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REGULAR ARTICLE

Knowledge recombination along the technology life cycle

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Abstract

This study sheds light on how recombination of different kinds of knowledge changes along the technology life cycle. From a theoretical point of view, the cyclical technology life cycle model is extended to account for the influence of recombination of different kinds of knowledge in the different life cycle phases. This model is empirically tested for the technological life cycle of wind power and photovoltaics in Germany for the period from 1970 until 2006. Patent forward citations are considered as recombinatorial success and inventors' patenting experience proxy different kinds of knowledge. Negative binomial regressions as well as rolling-window regressions are used to estimate the relevance of different kinds of knowledge along the technology life cycle. Results reveal that different kinds of knowledge matter along the technology life cycle. In the era of ferment, knowledge from domains external to the technology is relevant, but for the dominant design and the era of incremental change, new and specialized knowledge is most important. However, there are technological differences and deviations from the model. Rolling-window regressions reveal nuanced changes in the life cycle phases. The results have several policy and management implications, especially for the timing of whom to fund or hire for inventive activity.

Keywords Technology life cycle · Knowledge recombination · Wind power · Photovoltaics · Patent data · Rolling-window regression

JEL Classification O31 · O34 · Q55

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1 Introduction

Technologies develop by the inducement of new knowledge into the knowledge base, which is the result of the recombination of already existing knowledge and artifacts (Schumpeter 1912; Nelson and Winter 1982; Dosi and Nelson 2010, 2013). While there is an extensive stream of literature exploring the factors of recombinatorial success at the firm level (Kogut and Zander 1992; Savino et al. 2017), the influence of knowledge recombination on the technology knowledge base and its evolution over time is so far not well understood. It is well known that technologies evolve along their knowledge base, which itself shows certain dynamics and evolves over time (Malerba and Orsenigo 1996, 2000). Besides internal knowledge accumulation, the in-flow of knowledge from sources external to a technology is crucial for its evolution in terms of initiating, redirecting and refreshing the knowledge accumulation processes (Dosi and Nelson 2013). The way external knowledge diffuses into a technology, the source from which it comes, and the type of actors involved appear to be core determinants of that technology's further development (Grant 1996; Dosi and Nelson 2013).

The evolution of a technology can be stylized along a life cycle. Anderson and Tushman (1990) propose a cyclical model of a technological life cycle (TLC). The model distinguishes four phases, an era of ferment, the emergence of a dominant design, an era of incremental change and a discontinuity, which restarts the cycle. This TLC model has been widely used to analyze technological development and is extended into various dimensions, for example covering the influence of cognitive factors (Kaplan and Tripsas 2008), specific phases (Murmann and Frenken 2006) or the level of granularity (Taylor and Taylor 2012). However, knowledge, the technology's knowledge base and the influence of different types of knowledge along the TLC have been neglected from a theoretical and empirical perspective. While there is first empirical evidence that different kinds of knowledge matter along the technological development (Krafft et al. 2011, 2014a), no theoretical foundation has been provided explaining the underlying factors and processes. The aim of the paper is to close this gap by extending the Anderson and Tushman (1990) model proposing how recombination of different kinds of knowledge shapes a technology over its life cycle. The extension states that in each TLC phase different sources of knowledge are required for successful recombination and technological evolution.

The proposed extension of the Anderson and Tushman (1990) model is empirically tested for two technologies, namely, wind power (WP) and photovoltaics (PV). In particular the development in Germany for the period from 1970 until 2006 is analyzed. After the oil crisis in the 1970s both technologies were considered as means to reduce the dependency on fossil fuels and to mitigate climate change (Jacobsson and Johnson 2000). Since then, severe effort has been put forward to enhance the technologies and both are nowadays competitive with incumbent technologies (REN21 2015). These makes WP and PV ideal cases to analyze how technologies evolve and mature over their life cycle. The period covers several TLC phases and allows us to draw conclusions how knowledge recombination patterns change over time. Patent data is used to proxy the technological knowledge base, while inventors and their inventive experience are used to characterize different sources of knowledge. Patent forward citations are taken as recombinatorial success and proxy the contribution to the knowledge base (Carpenter et al. 1981; Harhoff et al. 1999, 2003, Jaffe and de Rassenfosse 2017). Negative binomial regressions are used to estimate the effect of different kinds of knowledge embedded in the inventors on the patents contribution to the knowledge base. Regressions are estimated for the overall period as well as for the different TLC phases. Furthermore, rolling-window regressions are used as a novel approach to capture dynamics on a fine grained level over time.

Results show that different sources of knowledge matter for technological evolution in general but differently in the phases of the TLC, by and large in line with the proposed theoretical model. For the overall technological development, inventors who possess specialized knowledge are most influential. In WP also, de-novo inventors matter, those who induce knowledge that has not been used before, as well as inventors who were previously active in unrelated technologies. Along the phases of the TLC, the era of ferment in WP is mainly shaped by inventors with unrelated knowledge but relevance shifts over time towards specialized and de-novo inventors. In PV, the era of ferment is shaped by several types of inventors, but here also a shift towards specialized inventors takes place over time. The rolling window regressions provide a more detailed picture and show how different kinds of inventors and their knowledge is also changing inside the phases.

These results contribute to a deeper understanding of the evolution of a technology's knowledge base and the knowledge dynamics that take place along the TLC. The understanding how knowledge matter in different stages of a technology is crucial for policy maker to implement relevant policies and support the relevant actors, as well as for management to pursue an appropriate R&D strategy. Furthermore, the theoretical contribution by the extension of the Anderson and Tushman (1990) model provides a general framework to understand technological evolution and the respective knowledge dynamics, as well as the influence of knowledge from different origins and its integration success into the knowledge base. This complements previous work and allows a detailed approach to understand recombination and technological development along the TLC. From an methodological point of view, the utilization of previous patents of inventors to distinguish different sources of knowledge allows us to analyze long term developments, which cannot be captured, for example, by surveys (Conti et al. 2014). Additionally, rolling-window regressions prove to be a useful approach to shed light on dynamics in technology evolution.

In the following, Section 2 reviews the literature about knowledge base, knowledge recombination and their relevance for technological evolution and integrates these concepts into the TLC model, providing the theoretical framework for the empirical analysis. Section 3 introduces WP and PV as the technologies under consideration and discusses how they develop over time. Section 4 presents the data, econometric approach and the results. The last Section discusses findings and concludes.

2 A model for knowledge recombination along the technology life cycle

2.1 Knowledge recombination and the technology's knowledge base

The notion of a knowledge base describes a set of knowledge, practices and routines attributed to an object of observation, such as a firm, a technology or a country. The relevance of the knowledge base has been studied extensively at the micro (firm) level (e.g. Nesta and Saviotti 2005; Krafft et al. 2014a; Roper and Hewitt-Dundas 2015), but also on more macro dimensions such as the regional (e.g. Leydesdorff and Fritsch 2006b; Cantner et al. 2010) and the country level (e.g. King 2004; Leydesdorff et al. 2006a). The knowledge base is of central importance for innovative activity at the firm level (Nesta and Saviotti 2005; Antonelli and Colombelli 2013) and for firm survival (Colombelli et al. 2013). Concerning the knowledge base of a technology, the understanding how the knowledge base shapes technological development is scarce. While some studies focus on the structure of the knowledge inside an industry and show that there are certain dynamics in the knowledge base evolution (Yayavaram and Ahuja 2008; Krafft et al. 2011, 2014a) and shifts between different Schumpeterian regimes (Maleki et al. 2018), a general understanding how the knowledge base evolves and how the respective technologies are shaped is scarce.

The evolution of the knowledge base is driven by knowledge accumulation and introducing new knowledge into it (Malerba and Orsenigo 1996). This new knowledge stems from the recombination of previously existing knowledge, either from within the knowledge base, or from outside. The idea of knowledge recombination was already proposed by Schumpeter (1912) using the phrase *"Neue Kombinationen"*. This recombination basically leads to a never ending cycle, as Arthur and Polak (2006, p. 23) put it: *"New technologies are never created from nothing. They are constructed—put together—from components that previously exist; and in turn these new technologies offer themselves as possible components—building blocks—for the construction of further new technologies."* This continuous knowledge recombination extends and refreshes the knowledge base with new contributions of previously existing knowledge, which can be utilized to create new products, improve processes and foster economic growth (Weitzman 1996, 1998).

The knowledge recombination process is an increasingly complex (Jones 2009) and uncertain task (Fleming 2001). Several determining factors for success have been identified at the firm level (e.g. Kogut and Zander 1992; Savino et al. 2017). For example, the previous or stock of knowledge that the firm possess is of importance (Liyanage and Barnard 2003) as well as its characteristics in terms of structure and complementarity (Dibiaggio et al. 2014). The recombination of knowledge present in the firm is relevant, as well as the reconfiguration of existing combinations (Carnabuci and Operti 2013). Also, the combination of new and old knowledge is important for technological advancement (Nerkar 2003). Especially, the ability to tap on new or external sources of knowledge that can be integrated in the knowledge base is relevant (e.g. labor mobility, hiring specific labor, acquisitions, collaboration, suppliers, customers, ...; see Savino et al. (2017) for an overview). These underlying processes partly apply to the level of the technology.

The determinants of knowledge recombination on the technological level are not as well understood as on the firm level.[1] However, generic determinants such as uncertainty and the increasing complexity apply in a similar vein. Similar to the relevance of integrating external knowledge into the knowledge base of the firm, Nemet (2012) shows for energy technologies that tapping on knowledge from outside the technological domain results in a higher recombinatorial success than knowledge from within the technological domain. Also, Schoenmakers and Duysters (2010) show that radical inventions rely more likely on existing knowledge and combine knowledge across multiple domains compared to non-radical inventions. With respect to the accumulation of knowledge in a technology, Popp (2002) shows that the quality adjusted accumulation of knowledge in a technology has a positive effect on recombinatorial success.

Knowledge recombination takes place across the knowledge space. A technology can be viewed as a specific area of the knowledge space that constitutes its knowledge base. If knowledge is recombined within such a knowledge base, it can be considered specialized, since it combines parts of knowledge that are familiar already. The relation between a technology and knowledge that is outside its knowledge base can be characterized by the distance or proximity in the knowledge space. The distance is relevant for example in collaborations, where the decision to collaborate is influenced by the distance between partners in knowledge space (e.g. Cowan et al. 2007; Baum et al. 2010) or the overlap of firms' knowledge bases (Rosenkopf and Almeida 2003). The knowledge distance for recombination can be constructed either in a continuous way using patent classifications to calculate Euclidean distances or classification overlaps (e.g. Breschi et al. 2003; Benner and Waldfogel 2008; Bar and Leiponen 2012; vom Stein et al. 2015) or using binary categories such as related and unrelated knowledge. Applying this binary categorization to different technologies, Nemet and Johnson (2012) show that the use of related knowledge (they use the term "near") leads to more valuable inventions, in terms of forward citations. Youn et al. (2015) distinguish knowledge in "broad" and "narrow" to analyze general recombinatorial patterns for US patents and show that there is an increase of "narrow" recombinations over time.

2.2 Knowledge and the technology life cycle

The knowledge base of a technology is central to a technology's development. Malerba and Orsenigo (1996, p. 470) propose that the knowledge base itself is dynamic and "*changes in Schumpeterian patterns occurring during a technology and an industry life cycle*". These changes in the knowledge base occur because different kinds of knowledge enter the knowledge base and their contribution to technological development might be conditioned on the stage of the technology. The process of technological evolution can be modeled by a TLC similar to the product or industry

[1]There is a large body of literature on intra- and inter-technology spillover. However, this stream of literature captures the presence of such spillover, not their determinants and how they result in successful recombination of knowledge.

life cycle. In the TLC, neither the actual product is of importance nor the structure of the firms in the industry, but rather the application of the technology (see Taylor and Taylor 2012, for a discussion of the differences). With the technology as the unit of observation, the TLC allows us to understand how different kinds of knowledge alter the knowledge base over time.

There are several approaches to model a TLC. According to Taylor and Taylor (2012), these approaches can be generally distinguished into S-shaped and cyclical models. S-curve models depict technical progress usually in terms of cumulative diffusion or technical improvements over time. The S-curve models are closely related to the product life cycle covering a embryonic, growth, maturity and aging stage (Taylor and Taylor 2012). These stages are frequently applied to patent data to elaborate the state of a specific technology (Haupt et al. 2007). Cyclical models, especially the one by Anderson and Tushman (1990), present a macro view on the technology. In this model, a new discovery or breakthrough opens up new technological opportunities or trajectories and starts an era of ferment. This phase is followed by a phase in which a dominant design emerges and a main trajectory is established.[2] After the emergence of a dominant design, an era of incremental change follows in which the technology incrementally evolves along the trajectory until a new technological discontinuity disrupts the technology and the cycle begins again with a new or dramatically altered technology, replacing the current one.

While the TLC has been studied frequently in general, so far the underlying knowledge dimension that shapes the technological development has been neglected. However, with a focus on the knowledge base that constitutes a technology, there might be differences in the kind of knowledge necessary to alter and extend the knowledge base in different phases of the TLC. While it is widely accepted that a discontinuity in the knowledge base creates a new trajectory leading to a new technology (Dosi 1982), there is no general model of how different kinds of knowledge influence technological development over the TLC. There is the general concept of exploration and exploitation (March 1991) and the tendency to move from the former to the latter over time (Utterback and Abernathy 1975; Klepper 1996), along with the emergence of a dominant design (Utterback and Abernathy 1975; Murmann and Frenken 2006). However, a theoretical framework to integrate knowledge into the different phases of the TLC is missing.

Some empirical analyses try to understand how knowledge matters along the TLC and shape the evolution of a technology. Antonelli et al. (2010) use the co-occurrence of technological classes within patent applications to shed light on the dynamics of knowledge recombination for information and communication technologies, but do not consider a life cycle. Krafft et al. (2011) use social network analysis to elaborate on the relationship in co-occurrence of technological classes and show that, in biotechnology, the search process changes from exploration to exploitation in the

[2]While Anderson and Tushman (1990) rather see the emergence of a dominant design and a new discontinuity as a point in time, it is a short phase in which these phenomenon emerge, get recognized and development adapts towards it, especially on the technology level, which has different characteristics than the product level. See also Van de Ven and Garud (1993) and Kaplan and Tripsas (2008) who talk about the convergence towards a dominant design.

