systematically explore whether and how spatial stickiness may also decrease survival chances, in particular for firms operating in customized valuation systems which strongly depend on local demand conditions.

Third, our study contributes to the innovation system literature, and in particular the GIS framework, by empirically validating one of the key hypotheses derived from this heuristic. To date, innovation system studies are predominantly preoccupied with qualitative case studies that set a priori spatial and sectoral boundaries and thus disregard multi-sectoral and multi-scalar innovation dynamics (Hekkert et al., 2007; Stephan et al., 2017). Our study is among the first one's to illustrate the explanatory value and operability of the GIS approach's multi-scalar view on industries' innovation processes. It is to be seen as a first step in a more encompassing quantitative exploration of the GIS framework's key hypotheses on innovation dynamics in industries with complex value chains. An obvious improvement in this respect would be to quantify the categorization of the different value chain parts into GIS types. For instance, measures for publication/patenting intensity in innovation activities could be used to proxy the innovation mode while proxies based on production/market volumes might account for the valuation system in which firms are embedded.

Last but not least, the compilation of firm survival databases contains several methodological challenges which are well documented in the literature (Carlsson, 2016). I.e. our database could be expanded beyond two high-income countries. With a global sample of firms that includes key latecomer countries like China, one could explore the effects of the FiT in spatially more disaggregated ways. Our long-term analytical focus has further inherent data limitations, which hinder us from including firm-internal features such as financial assets, sales volumes or firm-internal absorptive capacity. The findings presented here should thus be triangulated with studies e.g. in management literature that are able to assess policy effects in a shorter timeframe and the recent past.

6. Conclusions

This paper aimed at developing a novel framework for analyzing life cycle dynamics in industries with complex global value chains. By integrating insights from industrial dynamics and innovation system literatures, we developed novel hypotheses on how diverse GIS configurations in parts of an industry's value chain influence the survival rates of related firms. We investigated life cycle dynamics empirically by disintegrating the value chain of the global solar PV industry into different parts and relating each part to a characteristic GIS configuration.

Our results show that a firm's position in the value chain and the related multi-scalar innovation system structure significantly affect its survival chances. Firms in parts of the value chain with a 'footloose' GIS configuration have shorter survival rates than firms which depend on GIS structures with spatially more 'sticky' elements. Policy interventions can accordingly be expected to have complex (and sometimes counter-intuitive) effects on firms operating in these multi-scalar, multi-sectoral structures. I.e. the expected positive effect of a FiT on firm survival in parts of the value chain with ‘spatially sticky’ valuation systems could not be empirically supported. Only weak evidence exists on its positive impact on a firm’s survival chances in very early stages of the industry life cycle. Demand-side policy’s effect on firm survival and innovation dynamics thus appears in need of further research. Based on the findings above and in line with previous research (Norberg-Bohm, 2000; Wilson, 2012; Winskel et al., 2014), we recommend policy making to tailor interventions to the spatially sticky parts of the value chain in particular within newly emerging industries that evolve in multi-scalar and sector-transcending ways.

This finding is of crucial importance, since innovation policies around the world increasingly aim at sustaining economic competitiveness while also mitigating climate change and other related grand challenges. Many of the related ‘mission-oriented’ policy strategies focused on supporting firms in the emerging ‘cleantech’ space with generous tariff cuts, R&D support and demand-side subsidy schemes. These policies usually target national and regional levels, without taking multi-scalar and multi-sectoral interdependencies into account. As a result, many national policy interventions create unintended competitive pressures and spatial spillovers to other places around the world. I.e. the German approach to support the energy transition with FiTs received substantial criticism for having indirectly subsidized PV firms in latecomer countries like China, instead of reaping the rewards in the local industry (e.g. Quitzow, 2015; Hoppmann et al. 2014). Our study explains the mechanisms behind the strong spatial spillovers in the core parts of the PV value chain and helps to understand why firms in the upstream and downstream parts of the industry experienced more stable survival patterns. Future policies supporting promising new growth industries could anticipate similar spillovers and leverage first-mover advantages by conducting a detailed GIS analysis of the respective value chain, following the model presented here.