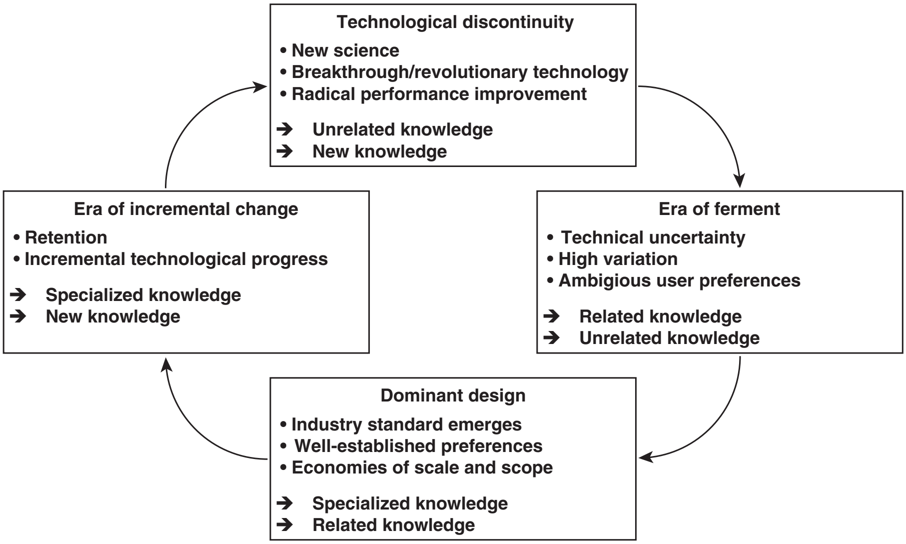

Fig. 1 Technology life cycle phases and respective relevant knowledge. Source: Extension based on Tushman and Rosenkopf (1992), Kaplan and Tripsas (2008), and Taylor and Taylor (2012)

recombination process. Krafft et al. (2014a) use the properties of the biotechnology and telecommunication knowledge base to elaborate on the phases of exploration and exploitation. They show that sectoral differences can be attributed to the phases of the knowledge base. Furthermore, Krafft et al. (2014b) explore the relationship between the structure of the biotechnology knowledge base and technological alliances along the TLC. They find that during the evolution of the biotechnology, the search pattern become less random and more organized and knowledge becomes more related. However, they point out that, along a trajectory, this sequence is not always the case.

In the following, the missing link between the evolution of a technology's knowledge base and the phases of the TLC is proposed by extending the Anderson and Tushman (1990) TLC model. In each phase of the TLC the relevance of different sources of knowledge is derived and how these knowledge can alter and extend the knowledge base.[3] The result is summarized in Fig. 1, which expands the initial graphical representation presented in Tushman and Rosenkopf (1992) with the relevant knowledge in each phase.

1. **Era of ferment**: The era of ferment starts the development of a new technology, following the discovery of a new technological principle, technological disruption or scientific discovery (Anderson and Tushman 1990; Tushman and Rosenkopf 1992). The new technology is not well understood and uncertainty prevails about the technology's characteristics and application (Kaplan and Tripsas 2008). The knowledge base is rather small and unstructured (Krafft et al.

[3]The proposed extension can also be adapted to other models of the TLC, for example, the S-shape development proposed in Haupt et al. (2007) or Cetindamar et al. (2016). See also Taylor and Taylor (2012), who try to unify the different TLC models.

2011). Here, experimentation and exploration are the main inventive activities (March 1991). First applications are derived and (product) variation is high (Van de Ven and Garud 1993). Niche markets emerge or are created, in which experimentation can take place to gain further understanding of the technology and required characteristics (Kemp et al. 1998).

Since in the era of ferment the knowledge base itself is rather small and unstructured, related and unrelated knowledge from other technological fields is important. This external knowledge is induced into the knowledge base and supports the development of the technology by recombination with existing knowledge already present in the knowledge base. This related and unrelated knowledge is able to provide new combinatorial possibilities from different fields and experiment with new ways of applications and characteristics. However, due to the high technological uncertainty, failure is very likely (Fleming 2001).

2. **Dominant design**: The emergence of a dominant design is characterized by increasing economies of scale and scope, network externalities and standardization (Utterback and Abernathy 1975; Arthur 1989; Anderson and Tushman 1990; Klepper 1996; Murmann and Frenken 2006). The knowledge base becomes broader and structured, which supports the emergence of the dominant design (Krafft et al. 2011). There are several factors on the firm and environmental level that are influential as well (Suarez 2004), such as the emergence of institutions that facilitate knowledge exchange among actors (Kaplan and Tripsas 2008). The dynamics in the knowledge base play also a role, since the structure of the knowledge base changes and becomes denser (Krafft et al. 2011).

   The knowledge base is enhanced with knowledge from related fields that share the same principles and allow useful recombinations to establish wider levels of application for the dominant design (Murmann and Frenken 2006). At the same time, the number of variation is reduced and a single trajectory emerges and development focuses along this trajectory (Metcalfe 1995). Here, specialized and detailed knowledge about the core principles of the technology is relevant to increase performance and application opportunities to expand the number of possible adopters.
3. **Era of incremental change**: After the emergence of a dominant design, incremental change by solving rather small problems or improving performance along the technological trajectory takes place (Dosi 1982; Sahal 1985; Anderson and Tushman 1990). In this phase, the knowledge base is large and detailed, the technological principles are well understood and the dominant design is working. This era is characterized by exploitation of the knowledge base by localized search along the trajectory (Nelson and Winter 1982; Levitt and March 1988). Incremental improvements occur in a routinized way (Henderson and Clark 1990) and inertia exists towards switching the direction of search (Kaplan and Tripsas 2008). Social, political and organizational routines are established as well (Tushman and Rosenkopf 1992). Nevertheless, certain dynamics still exist along the trajectory (Funk 2009; Dokko et al. 2012; Lee and Berente 2013).

In the era of incremental change, specialized knowledge is necessary to solve the incremental problems, which allows further progress. Very detailed knowledge and experience is necessary for the incremental improvements. But also new knowledge might be relevant for further progress. New knowledge might come from a new generation of scientists and engineers, who are not primed towards a specific concept or way of thinking and can integrate their new ideas. Since over time specific educational facilities are established that provide detailed training in the field, this new knowledge can become particularly relevant in the era of incremental change (Baumol 2004; Vona and Consoli 2015).

4. **Technological discontinuity**: The emergence of a technological discontinuity disrupts the technology and might establish a new trajectory. In this phase, the knowledge base is exhausted and technical opportunities are scarce. The disruption is usually assumed to be exogenous to the technology (Dosi 1982; Tushman and Anderson 1986). It can occur if the technology reaches its natural limits (Sahal 1985), the opportunity space for further improvement is exhausted (Fleming 2001; Adner 2004) or customers radically shift their preferences (Tripsas 2008). However, recently the idea that the discontinuity can emerge out of the incremental improvements, which become radical by accumulation (Funk 2009) or social interaction (Dokko et al. 2012), is discussed.

   In this stage, the exhausted knowledge base can be rejuvenated by a disruption that can open up new recombinatorial possibilities. For the further evolution of the knowledge base, unrelated knowledge is most likely to refresh the technology in a disruptive way. Radical new ways of recombination can emerge out of these new opportunities. Furthermore, new unexploited ideas and knowledge can induce the discontinuity, especially if accumulated over time. If the unrelated or new knowledge gets successfully recombined with the knowledge base, a rejuvenation of the technology takes place and the life cycle starts again with a drastically altered or completely new technology.

2.3 Inventors and knowledge recombination

To understand the development of a technology, it is crucial to determine which factors influence the evolution of the underlying knowledge base. Since knowledge is embodied in people, the inventor who is able to create new and recombine existing knowledge is the core determinant for the evolution of the knowledge base. The individual person possess knowledge and competences, especially tacit ones, which are relevant for recombination and technological advancement (Grant 1996; Mascitelli 2000). The inventor can gain and use his knowledge from learning-by-doing, experimentation and application (Arrow 1962). This extends the inventor's stock of knowledge and makes the inventor more effective in future inventive activity in recombination (Conti et al. 2014), but with diminishing returns to novelty (Audia and Goncalo 2007; Conti et al. 2014). However, the process of recombination is influenced by uncertainty about the usefulness of the outcome of the recombination process (Fleming 2001), and specific characteristics of the inventor play an important role for recombinatorial success.

Several findings reveal which inventor characteristics lead to successful recombinations and inventions. Gruber et al. (2013) show that the kind of education an inventor received influences the ability to combine knowledge from different fields. They show that scientists are better in integrating distant knowledge than engineers. Besides the kind of training the inventor receives, the breadth and depth of the knowledge the inventor possesses also has an influence, as shown by Boh et al. (2014). Conti et al. (2014) find that the previous inventive activity positively influences new inventions. In addition, Mohammadi and Franzoni (2014) show that for scientists' knowledge relatedness influences the technological value of inventions. Meyer (2006) demonstrates that scientists in nanotechnology who invent at the same time are more effective than non-inventing scientists. Scandura (2019) shows that the success of inventors is influenced by the type of knowledge they use. Based on survey data, she reveals that combining scientific and market knowledge enhances inventive output.

While the characteristics of inventors are of importance, their origin in the knowledge space also play a role. Mobile inventors, which enter a technology from outside the technology's knowledge domain, may alter a technology's knowledge base and enhance recombination possibilities. Those inventors can transport or spill over their knowledge about a specific technology to a new one by moving between technologies and industries and carrying their knowledge and experience with them (Song et al. 2003; Hoisl 2007). By entering a technology, in terms of creating an invention in this field, the knowledge these people possess may increase the knowledge base of the technology into which they move. It can be assumed that, during the process of invention, the knowledge an inventor holds is recombined with knowledge present in the technology to which the inventor moves and increases the knowledge base, especially if the invention is followed up by other inventors. This transfer of knowledge is important for the technology's progress and shapes the direction into which a technology develop (Schoenmakers and Duysters 2010). Here, the distance in the knowledge space plays a role again, since these inventors can originate from related technologies that are near or familiar with the technology or from unrelated technologies, which do not share common principles. Their movement from one technological field to another allows them to combine their previous knowledge with the one present in the technology's knowledge base into which they move.

Based on the different characteristics and technological origin of inventors, inventors can be distinguished into four different groups based on their inventive experience. The characteristics these inventors have may influence their success of recombination, especially in different phases of the TLC. The distinction between different kinds of inventors can be drawn from the inventor's personal knowledge and the knowledge base of a technology.

1. **New Inventors**: Inventors have no inventive experience, which implies that their first invention contributes to the technology's knowledge base. They may have gotten educational training in this field (Vona and Consoli 2015) but show no experience with inventive activities yet. They can also be customers who want specific features or characteristics of a technology and introduce them on their own (von Hippel 1976, von Hippel 1988, 2010) or the classical tinkerer (Bettiol

et al. 2014). They have the advantage that they are not primed by any previous inventive activity and can bring novel and unexploited ideas with them. However, they lack experience and tacit knowledge in inventive activity and may not fully understand the technology.

2. **Specialized Inventors**: Specialized inventors have contributed to the technology's knowledge base by previous inventive activity. Due to their repetitive inventive activity, they benefit from learning-by-doing (Arrow 1962) and have accumulated knowledge in the technology that gives them a deep understanding of it (Conti et al. 2014). They are able to see opportunities for further improvement of the technology or their previous inventions. However, it can be assumed that they face diminishing returns of success, since they might follow an exploitative path, as suggested by Audia and Goncalo (2007).
3. **Related Inventors**: Related inventors have contributed to technological fields that are related to the technology into which they move. These inventors are familiar with the technological field or underlying technological principles and can transfer related knowledge from other technologies or technical applications to the knowledge base under consideration. These inventors are able to recombine their previous knowledge with the knowledge already present in the knowledge base. Uncertainty about the recombinatorial success should be low, but radical contributions are not that likely.
4. **Unrelated Inventors**: Unrelated inventors show no inventive background related to the technology's knowledge base into which they move. These inventors generated inventive output in unrelated technologies and changed their field of inventive activity. By the shift from one technology to another, they carry with them specific knowledge from the former field of activity that may not be present in the technology's knowledge base and they may combine this knowledge with the knowledge present already in the knowledge base. However, the knowledge they possess for recombination might be difficult to integrate into knowledge present in the technology and unsuccessful recombinations are likely (Fleming 2001).

These different types of inventors are the carriers of specific knowledge and can by their inventive activity recombine their knowledge with the knowledge present in a technology. In line with the extension of the Anderson and Tushman (1990) model, they provide the necessary different kinds of knowledge that influences the technological progress along the TLC. In the following the extended model and the influence of different kinds of inventors along the technology life cycle is tested with renewable energy technologies in Germany.

3 Renewable energies and their technology life cycle

3.1 Wind power and photovoltaics in Germany

To test the proposed extension and the effect of different sources of knowledge along the TLC, wind power (WP) and photovoltaics (PV) are chosen from the field of renewable energies. In the light of emerging environmental problems such as climate change, but also resource scarcity and rising energy consumption, alternative energy technologies are demanded. Since the oil crisis in the 1970s, renewable energy technologies, especially WP and PV, emerged and diffused in the electricity market (Jacobsson and Johnson 2000). During the last 40 years, these technologies underwent a remarkable development to catch up with incumbent technologies in terms of efficiency and cost competitiveness. The evolution of these technologies is driven by inventions and knowledge accumulation extending the knowledge bases of the technologies. Nowadays, WP and PV are cost competitive and contribute a substantial share of electricity in several countries (REN21 2015).

The technologies developed globally but, in the following, only the situation in Germany from 1970 until 2012 is considered. Germany can be seen as a forerunner for both technologies due to high inventive activity, installed capacity and policy support. The German government implemented various policy instruments to support the development and served in some period as the largest market (Lauber and Mez 2004). Figure 2 shows the R&D expenditures as well as the diffusion (by annual installed capacity) of both technologies over the last 40 years as well as the main demand pull policies. Over time, there was a shift from direct R&D subsidies to demand inducing policies that created a niche market for the technologies and supported their diffusion. This favorable environment helped the technologies to develop and the different instruments had vast effect on inventive activity (Johnstone et al. 2010; Wangler 2013; Cantner et al. 2016).

3.2 Technology life cycle phases

Several attempts to distinguish technological phases for WP and PV are proposed in the literature, which mimic the TLC but also to some extend an industry life cycle. For example, Bergek and Jacobsson (2003) distinguish two phases in the worldwide WP development, a phase of experimentation from about 1975 until 1989 and a phase of turbulence and growth from 1990 until 1999. Wilson (2012) derives similar phases for the development in Denmark. Harborne and Hendry (2009) argue that, even though a dominant design seemed to emerge at the end of the 1980s, variation and experimentation was still high at the end of the 1990s. According to Huenteler et al. (2016b), WP follows a complex-products and systems life cycle (Davies 1997) and a dominant design emerged already in the late 1980s. Since then, WP has been in the era of incremental change. Hemmelskamp (1998) does not analyze a TLC in particular, but points out that even two dominant designs emerge for small and large wind turbines in the middle of 1990s. For Germany, the development for WP can, according to Bruns et al. (2009) and Bruns and Ohlhorst (2011), be distinguished in a pioneering phase from 1975 to 1985 followed by a rethinking/adopting framework period until 1990 succeeded by a breakthrough period until 1995. Then a three year transitory setback period was proposed followed by a second boom period until 2002. After 2002, consolidation in the industry took place and, according to them, a divergence of the trajectory took place.

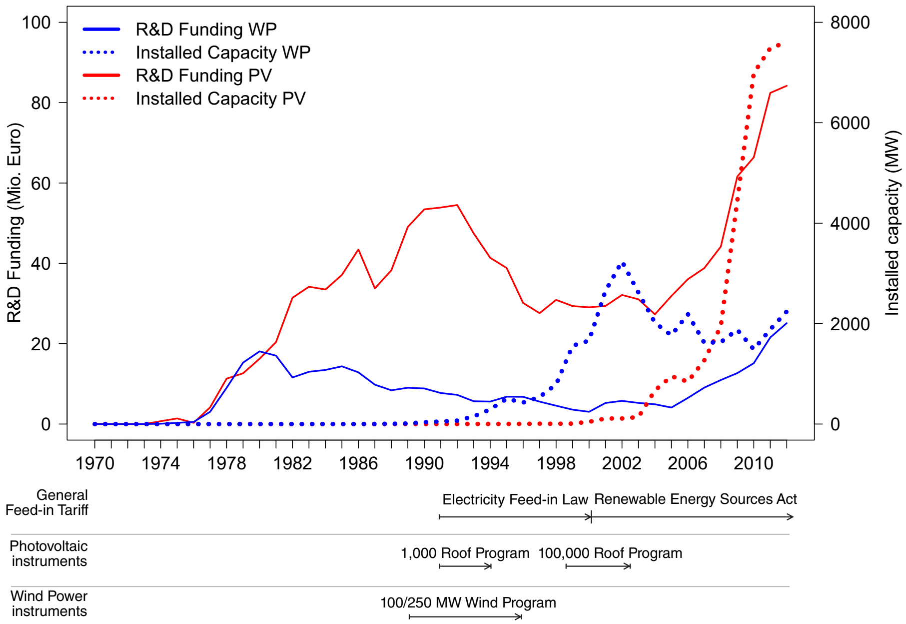

Fig. 2 Wind power and photovoltaics policy instruments in Germany. Data source: Cantner et al. (2016)

PV can, according to Peters et al. (2012), be distinguished in three phases on the global level. The period 1974-1985 is a first boom phase, followed by a stagnation phase until 1994 and from 1995 onwards a second boom phase. Huenteler et al. (2016b) analyze the technology in detail and conclude that PV followed a mass-produced goods life cycle (Abernathy and Utterback 1988) and a dominant design emerged in the early 1990s. Since then, PV has been in the era of incremental change. For the development specifically in Germany, Jacobsson et al. (2004) distinguish the development of PV in two phases, a first until 1989, which they consider a science-based experimentation phase, and a growth phase from 1990 until 2001. Bruns et al. (2009) distinguish the development of PV in five phases. They attribute the period 1970-1985 as a pioneering phase, followed by a phase with reduced private and public R&D until 1991, when a demand inducing policy instrument was implemented that allowed first larger scale tests. From 1994 until 1998 there was a phase of slow down and uncertainty, followed by a breakthrough phase form 1999 until 2003 and from 2004 onwards a booming phase.

Since there is no clear distinction of the TLC phases in the literature, the technologies are separated in phases based on the diffusion and the political support they received in Germany (see Fig. 2 and Table 1).[4] For this purpose, especially the

[4]Since technological development unfolds over time, retrospective identification of phases is difficult and depends on the point in time the distinction is made. This explains the above variation in periods and assessments in the future will most likely derive different phases than the ones distinguished in the following. However, there are methods available to distinguish TLC phases based on patent data (e.g.

distinction between demand-pull and technology-push policies is useful (Mowery and Rosenberg 1979), since the policy support changed over time towards more demand oriented support. Several studies show that policy instruments decisively influenced the technological development, especially demand pull policies (Johnstone et al. 2010; Wangler 2013; Cantner et al. 2016). These policies induced demand for the technologies, which reaped economies of scale and helped to establish a dominant design.

In the case of WP, the technological development can be separated into three phases until today.[5] The era of ferment starts in Germany around 1970 and lasts until 1995. This period covers the experimental phase in the beginning of the 1980s where the large scale pilot turbine GROWIAN was constructed but failed in operation (Bergek and Jacobsson 2003). However, the first successful small scale applications were supported by the 100/250 MW wind program in the end of the 1980s, which proved the technological feasibility (Harborne and Hendry 2009). Additionally, the first feed-in tariff was introduced in 1991 and supported technology independent diffusion of renewable energy (see Bergek and Jacobsson 2003; Bruns et al. 2009, for a detailed discussion of the policy instruments). These instruments created a niche market that provided opportunities and testing ground for commercial applications. The emergence of a dominant design took place from 1996 until 2000 and is characterized by massive up-scaling of the turbine size and a surge in installed capacity in Germany due to the demand policies. The turbine design converged to a three blade rotor facing the wind with a variable-speed gearbox (Harborne and Hendry 2009; Milborrow 2011; Huenteler et al. 2016b). This so called Danish-design is used in nearly all wind turbines today. The era of incremental change starts in 2001 and is characterized by a reduced annual installed capacity, but increasing exports and further up-scaling. The focus of inventive activity switched to other components such as mounting and encapsulation or grid connection of turbines (Huenteler et al. 2016a), which are not fundamental to the technical principle. Also, offshore turbines were developed and installed, but they do not substantially differ from onshore turbines and a discontinuity seems not yet to have emerged.

In the case of PV, the era of ferment covers the years from 1970 until 1997 and is characterized by massive R&D subsidies and first experimental demand policies that created a niche market (Jacobsson et al. 2004).[6] In this phase, various actors engaged in PV R&D and research institutes were founded, providing scientific infrastructure and public funding allowed experimentation with the technology

Haupt et al. 2007; Lizin et al. 2013; Chang and Fan 2016), but this approach is neglected since the same data will be used to explain changes in the phases later on.

[5]In the case of WP, it is hard to track a discontinuity that opened up the trajectory. The underlying technological principle has been used for several hundred years in wind-mills to create mechanical energy. The first wind turbine to produce electricity was constructed in 1888 and the technology was used in small scale until 1950 but then disappeared in favor of other technologies until its renaissance after the oil crisis (Shepherd 1994; Nielsen 2010).

[6]The photovoltaic effect was discovered already in 1839, but the first conventional photovoltaic cell was developed by Chapin et al. (1954). This can be seen as the emergence of the trajectory. However, due to high costs, application was limited and PV was mainly used to power satellites and off-grid applications (Perlin 2002). Only after the oil crisis was PV seriously considered for large scale electricity production.

Table 1 Summary of the TLC phases for wind power and photovoltaics

	Wind power	Photovoltaics
Era of ferment	1970-1995	1970-1997
Dominat design	1996-2000	1998-2006
Era of incremental change	2001-	2007-

(Jacobsson et al. 2004; Herrmann and Töpfer 2016). The emergence of a dominant design lasted from 1998 until about 2006 and covered the vast increase in installed capacity due to implemented demand policies and cost reductions. The 100,000 roof program created favorable economic conditions to install PV and the later introduced renewable energy source act substantially improved the investment conditions and created strong market demand, which provided secure grounds to invest in R&D. During this period, manufacturing capacity and automation of production processes were established, which led to severe cost reductions and economies of scale. From 2007 onwards, the era of incremental change began with reduced policy support and international competition for German PV cell producers.

However, in PV, the phases represent only a general pattern, since there are several PV sub-trajectories with respect to the different cell types (Kalthaus 2019). For example, dye-sensitized solar cells were discovered in 1991 (O'Regan and Grätzel 1991) and the underlying principle is far different from the market dominating silicon wafer cells and their efficiency is far from conventional cells. These sub-trajectories emerged at different points in time and are in different phases of the development (see for example Lizin et al. (2013), who look at the life cycle of organic PV cells).[7]

4 Econometric approach

In the following, data as well as variables and the econometric approach to test the extended TLC model for WP and PV are explained. Negative-binomial regressions are used to analyze the relationship between different sources of knowledge and the success of knowledge recombination. Descriptive statistics and correlations can be taken from Appendix A.2 and A.3.

4.1 Data and variables

4.1.1 Patent data

The technological advancement and evolution of the renewable energy technologies and their knowledge bases can be observed in patent data. Patents are, despite their

[7] It could also be argued that the presence of sub-trajectories indicates that no dominant design emerged yet. But these sub-trajectories have different fields of application from application in space to integration in textiles or windows and are hardly competing in their specific field of application (Kalthaus 2019). For large scale, mass market applications silicon wafer cells are the most frequent ones (Huenteler et al. 2016b).

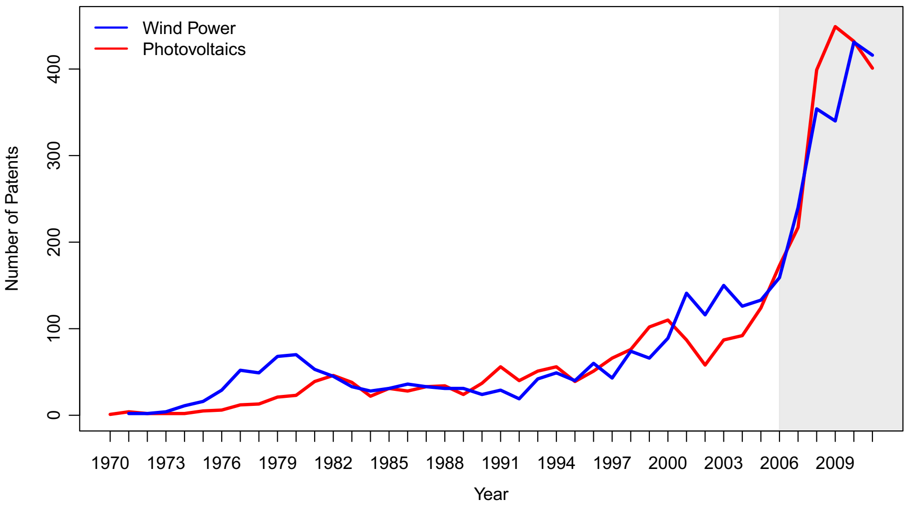

Fig. 3 Wind power and photovoltaics patents by German inventors

broadly discussed disadvantages, a good proxy for inventive activity and a technology's knowledge base (Griliches 1990; Hall and Harhoff 2012). Even though only a part of all inventions are patented (Arundel and Kabla 1998; Cohen et al. 2000), the codification of knowledge in a patent allows other inventors to utilize the knowledge and build upon it.

Patent data for the analysis is retrieved from the Worldwide Patent Statistical Database (PATSTAT) (EPO 2014). Patents for WP and PV are extracted by a combination of technology specific IPCs (International Patent Classification) and keywords (see Appendix A.1 for details). All priority application filed by German inventors in the period from 1970 to 2011 are considered. A patent is selected if at least one of its inventors resides in Germany. There are 3,765 WP and 3,589 PV patents in total (Fig. 3). However, for the following analysis, only a subset until 2006 is considered, since the patents need some time to receive forward citations, which are the information of interest. For the set until 2006, there are 1,984 WP patents and 1,691 PV patents that are the units of observation.

4.1.2 Dependent Variable: Forward citations

The success of knowledge recombination and the contribution of a patent to the knowledge base can be approximated by the forward citations it receives. A forward citation of a patent is a citation of this patent by another patent, which considers the cited patent as prior art. The general assumption is that the more forward citations a patent receives, the more valuable in technological terms it is for the evolution of a specific technology (Carpenter et al. 1981; Trajtenberg 1990; Harhoff et al. 1999, 2003; Czarnitzki et al. 2011; Jaffe and de Rassenfosse 2017). If a patent receives many citations it can even be considered radical or breakthrough (Ahuja and Lampert 2001; Conti et al. 2014), while if it receives no citations, it is most likely that the

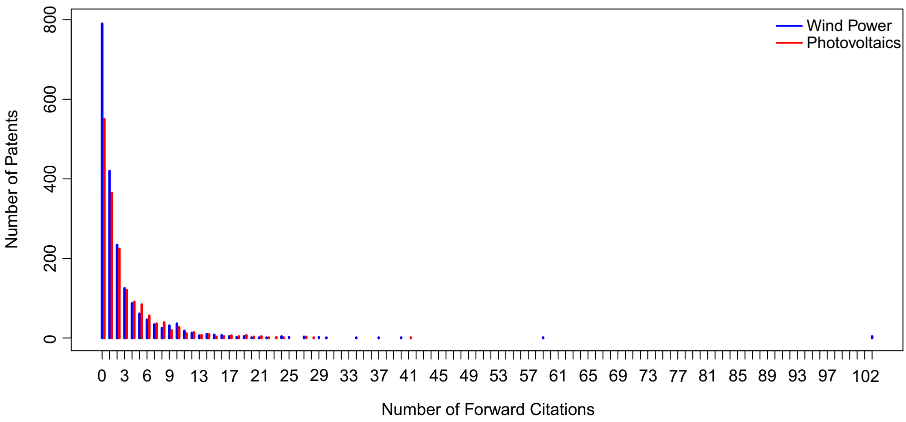

Fig. 4 Distribution of forward citations per patent

recombination was a failure and the patent has no value for the knowledge base or further inventions.