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Appendix A

Description of the Japanese PV databases and search strategy

We started the data search on the Japanese PV industry with 65 firms derived from the National Survey Reports (NSR) by the IEA from 2002 to 2016. In each year, national PV experts of the IEA conducted the survey reports by focusing on national markets, policies, industries and R&D activities. Some information such as installed capacity of PV or module prices date back until 1990 and thus provide a suitable source for studying industry dynamics. However, since the NSR does not include information on firms from the whole value chain, we complemented information on the remaining firms using an internet search and two additional databases. The first one is provided by the main governmental R&D organization in Japan, i.e. NEDO. We searched the NEDO database for new firms using reports on current and completed governmental PV projects, which resulted in the identification of 51 additional firms. Furthermore, we extracted data from ORBIS, a standardized database on over 275 million private firms worldwide. The North American Industry Classification System (NAICS) was used to scout for additional firms. We applied the primary codes 221114 (Solar Electric Power Generation) and 334413 (Semiconductor and Related Device Manufacturing) and matched the information with the IEA and NEDO database, which led to 11 additional firms. As above, we further examined homepages or related websites of the identified firms to classify their activities in the PV value chain and to aggregate them based on their M&A activities, which reduced the sample to a total number of 127 Japanese PV firms.

Appendix B

Table A.1: Robustness check for indirect influences.

Dependent variable: Hazard Rate	Model Indirect	Model Upstream	Model Downstream
Footloose	.621**	.465	.616*
FiT	-.014	-.007	-.007
Tech entry	2.117*	1.776	1.766
Firm size	-1.123***	-1.199***	-1.192***
New firm	-.663***	-.698***	-.682***
Mainly PV	.693**	.760**	.751**
Diversify	-.872***	-.866***	-.875***
German	-.404	1.947***	1.957***
Capacity	-.206	-.174	-.174
Incr. change	.387	.831	.830
Competition	-.081	.119	.120
R&D support	.170	.143	.143
Invest support	.035	.358**	.357**
Demo support	-.105	-.058	-.058
CO2 emissions	.000		
Commodity prices	.023**		
GDP	.000		
Upstream		-.212	
Downstream			.072
Log-likelihood	1072.728	1082.169	1082.350
Chi-square	337.365***	318.595***	318.677***

Sign.: *** p < .01, ** p < .05; * p < .1

Table A.2: Robustness check for competing risks and discrete time.

Dependent variable: Hazard Rate	Model Exit by Insolvency	Model Exit by M&A	Model Discrete Time
Constant			-7.982***
Footloose	.726**	.320	1.653***
FiT	-.021	-.004	-.005
Tech entry	-10.495	1.355	-1.166
Firm size	-.780**	-1.942***	.333
New firm	-.365	-1.331***	.144
Mainly PV	1.264***	-.167	1.024***
Diversify	-.960***	-.678	-.676**
German	1.427**	2.894***	.917*
Capacity	-.252	-.144	-.046
Incr. change	1.751**	-.335	1.229**
Competition	.143	.055	.281
R&D support	.047	.255	.058
Invest support	.250	.559*	.469**
Demo support	-.122	.033	-.159
Log-likelihood	683.244	375.144	701.933
Chi-square	257.027***	107.269***	373.052***
R^2			35.5

Sign.: *** p < .01, ** p < .05; * p < .1

Table A.3: Robustness check for early industry stages (< 2005).

Dependent variable: Hazard Rate	Model R1	Model R2
FiT	-.138	-.139
FiTxStandardized	.007	
FiTxCustomized		-.052
Firm size	-.693	-.650
New firm	-.571	-.533
Mainly PV	-.232	-.251
Diversify	-1.586	-1.576
German	3.501**	3.516**
Capacity	.001	.001
Competition	-.014	-.014
R&D support	-.343	-.338
Invest support	2.730	2.729
Demo support	.673	.668
Log-likelihood	62.725	62.642
Chi-square	62.637***	63.133***

Sign.: *** p < .01, ** p < .05; * p < .1