The forward citations are collected on the patent family level in the first five years after the priority application (Bakker et al. 2016). This five year truncation is used to grant all patents the same time span to receive citations and avoid a bias towards older patents (Lanjouw and Schankerman 2004). Forward citations added by examiners are not considered separately, even though they can indicate higher importance of the cited patent (Alcácer and Gittelman 2006; Yasukawa and Kano 2014). Figure 4 displays the distribution of forward citations by technology. The distribution is highly skewed and 33% of the PV and 40% of the WP patents receive no citation in the first five years after application. On average, WP receives about 2.6 citations and PV 2.7 citations per patent in the first five years after application.

4.1.3 Explanatory variables: Type of inventor

To understand the influence of different sources of knowledge on the technological development, the inventors on the patent are assigned to the four different groups, elaborated in Section 2.3. Since the assignment to the different groups is sensitive to the data quality, cleaning up the patent data is necessary. The inventor names were manually harmonized by correcting obvious typos[8], academic titles or name order, controlling for patent applicant, address and year of application, to avoid inflating the number of inventors.[9] In total, there are 1,675 unique inventors on WP patents and 2,203 unique inventors on PV patents.

[8]There have been different algorithms proposed to clean patent data (Raffo and Lhuillery 2009; Miguélez and Gómez-Miguélez 2011) but they were not able to provide appropriate results. However, there are several sets of harmonized inventor names, but these sets were either not available for different application offices or were specified for a certain group of inventors, such as scientists.

[9]Technically, the different person-IDs from the PATSTAT database for one person are attributed to one unique identifier used to describe the inventor.

All filed patents for each inventor are collected from PATSTAT to construct the inventor's patenting history, similar to the approach used by Jones (2009). The patenting history is used to determine the type of inventor. Thereby, the type of inventor is reassessed with every new patent he files in the technology. The first type, *New Inventors*, are those without previous patenting experience who patent their first patent in the technology. The second type of inventors, *Specialized Inventors*, are inventors who patented previously only in the respective technology. If a *New Inventor* patents a second patent in the technology, he becomes a *Specialized Inventor* on this second patent. For the third and fourth type of inventors, who have an inventive history in either related or unrelated technologies, the distinction becomes a bit different: The field of former patenting activity of an inventor is indicated by the IPCs to which his previous patents are assigned.[10] The inventor is considered to be related to the technology, so a *Related Inventor*, if one of the IPCs on previous patents not belonging to the technology has also been used in the respective technology before; if not, the inventor is considered an *Unrelated Inventor*.[11] The IPCs of all previous patents in WP or PV are accumulated over time and compared to the inventor's patenting history.[12] If any of the inventor's patents IPCs coincides with an IPC that is already used in the technology, the inventor belongs to *Related Inventors*.[13] This approach allows a dynamic change of the criteria for *Related Inventors* and *Unrelated Inventors* if new concepts are introduced into the knowledge base. The first time an IPC is introduced by an inventor in the technology, it is no longer unrelated to the technology but related.[14] Since the empirical analysis is conducted on the patent level, the different types of inventors on a patent enter the regression as a count variable each.

The distribution of the different kinds of inventors over time is presented in Fig. 5. In both technologies, *New Inventors* are the largest group. This is persistent over time, indicating that there is a high number of new people starting inventive activity

[10] Using IPCs to assign inventors to related and unrelated knowledge has some caveats. For example, classifications can change over time and a related inventor can become unrelated (or vice versa) due to changes in the classification system.

[11] If an inventor has patented in related and unrelated fields, the inventor is assigned to *Related Inventors*. If an inventor patents first in an unrelated field and afterwards in a related field, he becomes then a *Related Inventor*.

[12] Patents from 1965 until 1969 are used to create an initial set of IPCs, otherwise the first inventors would be unrelated by default.

[13] The distinction between *Related Inventors* and *Unrelated Inventors* is influenced by how detailed the technological relatedness is constructed. The minuteness of detail of the technological relatedness can be proxied by the hierarchical nature of the patent classification system. The IPC consists of eight different fields, e.g. physics or electricity. These fields have several classes and subclasses (about 640, usually referred to as four-digit IPCs). Several studies use these four-digit IPCs to distinguish between different technological fields (e.g. Nemet and Johnson, 2012). There are also groups (about 7,000) and subgroups (more than 70,000) that represent more fine grained distinctions of the technology. In the current case, the level of groups is used to assign the inventors to the related and unrelated category. Using the subgroup level would drastically reduce the related group, since there would be no overlap on a higher level, while using only the subclasses would drastically reduce the unrelated group, since general technological principles would be the same in most cases.

[14] Since this is a rather strong assumption, a robustness test is done where inventors are assigned to the related and unrelated group if the patent belongs to a similar technology field or not. See Section 4.4 for this robustness test.

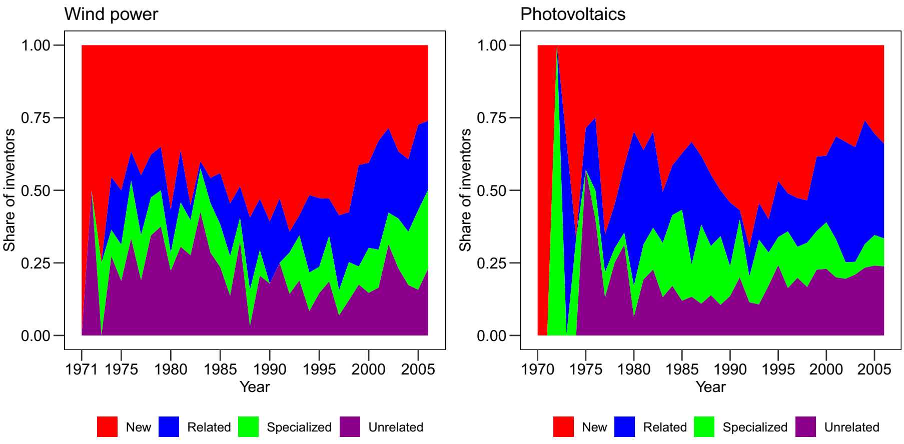

Fig. 5 Share of inventor types per technology over time

in these technologies. Furthermore, since inventions are a rare event, a considerable amount has only one invention, or they change their focus and continue their inventive activity in other domains (Menon 2011). *Related Inventors* are the second biggest group in both technologies. But in WP, *Unrelated Inventors* have a high share in the early years, indicating an experimental phase. *Specialized Inventors* are the smallest group in both technologies, indicating that specialization in one technology does not take place that much. Further information about the number of patents per inventor and the overall number of inventors is provided in Appendix A.4.

To understand better the effect of different kinds of knowledge embedded in the inventors, intermediate groups are created to assess the effect if inventors are separated into different types. Two intermediate groups are constructed: First, *Experienced Inventors* who are all the inventors who have patenting history (sum of *Specialized Inventors*, *Related Inventors* and *Unrelated Inventors*) to test if it matters if an inventor has previous experience. The second group, *Knowledgeable Inventors*, are the inventors who come from outside the technology's domain and patented in related and unrelated fields (sum of *Related Inventors* and *Unrelated Inventors*).

4.1.4 Control variables

While the source of knowledge embodied in inventors and their success of recombination has an influence on the received forward citations, other influential factors may be related to the patent itself. In the following, relevant control variables are discussed.[15]

[15]Besides the variables presented, there are several others that could have been considered, but are not used due to several reasons. For example, triadic patents are indicators of high value (Dernis and Khan 2004; Sternitzke 2009), but they are highly correlated with the family size and in favor of the family size neglected. Cited non-patent literature is also frequently used, but the data have hardly any such references and are according to Harhoff et al. (2003) only relevant for pharmaceutical and chemical patents. Claims per patent are also frequently counted (Lanjouw and Schankerman 1999), but most patents are filed at the German patent office, which does not publish the number of claims.

Team Size: An influential factor for the success of a patent, and also for knowledge recombination, is invention in teams. Patents invented in teams have usually a higher technological value than inventions by a single inventor (e.g. Wuchty et al. 2007; Jones 2009). The number of inventors on the patent is the sum of the different types of inventors.

Foreign Inventors: International collaboration has a positive effect on research and inventive activity in general (Adams 2013; Kerr and Kerr 2018). Patents might be invented in international teams and inventors from other countries are counted.

Number of IPCs: The technological breadth of the patent influences its technological importance. More basic patents, which can be applied to different kinds of technologies, might be more relevant for future development than highly specified patents (Lerner 1994). To approximate the breadth of the patent, the number of IPC groups to which a patent is assigned are counted.

Family Size: The size of the patent family to which the patent belongs is considered to be relevant for the technological importance of a patent. The bigger the family of a patent, which means that the priority patent is registered in other patent offices as well, the higher the number of forward citations (Putnam 1996; Lanjouw et al. 1998; Harhoff et al. 2003). Here, the size of the DocDB family is considered (Martínez 2011).

Backward Citations: The previous patents the inventor relied on to create the patent may influence its technological value (Harhoff et al. 2003). Lanjouw and Schankerman (1999), for example, show that patents with many backward citations are rather incremental compared to patents with no or only a few backward citations.

Granted Patent: If the patent is granted it usually is a good indicator of its novelty and relevance (Guellec and van Pottelsberghe de la Potterie 2000).

PCT Patent: If a patent is filed under the Patent Cooperation Treaty (PCT) the technological value can be higher (Guellec and van Pottelsberghe de la Potterie 2000).

New Combination: A patent can introduce a new IPC into the knowledge base that has not been used in the technology before. This might be a new combination that can be of higher value. Arts and Veugelers (2015) use a similar idea to capture previously uncombined technologies. A dummy variable is constructed by comparing all previous IPCs used in the technology and the patent under consideration. The dummy variable turns 1 if a patent introduces a new combination into the knowledge base.

USPTO: Patents filed at the United States Patent and Trademark Office (USPTO) receive usually a higher number of forward citations, since the USPTO requires indication of all prior art that could be relevant and this leads to a higher number of forward citations than a patent from the German or European patent office would receive (Michel and Bettels 2001; Nagaoka et al. 2010).

Year Effects: Year dummies capture time variant effects such as macroeconomic changes, political support, patent legislation changes or other factors that may influence patenting activity and quality in a specific year. Furthermore, the variable captures also the effect that due to the general increasing patenting trend younger patents have a larger pool of patents that could cite them.

PV Sub-trajectories: A PV system consists of different components and cell technologies, which develop intertwined with each other. There are different approaches to utilize the photovoltaic effect based on different light-absorbing materials. Simple PV cells use silicon wafers to produce electricity, while nowadays also thin-film materials and very recently organic and nano materials are used. Since they emerge at different points in time, they might require different kinds of inventive activity and have overlapping life cycle phases. To account for this, the patents for PV are distinguished into *PV Modules*, which is generic for each cell type and deals with the overall construction and installation of the cell, and the cell sub-trajectories, which can be distinguished based on their material into *Silicon Wafer Cells*, *Thin-Film Cells* and *Emerging Cells*. However, not all patents can be attributed to a specific technology and the distinction serves only as a rough indicator. Details about the distinction are provided in Kalthaus (2019).

4.2 Econometric approach

The dependent variable, the forward citations per patent, measures the success of the knowledge recombination and the resulting technological contribution to the knowledge base. Forward citations are non-negative and discrete and require non-linear count data models. Poisson distributions and regression models based on them are the natural starting point for econometric analysis of such data. However, Poisson regressions require equidispersion of the data. I test for equidispersion in the data and have to reject it, so the data are over-dispersed (the conditional variance exceeds the conditional mean of the data) and the standard errors are biased. This requires a negative binomial distribution, which allows for a more flexible parametric regression model, accounting for overdispersion (Cameron and Trivedi 1986; Hilbe 2011). Since the patent is the object of analysis (i), the data set is cross-sectional but has time information that allows separation of different life cycle stages. The stylized regression model is:

$$Forward\ Citation_i = \beta_1 Inventor\ Type_i + \beta_2 Controls_i \tag{1}$$

where Inventor Type is a vector of the four different kinds of inventors, namely, *New Inventors*, *Specialized Inventors*, *Related Inventors* and *Unrelated Inventors*, the explanatory variables of interest.

In the following, seven models for WP and six models for PV are estimated to analyze the relationship of different types of inventors and the number of forward citations. The first four models (see Section 4.3.1) cover the full period and are used to elaborate the relevance of the different inventor types in general. The first model uses only the *Team Size* of the inventor team to estimate whether the number of inventors on a patent has an effect. In the second model, the inventors are separated into *New Inventors* and *Experienced Inventors* to see if it makes a difference whether previous knowledge is present.[16] The third model separates the *Experienced Inventors* into *Specialized Inventors* who only invent in the respective technology and

[16] The *Team Size* is the sum of the different inventor types that are itself count variables and therefore *Team Size* is dropped due to multicollinearity in the following regressions.

Knowledgeable Inventors who have experience in other fields. Model four furthermore separates the *Knowledgeable Inventors* into *Related Inventors* and *Unrelated Inventors* to estimate whether the kind of previous knowledge has an effect. In the case of PV, two alternatives are estimated, distinguishing PV in sub-trajectories. Model 4a controls for patents that belong to *PV Modules* and the three PV cell sub-trajectories *Silicon Wafer Cells*, *Thin-Film Cells* and *Organic Cells* to account for different developments between cell technologies.

The next models (see Section 4.3.2) cover the different periods of the TLC derived in Section 3. In models five to seven for WP, the first three stages of the TLC are analyzed. For PV, only two periods are considered. Model five covers the period 1970-1997 and model six 1998-2006. Again, distinctions between the PV module and different cell sub-trajectories are made.

Since the proposed sub-periods in the last models are static and results could be sensitive to the exact separation of periods, rolling-window regressions are used to illustrate the importance of different types of inventors over time. Rolling-window regressions (alternatively called moving-window regressions) are usually applied to time series data to analyze whether structural changes occur in a specific subsample of a time-series (Fama and MacBeth 1973; Nyakabawo et al. 2015). The approach uses a fixed window of years sequentially from the start to the end of the overall observation period by dropping one year from the end and adding one to the beginning. In the current case, a time-series is not present, but based on the filing year of the patent, time periods can be constructed. When using this method, the selection of the window of years is of importance and has to make a trade-off between the accuracy of the effect, the degrees of freedom, and the coverage of the relevant period. This is especially a problem for time-series (see Pesaran and Timmermann (2005) for a discussion), but not necessarily for the current case, since multiple observations are present in each period, providing a sufficient degree of freedom. However, if the selected time period is too short, overall time variant effects that are otherwise captured by year dummies might influence the result. In the following, a time period of eight years is considered covering a sufficient large time period and degree of freedom per window. Furthermore, robustness tests for five and eleven years are discussed in Section 4.4.

4.3 Results

4.3.1 General influence of different inventor types

The regression results for the influence of different types of inventors for WP and PV are presented in Table 2. In the case of WP, the first model, the baseline, illustrates the overall influence of patent characteristics on forward citations. As suggested in the literature, most control variables influence the number of forward citations positively except *PCT Patent*, which does not have a significant coefficient. However, the negative coefficient of *New Combination* is surprising. The introduction of a new IPC into the technology seems to have a negative influence on the contribution to the knowledge base. This indicates that the extension of the knowledge base by bringing in new principles seems not beneficial. This is, however, in line with the argument of

Table 2 Regression results for different types of inventors

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power				Photovoltaics				
	Model 1 Full Period	Model 2 Full Period	Model 3 Full Period	Model 4 Full Period	Model 1 Full Period	Model 2 Full Period	Model 3 Full Period	Model 4 Full Period	Model 4a Full Period
Team Size	0.160 ***				0.049 **				
	(0.025)				(0.019)				
New Inventors		0.157 ***	0.163 ***	0.166 ***		0.032	0.032	0.033	0.033
		(0.040)	(0.039)	(0.039)		(0.030)	(0.030)	(0.030)	(0.030)
Experienced Inventors		0.170 ***				0.069 ***			
		(0.033)				(0.027)			
Specialized Inventors			0.424 ***	0.424 ***			0.154 ***	0.155 ***	0.169 ***
			(0.055)	(0.055)			(0.056)	(0.056)	(0.055)
Knowledgeable Inventors			0.080 **				0.049 *		
			(0.041)				(0.029)		
Related Inventors				0.069				0.042	0.056 *
				(0.047)				(0.030)	(0.029)
Unrelated Inventors				0.114 *				0.117	0.116
				(0.066)				(0.076)	(0.075)
PV Modules									−0.045
									(0.072)
Silicon Wafer Cells									−0.933 ***
									(0.326)
Thin-Film Cells									−0.236 **

Table 2 (continued)

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power				Photovoltaics				
	Model 1 Full Period	Model 2 Full Period	Model 3 Full Period	Model 4 Full Period	Model 1 Full Period	Model 2 Full Period	Model 3 Full Period	Model 4 Full Period	Model 4a Full Period
									(0.099)
Emerging Cells									−0.010
									(0.151)
Foreign Inventors		0.152 ***	0.142 ***	0.141 ***		0.017	0.021	0.023	0.013
		(0.040)	(0.041)	(0.041)		(0.059)	(0.059)	(0.060)	(0.058)
Number of IPCs	0.081 ***	0.081 ***	0.092 ***	0.093 ***	0.135 ***	0.134 ***	0.138 ***	0.140 ***	0.135 ***
	(0.025)	(0.025)	(0.024)	(0.024)	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)
Backward Citations	0.012 ***	0.012 ***	0.012 ***	0.012 ***	0.017 ***	0.017 ***	0.016 ***	0.016 ***	0.016 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
New Combination	−0.145 *	−0.146 *	−0.139	−0.143 *	−0.212 **	−0.213 **	−0.204 **	−0.206 **	−0.217 **
	(0.087)	(0.088)	(0.086)	(0.085)	(0.100)	(0.100)	(0.099)	(0.100)	(0.100)
Family Size	0.066 ***	0.066 ***	0.068 ***	0.069 ***	0.132 ***	0.131 ***	0.129 ***	0.130 ***	0.126 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
PCT Patent	0.267	0.266	0.127	0.127	−0.094	−0.085	−0.097	−0.126	−0.061
	(0.234)	(0.235)	(0.225)	(0.225)	(0.400)	(0.404)	(0.420)	(0.411)	(0.398)
Granted Patent	0.359 ***	0.359 ***	0.319 ***	0.321 ***	0.056	0.056	0.057	0.057	0.062
	(0.066)	(0.067)	(0.067)	(0.067)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
USPTO	1.146 ***	1.154 ***	1.033 ***	1.028 ***	0.979 ***	1.035 ***	1.031 ***	1.038 ***	1.137 ***
	(0.165)	(0.161)	(0.159)	(0.159)	(0.175)	(0.192)	(0.194)	(0.194)	(0.205)

Table 2 (continued)

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power				Photovoltaics				
	Model 1 Full Period	Model 2 Full Period	Model 3 Full Period	Model 4 Full Period	Model 1 Full Period	Model 2 Full Period	Model 3 Full Period	Model 4 Full Period	Model 4a Full Period
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1984	1984	1984	1984	1691	1691	1691	1691	1691
df	1940	1938	1937	1936	1646	1644	1643	1642	1638
loglik	−3478.858	−3478.796	−3462.796	−3462.620	−3356.730	−3356.106	−3354.165	−3353.734	−3343.702
AIC	7047.715	7051.591	7021.592	7023.240	6805.459	6808.211	6806.330	6807.468	6795.403
McFadden R^2	0.142	0.142	0.146	0.146	0.074	0.074	0.074	0.075	0.077

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

Fleming (2001), who claims that recombination is risky and may lead to failure. The negative effect can also indicate that the trajectory is already defined and integrating further technological principles in the knowledge base does not provide useful recombinations. In model 2, the inventors are separated into *New Inventors* and *Experienced Inventors*. We see that both have a highly significant coefficient, indicating that both sources of knowledge are relevant. This influence sustains if *Experienced Inventors* is further separated in *Specialized Inventors* and *Knowledgeable Inventors* in model 3. However, in model 4, the separation of the *Knowledgeable Inventors* reveals that only *Unrelated Inventors* has a weakly significant coefficient, while the *Related Inventors* has no significant influence in WP. In all models, *Foreign Inventors* has a significant coefficient, too, indicating that international collaboration are relevant for the technological development.

The regression results for PV show that, in the baseline model 1, the results are nearly similar to the ones for WP, but here, *Granted Patent* does not have a significant coefficient. Again, *New Combination* has a negative coefficient, which is significant, indicating that inducing new principles into the PV knowledge base is also not successful or necessary. Model 2 shows that, in PV, *New Inventors* does not have a significant coefficient, while *Experienced Inventors* does. This indicates that recombination in PV is only successful, if inventors possess previous experience and knowledge. Model 3 presents the distinction between *Specialized Inventors* and *Knowledgeable Inventors*. Both are statistically significant, but the *Specialized Inventors* has a comparably large coefficient, indicating that knowledge accumulation seems to matter more than a diverse set of knowledge. In model 4, only *Specialized Inventors* contributes to the technological development and the distinction between *Related Inventors* and *Unrelated Inventors* seems not to explain recombinatorial success. However, controlling for different sub-trajectories in model 4a reveals that *Related Inventors* has a weak significant coefficient, indicating that sub-trajectories have distinct recombination pattern and that the relevance of related knowledge is conditioned on the sub-trajectory. Contrary to WP, *Foreign Inventors* is not significant and inventive activity for PV in Germany does not benefit from international collaboration.

Overall, different sources of knowledge are relevant and the distinction reveals that knowledge embodied in different types of inventors influence recombinatorial success. There are differences between the technologies as well. While in WP *New Inventors* has a significant coefficient, it does not matter in PV. Also, the kind of knowledge from domains external to the technology's knowledge base matters. While in WP *Unrelated Inventors* is relevant for useful recombinations, in PV *Related Inventors* is relevant. Also the difference concerning *Foreign Inventors* is remarkable. However, the technological difference between WP and PV has also been shown by Cantner et al. (2016) and Huenteler et al. (2016b), but not with respect to the process of knowledge recombination.

4.3.2 Technology life cycle phases

In this section, the phases of the TLC are analyzed and regression results are presented in Table 3. For WP, model 5 shows the era of ferment in which *New Inventors*

Table 3 Results for the technology life cycle phases

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power			Photovoltaics			
	Model 5 Era of Ferment 1970-1995	Model 6 Dominant Design 1996-2000	Model 7 Era of incremental change 2001-2006	Model 5 Era of Ferment 1970-1997	Model 5a Era of Ferment 1970-1997	Model 6 Dominant Design 1998-2006	Model 6a Dominant Design 1998-2006
New Inventors	0.163 *	0.275 ***	0.146 ***	0.084 *	0.085 *	−0.007	−0.008
	(0.091)	(0.065)	(0.053)	(0.044)	(0.044)	(0.039)	(0.040)
Specialized Inventors	0.080	0.485 ***	0.499 ***	0.120	0.132 *	0.174 **	0.190 ***
	(0.175)	(0.165)	(0.060)	(0.077)	(0.076)	(0.075)	(0.072)
Related Inventors	0.236	−0.170	0.091 *	0.084	0.110 **	0.030	0.036
	(0.176)	(0.113)	(0.049)	(0.055)	(0.056)	(0.036)	(0.035)
Unrelated Inventors	0.337 **	−0.042	0.082	0.170	0.177	0.070	0.074
	(0.141)	(0.149)	(0.098)	(0.110)	(0.110)	(0.108)	(0.107)
PV Modules					−0.196 *		0.026
					(0.110)		(0.093)
Silicon Wafer Cells					−1.665 ***		−0.833 **
					(0.450)		(0.368)
Thin-Film Cells					−0.371 **		−0.136
					(0.155)		(0.130)
Emerging Cells					−0.368		0.126
					(0.311)		(0.169)
Foreign Inventors	−1.130 *	−0.764 **	0.172 ***	0.087	0.043	−0.006	−0.011
	(0.641)	(0.342)	(0.042)	(0.085)	(0.086)	(0.074)	(0.074)

Table 3 (continued)

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power			Photovoltaics			
	Model 5 Era of Ferment 1970-1995	Model 6 Dominant Design 1996-2000	Model 7 Era of incremental change 2001-2006	Model 5 Era of Ferment 1970-1997	Model 5a Era of Ferment 1970-1997	Model 6 Dominant Design 1998-2006	Model 6a Dominant Design 1998-2006
Number of IPCs	0.125	0.086 **	0.087 ***	0.158 ***	0.155 ***	0.116 **	0.108 **
	(0.078)	(0.043)	(0.032)	(0.028)	(0.027)	(0.046)	(0.045)
Backward Citations	0.025	0.024	0.011 ***	0.021 ***	0.023 ***	0.012 **	0.012 **
	(0.022)	(0.015)	(0.002)	(0.008)	(0.008)	(0.005)	(0.005)
New Combination	−0.194	−0.190	−0.132	−0.256 **	−0.301 **	−0.167	−0.163
	(0.204)	(0.146)	(0.120)	(0.125)	(0.123)	(0.154)	(0.154)
Family Size	0.147 ***	0.057 ***	0.076 ***	0.121 ***	0.111 ***	0.134 ***	0.132 ***
	(0.024)	(0.008)	(0.006)	(0.013)	(0.014)	(0.010)	(0.010)
PCT Patent	−0.595	−0.821 ***	0.110	-32.345 ***	−31.321 ***	0.108	0.188
	(0.983)	(0.306)	(0.225)	(0.526)	(0.534)	(0.404)	(0.393)
Granted Patent	0.342 **	0.640 ***	0.131	0.065	0.076	0.064	0.065
	(0.147)	(0.136)	(0.091)	(0.094)	(0.093)	(0.094)	(0.092)
USPTO	1.895 ***	0.741 *	1.016 ***	1.104 ***	1.214 ***	1.041 ***	1.107 ***
	(0.511)	(0.404)	(0.166)	(0.212)	(0.226)	(0.266)	(0.279)

Table 3 (continued)

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power			Photovoltaics			
	Model 5	Model 6	Model 7	Model 5	Model 5a	Model 6	Model 6a
	Era of	Dominant	Era of	Era of	Era of	Dominant	Dominant
	Ferment	Design	incremental change	Ferment	Ferment	Design	Design
	1970-1995	1996-2000	2001-2006	1970-1997	1970-1997	1998-2006	1998-2006
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	827	332	825	782	782	909	909
df	790	315	807	742	738	888	884
loglik	−832.361	−673.535	−1928.075	−1314.259	−1305.916	−2029.824	−2024.069
AIC	1740.723	1383.071	3894.151	2710.518	2701.833	4103.649	4100.139
McFadden R^2	0.082	0.073	0.096	0.070	0.075	0.059	0.062

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

and especially *Unrelated Inventors* show significant coefficients. While it was proposed in the extended TLC model that *Related Inventors* and *Unrelated Inventors* are decisive in this phase, only *Unrelated Inventors* seems to be able to successfully integrate distant knowledge into the knowledge base. The significance of *New Inventors* is interesting, since it shows that the technology benefited from inventors who started their inventive activity in WP. Here, anecdotal evidence supports the results. Inventors in the era of ferment were tinkerers and engineers who wanted to improve environmental conditions and provide technical alternatives to conventional energy production (Simmie et al. 2014). Concerning the control variables, *Number of IPCs* and *Backward Citations* lose their significance as well as the negative coefficient of *New Combination* compared to the full model. Interestingly, *Foreign Inventors* has a negative coefficient, indicating that knowledge from other countries goes along with lower recombinatorial success in this phase. Here, it could be that German inventors follow their own trajectory, and concepts developed in other countries seem not to be relevant in this phase.

Model 6 presents the results for the emergence of the dominant design. *New Inventors* as well as *Specialized Inventors* are decisive. It is, however, proposed in the model that *Specialized Inventors* and *Related Inventors* are relevant sources of knowledge in this phase. The results indicate that the dominant design in WP emerges out of the established trajectory and rely on acquired and accumulated knowledge and does not rely on further knowledge from related fields. Concerning the control variables, *Foreign Inventors* still has a negative coefficient, but the effect size decreases. Also, *PCT Patent* shows a significant negative coefficient.

In the era of incremental change, presented in model 7, again, *New Inventors* and *Specialized Inventors* have significant coefficients, which is in line with the proposed model. Additionally, *Related Inventors* seems to be able to integrate knowledge from adjacent technologies into the WP knowledge base, as indicated by the weakly significant coefficient. This could hint towards an upcoming discontinuity, maybe related to offshore WP. There is some evidence that the struggling German ship-building industry diversifies in offshore WP and provides competences for the development of offshore turbines and components (Fornahl et al. 2012). In this phase *Foreign Inventors* has a positive and significant coefficient, possibly integrating knowledge, which is not present in the knowledge base yet and increases the knowledge base. The other control variables show no unusual pattern, except *Granted Patents*, which is no longer significant.

For the different phases of the TLC in PV, model 5 and 6 present the results for the era of ferment and the emergence of a dominant design. Model 5 indicates that only *New Inventors* contributes to technological development. However, controlling for different sub-trajectories in model 5a reveals that also *Specialized Inventors* and *Related Inventors* have a positive and significant coefficient. *Unrelated Inventors*, as proposed in the model, does not matter, but *New Inventors* as well as *Specialized Inventors* do. Overall, a diverse set of knowledge is integrated in the knowledge base in this phase. Related literature shows that especially in the 1980s and 1990s a diverse set of actors (firms, research institutes, universities, ...) engage in PV R&D (Jacobsson et al. 2004) and the Fraunhofer Institute for Solar Energy Systems ISE was founded, which is until today central in Germany's PV research (Herrmann and

Töpfer 2016). Furthermore, contrary to WP, PV had in the era of ferment various applications to power off-grid solutions from calculators to satellites (Perlin 2002; Jacobsson et al. 2004). These diverse areas of application could explain the different sources influencing the technology, especially at the sub-trajectory level where either costs (mass production) or efficiency (space application) are relevant. The control variables show except from the very large coefficient for *PCT Patents* no unusual results and are invariant towards controlling for sub-trajectories. Similar to the overall models, *Foreign Inventors* is not significant.

During the emergence of the dominant design, only *Specialized Inventors* contributes to the technological development, whether controlling for sub-trajectories or not. Contrary to the theoretical expectation, *Related Inventors* shows no significant coefficient. The shift towards the *Specialized Inventors* from experimentation in knowledge recombination to a more routinized inventive process could be a result of the complexity of PV. If the basic principle of the material to convert radiation into electricity is understood, improvements require a sound understanding of the material to improve it further. This specialized knowledge seems to be generated according to (Jacobsson et al. 2004) by inventors in research institutes and universities. Considering the control variables, it is interesting to see that the negative coefficient of *New Combiantions* is not significant anymore.

Overall, it is immanent for both technologies that the knowledge relevant for further development changes over time from an explorative way to a more exploitative or routinized approach, as suggested by March (1991). Partially in line with the proposed model, the relevant sources shift from knowledge outside the knowledge base towards knowledge present in the knowledge base over the course of the TLC. In WP, the era of ferment is influenced from knowledge provided by *New Inventors* and *Unrelated Inventors* and in PV *New Inventors*, *Specialized Inventors* and *Related Inventors*. The dominant design is shaped in both cases by *Specialized Inventors*, in WP also by *New Inventors*. *Related Inventors* as proposed in the model does not matter in both cases. The era of incremental change in WP is as proposed influenced by *New Inventors* and *Specialized Inventors*, but also by *Related Inventors* which could lead the way towards a discontinuity. Noteworthy is also that in WP *Foreign Inventors* becomes important over time, indicating that either knowledge from outside the country's domain becomes relevant, or inventors emigrate but still collaborate with German inventors.

4.3.3 Rolling-window regressions

The dynamics along the technological development can be analyzed fine grained by rolling-window regressions. They allow us to analyze changes in the coefficient sizes of the different types of inventors, also inside the TLC phases. The rolling-window regressions here use an eight-year window[17] sequentially from the start to the end of the overall observation period by dropping on year from the end and adding one to

[17] Sensitivity tests for five and eleven years are discussed in Section 4.4.

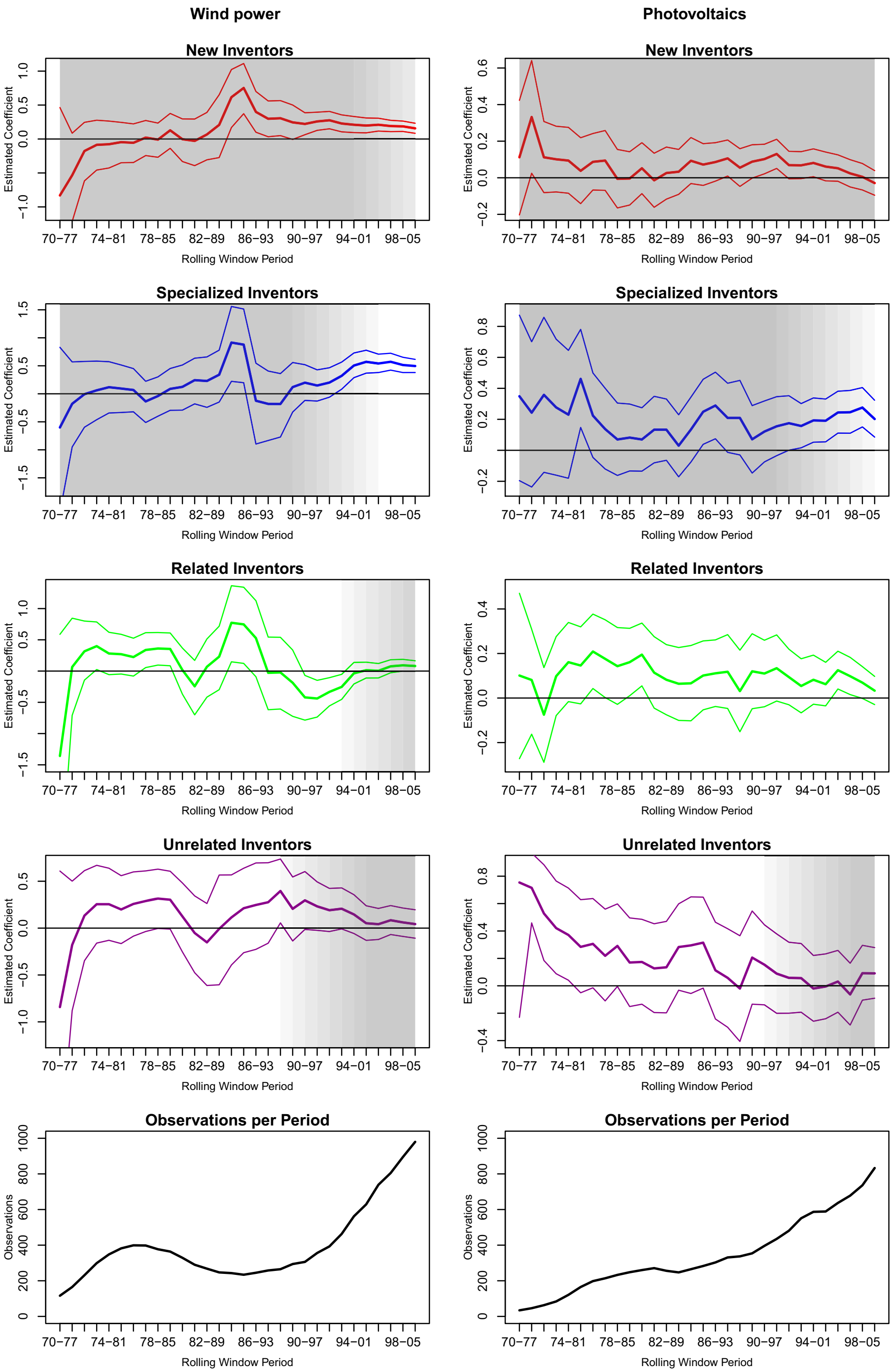

Fig. 6 Eight year long rolling-window regression results for wind power and photovoltaics

the beginning. For WP, model 4 is used and for PV, model 4a to estimate the rolling-window regressions. Figure 6 presents the results for WP and PV graphically.[18] The coefficients for the different inventor types of the regressions are plotted along with the 10 % confidence intervals for each eight-year period. To test the proposed TLC model, the time periods in which the respective inventor type should be relevant are non-shaded in Fig. 6. Since the periods are overlapping, the transition periods are symbolized by an increasing brightness, indicating the increasing relevance of the respective inventor type.

In the rolling-window regressions for WP, *New Inventors* should have an effect in the era of incremental change, which begins in 2001. There is a significant coefficient already from the end of the 1980s onward, which is persistent until the end of the observation period. This indicates that fresh knowledge is constantly recombined and introduced into the knowledge base. Shedding more light on the results from the analysis of the TLC phases, we see that in the era of ferment, the coefficient for *New Inventors* is not significant for about the first 15 years, but has a comparable large coefficient onward, which is partly captured by the regression of the complete era of ferment. The influence of *New Inventors* can be the result of the changing approach towards WP in Germany after the failure of the GROWIAN project in the beginning of the 1980s. Since this large scale wind turbine failed, focus was put on small scale turbines and new actors entered the technology (Bergek and Jacobsson 2003). *Specialized Inventors* is supposed to be relevant in the emergence of the dominant design and the era of incremental change. The results show that the coefficient for these inventors become significant from the beginning of the 1990s onwards and contribute substantially to the technological development until the end of the observation period. Besides two periods in the 1980s, they are not significant in the era of ferment. Here, the results are in line with the results from the TLC regressions.

Related Inventors should play a role in the era of ferment and the emergence of the dominant design. In the era of ferment they have a significant coefficient only in a few periods and even reduce the number of forward citations a patent receives in some periods covering the emergence of the dominant design. Only towards the end of the observation period, *Related Inventors* becomes slightly significant and seems to play a role again, which is also shown in the TLC regression. The rolling-window regressions reveal a significant negative coefficient in some periods, which is unnoticed in the TLC regressions. *Unrelated Inventors* is supposed to have an effect in the era of ferment. The results show basically no significant coefficient at all. Only in some periods in the era of ferment, the coefficient is close to being significant. This contrasts with the results from the regression for the era of ferment, which estimates a significant coefficient. However, the number of observations are quite low in these rolling-window regressions and the power of the regression could be too low. Towards the end of the observation period, there is no significant coefficient of these

[18]The variation in the plotted graph is can be influenced by the drop of observations from the last year and the inclusion of the added year. Furthermore, the number of observation changes, which also influences the regression results, especially the precision of the estimate. This implies that each period can be considered on its own, but changes from one period to another should be interpreted with caution.

inventors at all, indicating that knowledge from outside the technology's domain does not matter and *Unrelated Inventors* seems not to disrupt the technology until then.

In PV, only the first two phases can be analyzed in which *New Inventors* is not supposed to have an influence. Concerning the results, this seems to be the case. Only in a few periods in the beginning of the 1990s is there a significant positive coefficient. This significant coefficient is also present in the TLC regression. *Specialized Inventors* is supposed to matter while the dominant design emerges. Here, we can see an increase of the coefficient in this period in line with the model. In the earlier periods, there are only a few periods in which these inventors have a significant coefficient, which is also reflected in the TLC regression for the era of ferment.

Related Inventors should have an influence in both phases. However, the results indicate only a few periods where these inventors actually have a significant coefficient. While the TLC regressions show that in the era of ferment the *Related Inventors* has a quite large coefficient, the rolling-window regressions reveal that, in the different periods, the coefficient is not that large, although this might be influenced by the low number of observations in each window. *Unrelated Inventors* is supposed to recombine successfully knowledge in the era of ferment. The results indicate that especially in the early years this is the case, although later on, the significance of the coefficient vanishes. Contrary, the TLC regression finds no significant coefficient in the era of ferment at all, neglecting an influence in the early years of this phase.

Overall, the rolling-window regression provide further insights into the dynamics of knowledge recombination. In both technologies we see shifts of relevance of different inventor types over time. For WP, we can observe that *New Inventors* and *Specialized Inventors* become relevant, *New Inventors* even much earlier than expected. In line with the model, but only partially significant in the era of ferment are *Related Inventors* and *Unrelated Inventors*. Contrary to the expectation, *Related Inventors* has a negative coefficient in some periods of the dominant design. In PV, the results are in general not that pronounced, but partially in line with the model. *New Inventors* plays basically no role, as expected, and *Specialized Inventors* has a significant coefficient only while the dominant design emerges. *Related Inventors* should have had an influence along the whole observation period, but shows only a significant coefficient in some periods. *Unrelated Inventors* shows as expected an influence early on, but not during the whole era of ferment. The results of the rolling-window regression mirror pretty much the results of the TLC phases in WP, while in PV there are some differences which show up in the era of ferment and are not captured by the TLC regressions.

4.4 Robustness

Several robustness test are performed concerning the distinction of inventors, possible team effects and the rolling-window regression length. The distinction of the inventors into *Related Inventors* and *Unrelated Inventors* is based on the presence of the IPCs in the knowledge base of the technology. This criterion changes over time as the knowledge base grows. A robustness test is done to see if this distinction and the change of classification criteria influences the overall results. The assignment of inventors to the two groups is in the following exogenously imposed using technology fields based on an extended version of the OST-INPI/FhG-ISI technology nomenclature classification (OECD 1994; Schmoch 2008). This classification contains five main technological fields and 35 subgroups. The subgroups provide the possibility to assign the inventor type according to the general field of previous application. To distinguish between *Related Inventors* and *Unrelated Inventors*, inventors who possess experience in the technological field "electrical machinery, apparatus, energy" for both technologies, and "engines, pumps, turbines" for WP and "semiconductors" for PV are assigned to be *Related Inventors*. These fields cover the underlying principles of the technologies and most IPCs of the WP and PV patents are assigned to these fields. If inventors do not have experience in these fields, they are supposed to be *Unrelated Inventors*.

Table 10 shows the results for WP and PV for model 4 and the TLC phases. For WP, we see in model 4 that *Unrelated Inventors* is no longer significant. In the first phase of the TLC, the coefficient of *Unrelated Inventors* becomes slightly larger, but *New Inventors* is no longer significant. In the second phase, the coefficient for *Unrelated Inventors* becomes significant, however, with a negative coefficient. In the last phase, no changes occur. In PV, Model 4a shows basically no differences, while in the era of ferment *Specialized Inventors* loses its weak significance. In the second phase, no changes occur. In general the results show that there is some sensitivity towards the distinction between *Related Inventors* and *Unrelated Inventors*, but the effects are only marginal and do not affect the overall pattern.

While the results show that different kinds of inventors are relevant for successful knowledge recombination along the TLC, inventive activity is increasingly conducted in teams (Wuchty et al. 2007). While the general trend of increasing team size over time is captured by the year dummies, the team composition is not accounted for. The effect of team composition and heterogeneous teams on knowledge recombination and creativity is an increasing stream of literature (Singh and Fleming 2010; Uzzi et al. 2013; Lee et al. 2015). To account for possible effects of team composition, interactions between the different kinds of inventors are estimated.

The results of the interaction of different inventors are presented in Table 11. In general, the average team size is rather low, with 1.4 for WP and 2.1 in PV and heterogeneous teams are a rare event, as shown in Table 9 in the Appendix. For WP, accounting for different interactions does not change the results in model 4, but increases the coefficients. The interactions are mostly negative and significant, indicating that knowledge recombination in heterogeneous teams does not increase the invention's usefulness in general. In the era of ferment, the results do not change, but the interaction between *Related Inventors* and *Unrelated Inventors* is positive and significant, indicating that in this phase combining knowledge from different fields external to the technology influences recombinatorial success. The phase in which the dominant design emerges shows deviating results. *New Inventors* and *Specialized Inventors* are no longer significant and *Related Inventors* is negative and significant. The interaction terms, however, show that again *Related Inventors* and *Unrelated*

Inventors but also *Specialized Inventors* and *Related Inventors* are positive and significant. In this phase, the team composition really seem to matter and influence the emergence of the dominant design. However, the number of team compositions is very low. For example, the very large and negative coefficient of *Specialized Inventors* and *Unrelated Inventors* is striking, but this team composition occurs only three times. The era of incremental change shows again no deviation and the interactions are mostly negative and significant.

In the case of PV, there are differences in model 4a. Here, *New Inventors* and *Unrelated Inventors* become significant as well. Concerning the interactions, there is a negative, significant coefficient of the combination of *New Inventors* and *Unrelated Inventors*. This indicates that their joint inventive activity produces less valuable patents as if they invent on their own. *Specialized Inventors* and *Related Inventors* keep their positive and significant coefficients. In the era of ferment, we observe that *Specialized Inventors* and *Related Inventors* are no longer significant, but *Unrelated Inventors* becomes significant. However, none of the interactions is significant. This result is quite puzzling. In the emergence of the dominant design, there are no deviations from the initial model. Here, also the interaction *New Inventors* and *Unrelated Inventors* has a negative coefficient.

Overall, the general results seem to be robust towards the inventor interaction and the effect of heterogeneous teams matter in WP for the emergence of the dominant design and in PV for the era of ferment. In most cases, heterogeneous teams exhibit a negative influence, which is contrary to the previous findings of this stream of literature. Especially in PV, controlling for team composition reveals effects for *New Inventors* and *Unrelated Inventors* in the full model. Nevertheless, the measurement of team composition is rather crude, since inventor types are counted and larger teams have an overproportional influence. Interestingly, there are some hints that the influence of team composition changes along with the TLC, but a more detailed analysis is left for further research.

The rolling-window regression provided interesting insights about the dynamics inside the TLC phases. However, the effects might be dependent on the length of the time window. Shorter time periods should increase the volatility, since the number of observations is decreased and opposing effects might not be averaged out. Longer time windows will increase the model fit and outlier effects are not that pronounced. To illustrate and analyze the sensitivity of the previously applied eight-year window, a five-year as well as an eleven-year window are estimated to capture more short term as well as long term patterns. The results are presented in Appendix A.5.

As expected, with a shorter time window the results are more volatile and not as often significant as in the eight-year case. Here, the lower number of observations per regression is a problem and the first five periods are omitted because they cannot be reliably estimated. The overall pattern, however, stays in both technologies the same. In the eleven-year case the volatility of the coefficients is smaller and also the confidence intervals are smaller. However, the overall results converge and smaller changes are not that frequent anymore. In general, the results stay by and large the same as in the eight-year case.

5 Discussion and conclusion

The aim of the paper is to understand how recombination of different kinds of knowledge changes along the technology life cycle. For this purpose, the Anderson and Tushman (1990) model is extended to integrate different kinds of knowledge in the technology life cycle (TLC) phases. The proposed model extension is empirically tested for the TLC of wind power (WP) and photovoltaics (PV) in Germany. Different kinds of knowledge are proxied by inventors' patenting experience. This experience can be absent in the case of new inventors, specialized in the technology or earned by inventive activity in related or unrelated fields. Overall, the results indicate that different kinds of knowledge matter along the TLC and are mostly in line with the theoretical model. While it has been proposed that the utilization of knowledge changes from exploration towards exploitation over time (March 1991; Klepper 1996), the results presented here reveal a more detailed picture of the utilization of different sources of knowledge along the TLC. The different phases of the TLC are characterized by specific knowledge and even inside the phases, relevant sources of knowledge change, providing a more detailed picture compared to previous empirical findings (Krafft et al. 2011, 2014a). The results help to better understand the process of knowledge recombination, technological development and provides relevant insides for policy and management.

Summarizing the results reveals technological differences in the relevance of knowledge for technological advancement, but the general expected shift of different sources of knowledge over time is evident. For the overall technological development from 1970 until 2006 specialized knowledge is relevant in both technologies. While WP is also influenced by new and unrelated knowledge, PV benefits from related knowledge, indicating first technological differences. Concerning the TLC phases, in the era of ferment, WP benefits from unrelated knowledge as expected, while related knowledge does not play a role. In PV it is the opposite: related knowledge is relevant, but not unrelated knowledge. While PV uses the same material as the semiconductor technologies, which explains the strong influence of related knowledge, WP seems not to have such an adjacent technology from which it can benefit, but relies on unrelated knowledge from other fields instead. Furthermore, both technologies benefit from new knowledge and PV also from specialized knowledge, indicating that a diverse set of knowledge is required for technological development in the era of ferment. The emergence of the dominant design is as expected highly influenced by specialized knowledge in both technologies. However, related knowledge, as proposed in the model, does not matter for either technology. In WP, also new knowledge is of importance. The era of incremental change can only be observed in WP and is as proposed highly influenced by new and specialized knowledge. Furthermore, related knowledge contributes to some extend, maybe paving the way towards a discontinuity in offshore WP. The results are overall robust to an alternative distinction between related and unrelated knowledge, as well as controlling for team composition.

The rolling-window regressions depict the influence of different sources of knowledge in a continuous way and results are not bound to the pre-defined phases of the TLC. In general, the relevance of different kinds of knowledge varies over time similar to the TLC phases but relevant differences are revealed. In WP, the earliest windows show that no specific kind of knowledge seems to matter, but this could be attributed to the rather small sample size in the early periods. In the beginning of the 1980s, related and unrelated knowledge have an effect in some windows, which is in line with the theoretical proposition. However, not noticed in the TLC regression, related knowledge has a negative effect in some later periods. New knowledge becomes relevant from the 1990s onwards and some years later specialized knowledge as well. In PV, new knowledge hardly matters for technological development. Specialized knowledge is especially relevant towards the end of the observation period and an increasing trend is observable. Related and unrelated knowledge is relevant in some periods in the era of ferment, but the magnitude is smaller than suggested in the normal regressions. Since the effects of different kinds of knowledge vary over time and are not always in line with an imposed distinction of TLC-phases, using rolling-window regression to determine the TLC phase of a technology can be used as new way to characterize technological development in a continuous way.

While the relevance of the different types of knowledge in the phases in most cases is in line with the proposed model extension, notable deviations exist. Some deviations can be attributed to the nature of the technology, for example, the presence of a large sector of related knowledge in the case of PV and the absence of such a sector in WP, which seem to drive the results in the era of ferment. However, in the phase of the dominant design, in both technologies related knowledge does not play a role. The model could be adapted to incorporate this and remove the expected relationship. The results also show that new knowledge is relevant, especially in the early phase and the constant inflow of fresh inventors seems relevant to extends the knowledge base.

Overall, the findings help to better understand the development of both technologies. As shown previously, WP and PV show different patterns in their development (e.g. Cantner et al. 2016; Huenteler et al. 2016a). This holds also for knowledge recombination. Especially in WP it is evident that various kinds of knowledge are recombined to generate useful inventions. In line with qualitative evidence (Bergek and Jacobsson 2003; Fornahl et al. 2012; Simmie et al. 2014), external knowledge and competencies refresh the knowledge base and the technology continuously over time. In PV, knowledge accumulation is the main diving force and specialization of the technology seems to be key for successful inventive activity. Since PV became a mass-market product over time, technological advancement is rather incremental (Huenteler et al. 2016b), where this specialized knowledge is of particular importance. However, in PV, different sub-trajectories with respect to the cell technology are present and they develop simultaneously, but have partly different areas of application. They have their own life cycle, as previously shown by Lizin et al. (2013) for organic PV cells. In WP, such different technological concepts are not present, but, as shown by Huenteler et al. (2016a), the design hierarchy matters and the focus on different components changes over time. For both technologies, additional research is necessary to provide further insights how knowledge is relevant for technical progress in different sub-trajectories or components.

From a theoretical perspective, integrating a knowledge dimension in the Anderson and Tushman (1990) model joins the TLC concept with research on knowledge recombination and with research concerning inventor’s personal characteristics. The proposed framework proved useful to analyze knowledge dynamics and has implications for further research. First, the paper provides a theoretical foundation and empirical evidence for a more profound understanding of the relevance of knowledge along the TLC and that recombinatorial patterns change over time. Previously, these dynamics had not been considered, but different kinds of knowledge seem to be decisive for recombinatorial success and technological development in the TLC phases. Second, the results show that the technology's knowledge base is shaped over time by different kinds of knowledge. Knowledge accumulation and refreshing the knowledge base with knowledge from outside the technology's knowledge domain are necessary, but conditioned on the TLC phase. This provides some implications for studies of industrial dynamics. The dynamics in an industry's underlying technology allow us to infer towards the life cycle of the industry as well, since here actors transform the knowledge into products and eventually in market shares. This knowledge is, however, generated by a diverse set of actors, such as research institutes, universities, users, tinkerers and knowledge is not bound to the firm. Integrating the overall TLC in studies on industrial dynamics helps us to understand how technologies and the related industry and its firms evolve. Third, the personal characteristics of inventors seems to be relevant for knowledge recombination. This dimension was absent in previous studies of knowledge recombination and the actual persons involved in the recombinatorial process needs further research. Fourth, the chosen technologies provide new cases besides the commonly used biotechnology and ICT studies considered for knowledge recombination. Using WP and PV, it is demonstrated that the success of recombination is technology dependent and expanding the set of considered technologies enhances the general understanding of recombinatorial processes.

From a methodological point of view, using rolling-window regressions provide an interesting approach to track dynamics over time and should be included in the toolbox for research on dynamics in the economics of innovation. Furthermore, the use of inventor's previous patents to reason about the embodied knowledge and experience seems to provide interesting possibilities to observe aggregated phenomena but also individual inventive biographies. However, here manual data cleaning was necessary and applying it to larger scale studies requires higher data quality. Nevertheless, this approach has several advantages compared to surveys, which are limited in size and time period and reachability of inventors.

The results lead to several policy and managerial implications. First, different kinds of knowledge are relevant in different phases of technological development. These changing requirements need to be considered in instrument and funding decisions by policy maker. While the effect of different types of policy instruments has been studied previously (Mowery and Rosenberg 1979; Peters et al. 2012; Cantner et al. 2016; Rogge and Reichardt 2016), the effect of instruments in specific phases of the TLC needs to be on the policy maker's agenda as well. If policy aims to support R&D of a technology in the era of ferment, funding should be granted to actors from diverse fields, and while increasing the efficiency along the established trajectory, specialized actors should be in the focus. The same principle holds for firms and their decision whom to hire for inventive activity. Second, technological development is not a uniform process across technologies but different kinds of knowledge are relevant for each technology. The technology inherent differences need to be considered, which is a difficult task for policy making.

The analysis faces certain shortcomings and limitations that leave room for further research. First, the proposed framework has been only applied to two technologies in Germany. Here, further technologies and broader geographical coverage are necessary. Also, not all phases of the TLC could be analyzed due to the technologies' nature. Especially in PV, only two phases are covered by the analysis. Testing this model with other technologies, especially with ones that faced a discontinuity, would improve its reliability. The framework can also be refined and extended to capture other dimensions of knowledge, such as tacit components or search behavior. Second, there are several areas that could not be explored in more detail, such as the team composition, which seems to matter partly, and changes along the TLC. Sub-trajectories play a role in the TLC and a more detailed analysis could provide further insights on technological development. Third, the analysis relies on patent data, which has several limitations. Among them is the use of IPCs as a rough proxy of related and unrelated knowledge, which can be quite ambiguous. Also, not all inventions are patented and the knowledge base and its dynamics are not fully captured. To complement the understanding of knowledge recombination along the TLC, other sources such as publication data, related product characteristics or interviews with inventors can be considered to overcome limitations of patent data. Lastly, there are several sources of endogeneity that need to be addressed in further research. Especially the fact that the decision to engage in inventive activity is conditioned on the life cycle (for example, costs, market size, policy support, ...) and can influence the results. The development of the technology and the knowledge it requires co-evolves and imposes challenges on the econometric approach.

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A Appendix

A.1 Patent selection approach

The WP and PV patents were queried from Patstat (EPO 2014) by combining IPCs and keywords. Title and abstract of the patent documents are searched for the keywords, while restricted to the specific IPCs. The selection criteria for WP is based on the suggestions from the WIPO Green Inventory and own elaboration. For PV, a detailed elaboration on keywords and IPCs is provided in Kalthaus (2019). The “_” and the “%” symbol are used as wildcards for single and multiple characters. “|” an “+” are logic operators for “or” and “and” combinations of keywords. The SQL code for the search strategy is available on request.

Table 4 List of IPC and keywords for patent selection

Tech.	Sub-trajectory	IPCs	Keyword combination
WP		F03D%	
		H02K 7/18	(%wind% + (%turbine% | %power% | %mill% | %energ%))
		B63B 35/00	
		E04H 12/00	
PV	Silicon wafer cells	H01L 21%	((%monocrystalline_silicon% | %monocrystal_silicon% | %crystal_silicon% |
		H01L 31%	%silicon_crystal% | %silicon_wafer%) + (%photovoltai% | %solar%))
		C30B 15%	| %back_surface_passivation% | (%pyramid% + %etching% + %silicon%)
		C01B 33%	((%polycrystalline_silicon% | %multicrystalline_silicon% | %poly_si% | %polysilicon%)
		C30B 15%	+ (%photovoltai% | %solar%)) | (%ribbon% + (%photovoltai% | %solar% | %silicon%))
		C30B 29%	| (%edge_defined_film_fed_growth% + %silicon%) | %metal_wrap_through% |
		H01L 21%	%emitter_wrap_through% | %ribbon_growth%
		H01L 31%	
	Thin-film cells	C23C 14%	((%chemical_vapour_deposition% | %PECVD% | %physical_vapour_deposition% | %PVD% |
		C23C 16%	%solid_phase_crystallization% | %laser_crystallization% | %nanocrystalline% | %microcrystalline%)
		H01L 21%	+ (%photovoltai% | %solar% | %silicon%)) | ((%tandem% | %amorphous_silicon% |
		H01L 27%	%silicon_substrate% | %silicon_film%) + (%photovoltai% | %solar%)) | %staebler_wronski%
		H01L 29%	
		H01L 31%	
		C23C 14%	((%cadmium_Telluride% | %CdTe% | %copper_indium_diselenide% | %CIS% |%CuInSe%|
		C23C 16%	%indium_tin_oxide% | %gallium_arsenide% | %GaAs% | %roll_to_roll% | %surface_textur% |

Table 4 (continued)

Tech.	Sub-trajectory	IPCs	Keyword combination
		H01L 21%	%thin_film% | %thinfilm%) + (%photovoltai% | %solar%)) | %Copper_indium_gallium_diselenide% |
		H01L 25%	%CuInGeSe% | %CIGS% | %copper_zinc_tin_sulfide% | %CZTS% | %kesterite%
		H01L 27%	
		H01L 29%	
		H01L 31%	
	Emerging cells	C08K 3%	((%dye_sensiti% | %titanium_oxide% | %titanium_dioxide% | %TiO2% | %organic% | %polymer%)
		C08G 61%	+ (%photovoltai% | %solar)) | %gr_tzel% | %graetzel% | %hybrid_solar_cell%
		H01B 1%	
		H01G 9%	
		H01L 21%	
		H01L 31%	
		H01L 51%	
		H01M 14%	
		H01G 9%	((%quantum_dot% | %perovskite% | %organic_inorganic% | %plasmon% | %nanowire% |
		H01L 31%	%nanoparticle% | %nanotube%)) + (%photovoltai% | %solar))
		H01L 51%	
		H01M 14%	
	PV modules	H01L 21%	((%anti_reflection% | %encapsulat% | %back_contact% | %buried_contact% | %bypass_diode% |
		H01L 25%	%rear_surface_protection% | %back_sheet% | %building_integrat% | %mounting_system%)
		H01L 27%	+ (%photovoltai% | %solar)) | %solar_panel% | %photovoltaic_panel% | %solar_modul% |
		H01L 31%	%solar_cell_modul% | %photovoltaic_modul% | %solar_cable% | %photovoltaic_wire% | %solar_array% |
		H01R 13%	%photovoltaic_array% | %BIPV% | %solar_park% | (%spacecraft% + (%photovoltai% | %solar_cell%))
		H02N 6%	
		H02S 20%	
		H02S 30%	
		B64G 1%	
		E04D 13%	
	Other	B64G 1%	(%photovoltai% | %solar_cell%)
		C01B 33%	
		C08K 3%	

Table 4 (continued)

Tech.	Sub-trajectory	IPCs	Keyword combination
		C08G 61%	
		C23C 14%	
		C23C 16%	
		C30B 29%	
		C30B 15%	
		E04D 13%	
		F21S 9%	
		G05F 1%	
		H01B 1%	
		H01G 9%	
		H01L 21%	
		H01L 25%	
		H01L 27%	
		H01L 29%	
		H01L 31%	
		H01L 51%	
		H01M 10%	
		H01M 14%	
		H01R 13%	
		H02J 7%	
		H02M 7%	
		H02N 6%	
		H02S 99%	
		H02S 20%	
		H02S 30%	

A.2 Decriptives

Table 5 Descriptive statistics for wind power and photovoltaics

	Tech.	Min	Median	Mean	Max	SD
Forward Citation	WP	0	1	2,628	103	6,202
	PV	0	1	2,723	41	4,008
New Inventors	WP	0	0	0,546	6	0,753
	PV	0	1	0,820	10	1,053
Specialized Inventors	WP	0	0	0,208	4	0,475
	PV	0	0	0,260	4	0,574
Related Inventors	WP	0	0	0,362	6	0,633

Table 5 (continued)

	Tech.	Min	Median	Mean	Max	SD
	PV	0	1	0,808	8	1,052
Unrelated Inventors	WP	0	0	0,221	4	0,454
	PV	0	0	0,136	3	0,379
Team Size	WP	1	1	1,384	8	0,886
	PV	1	2	2,132	13	1,465
Experienced Inventors	WP	0	1	0,791	7	0,776
	PV	0	1	1,205	8	1,129
Knowledgeable Inventors	WP	0	0	0,583	7	0,715
	PV	0	1	0,944	8	1,075
Foreign Inventors	WP	0	0	0,047	7	0,405
	PV	0	0	0,108	5	0,477
Number of IPCs	WP	1	2	2,042	10	1,343
	PV	1	2	2,381	10	1,414
Backward Citations	WP	0	2	3,236	171	7,307
	PV	0	3	4,263	154	6,388
New Combination	WP	0	0	0,148	1	0,355
	PV	0	0	0,225	1	0,418
Family Size	WP	1	1	3,033	35	4,682
	PV	1	1	2,957	31	3,059
PCT Patent	WP	0	0	0,011	1	0,102
	PV	0	0	0,008	1	0,091
Granted Patent	WP	0	0	0,290	1	0,454
	PV	0	0	0,357	1	0,479
USPTO	WP	0	0	0,027	1	0,161
	PV	0	0	0,018	1	0,132
PV Modules	PV	0	0	0,215	1	0,411
Silicon Wafer Cells	PV	0	0	0,021	1	0,142
Thin-Film Cells	PV	0	0	0,100	1	0,300
Emerging Cells	PV	0	0	0,054	1	0,227

A.3 Correlations

A.4 Inventor Types

In this section, detailed information about the number of the different kinds of inventors, their patents and team composition are presented. Table 8 shows the number of different types of inventors. These numbers do not sum up to the total number of inventors, since the inventor type can change over time, for example, if a *New Inventor* continues his inventive activity and becomes a *Specialized Inventor*.

Table 6 Correlations for wind power

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Forward Citation	—															
2	New Inventors	−0.022	—														
3	Specialized Inventors	0.216	−0.177	—													
4	Related Inventors	0.033	−0.269	−0.137	—												
5	Unrelated Inventors	−0.081	−0.245	−0.120	−0.168	—											
6	Team Size	0.243	0.428	0.268	0.315	0.113	—										
7	Experienced Inventors	0.112	−0.471	0.430	0.634	0.376	0.487	—									
8	Knowledgeable Inventors	−0.022	−0.394	−0.197	0.779	0.487	0.350	0.800	—								
9	Foreign Inventors	0.358	−0.021	0.091	−0.027	−0.018	0.459	0.023	−0.035	—							
10	Number of IPCs	0.131	0.003	−0.051	0.147	−0.062	0.046	0.052	0.090	−0.006	—						
11	Backward Citations	0.603	0.005	0.112	0.028	−0.082	0.155	0.043	−0.027	0.246	0.115	—					
12	New Combination	0.006	0.041	−0.048	0.048	0.013	0.039	0.017	0.051	−0.024	0.510	0.012	—				
13	Family Size	0.247	−0.127	−0.006	0.215	−0.088	0.010	0.121	0.135	0.027	0.241	0.102	0.085	—			
14	PCT Patent	0.027	−0.016	0.090	−0.005	−0.018	0.022	0.041	−0.015	0.000	−0.007	0.042	−0.029	0.047	—		
15	Granted Patent	0.220	0.029	0.138	0.027	−0.091	0.118	0.054	−0.034	0.102	0.180	0.239	0.111	0.242	−0.066	—	
16	USPTO	0.489	0.004	0.217	−0.060	−0.053	0.207	0.053	−0.087	0.344	0.006	0.419	0.001	0.041	−0.017	0.204	—

Table 7 Correlations for photovoltaics

		1	2	3	4	5	6	7
1	Forward Citation	—						
2	New Inventors	−0.005	—					
3	Specialized Inventors	0.071	−0.046	—				
4	Related Inventors	0.145	−0.158	−0.156	—			
5	Unrelated Inventors	0.011	−0.048	−0.051	−0.119	—		
6	Team Size	0.165	0.566	0.235	0.520	0.101	—	
7	Experienced Inventors	0.175	−0.187	0.346	0.812	0.199	0.638	—
8	Knowledgeable Inventors	0.146	−0.172	−0.171	0.937	0.236	0.545	0.865
9	Foreign Inventors	0.105	−0.026	0.004	0.025	−0.055	0.312	0.006
10	Number of IPCs	0.083	0.018	−0.097	0.081	0.015	0.036	0.030
11	Backward Citations	0.076	0.015	0.058	−0.048	−0.022	0.017	−0.022
12	New Combination	−0.015	0.021	−0.069	−0.001	0.075	0.004	−0.011
13	Family Size	0.378	0.041	0.088	0.180	−0.014	0.227	0.208
14	PCT Patent	0.011	−0.022	0.061	−0.033	0.002	−0.008	0.001
15	Granted Patent	0.051	0.064	0.047	−0.003	−0.023	0.079	0.014
16	USPTO	0.122	−0.024	0.025	−0.031	−0.048	0.077	−0.032
17	PV Modules	−0.052	−0.060	−0.012	−0.097	−0.055	−0.151	−0.115
18	Silicon Wafer Cells	−0.056	−0.007	0.064	0.105	−0.019	0.095	0.125
19	Thin-Film Cells	−0.052	0.021	0.076	0.036	0.021	0.086	0.079
20	Emerging Cells	0.048	0.076	−0.032	0.163	−0.059	0.160	0.116

Table 7 (continued)

8	9	10	11	12	13	14	15	16	17	18	19	20
—												
0.005	—											
0.084	−0.001	—										
−0.054	0.070	−0.005	—									
0.025	−0.006	0.532	−0.010	—								
0.171	0.115	0.124	0.042	0.056	—							
−0.032	0.020	−0.029	0.025	−0.049	−0.009	—						
−0.011	0.070	0.044	0.248	0.041	0.105	−0.068	—					
−0.047	0.364	−0.046	0.265	−0.008	−0.020	−0.012	0.105	—				
−0.115	−0.058	−0.038	0.041	−0.117	−0.158	0.000	0.015	−0.038	—			
0.096	0.011	−0.024	−0.016	−0.029	−0.014	0.078	−0.030	−0.020	−0.076	—		
0.043	0.028	−0.069	0.049	−0.048	−0.055	−0.030	0.101	0.149	−0.059	0.021	—	
0.139	0.050	0.105	−0.036	0.052	0.028	0.036	−0.081	0.027	−0.024	−0.017	−0.019	—

Figure 7 displays the number of patents each inventor possesses in the technologies. The very skewed distribution is common for patent data (Menon 2011) and scientific output in general (Lotka 1926). It is not possible to infer from the number

Table 8 Number of inventors

	Wind power	Photovoltaics
New Inventors	1083	1387
Specialized Inventors	413	440
Related Inventors	596	920
Unrelated Inventors	560	677

of patents to the type of inventor. *Related Inventors* and *Unrelated Inventors* can have only one patent or inventors who start and continue their inventive activity have more than one patent. Remarkably is the WP inventor with 127 patents. This inventor is the founder of a major German wind turbine manufacturer.[19]

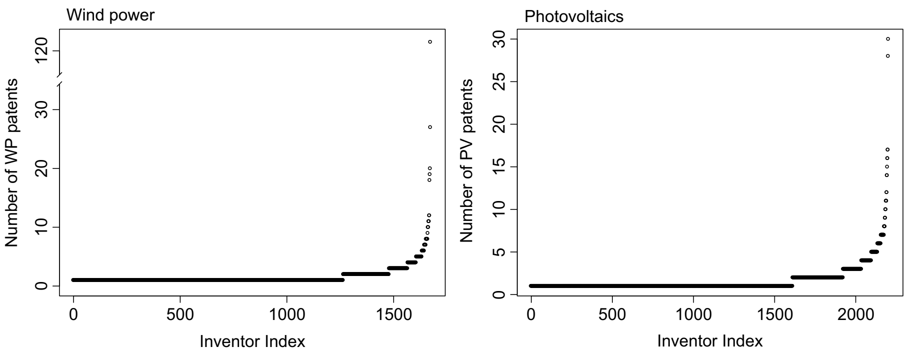

Fig. 7 Number of wind power and photovoltaics patents each inventor possess

Table 9 shows the team composition frequency in WP and PV. It shows how often a specific combination of inventors occurs together on the same patent. The diagonal elements indicates cases, where only one or multiple inventors with the same kind of knowledge are inventors of the patent. Off-diagonal values count the frequency of the specific team composition on a patent. Teams with more than two different kinds of inventors are neglected but hardly present. The data shows that WP has hardly any heterogeneous teams and most patents are filed by one or multiple inventor of the same type. In both technologies, teams comprising New and Related as well as New and Specialized Inventors are the most frequent.

A.5 Robustness tests

[19] Reestimating the WP models without patents from this inventor does not change the results. To account for frequent inventors in general, a dummy variable is created for patents with an inventor who has ten or more patents in the respective technology. The overall results did not change if for such frequent inventors is controlled. Results are available on request.

Table 9 Frequency of team compositions in wind power and photovoltaics

	Wind power					Photovoltaics				
	New inventors	Specialized inventors	Related inventors	Unrelated inventors	Foreign inventors	New inventors	Specialized inventors	Related inventors	Unrelated inventors	Foreign inventors
New Inventors	696					441				
Specialized Inventors	54	232				146	111			
Related Inventors	73	43	474			292	114	438		
Unrelated Inventors	45	35	35	307		82	27	58	85	
Foreign Inventors	20	17	7	8	0	51	24	72	8	0

Table 10 Regression results for alternative inventor specification

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power				Photovoltaics		
	Model 4 Full Period	Model 5 Era of Ferment	Model 6 Dominant Design	Model 7 Era of incremental change	Model 4a Full Period	Model 5a Era of Ferment	Model 6a Dominant Design
	1970-2006	1970-1995	1996-2000	2001-2006	1970-2006	1970-1997	1998-2006
New Inventors	0.163 ***	0.142	0.269 ***	0.146 ***	0.033	0.083 *	−0.007
	(0.039)	(0.094)	(0.067)	(0.053)	(0.030)	(0.044)	(0.040)
Specialized Inventors	0.425 ***	0.052	0.489 ***	0.508 ***	0.164 ***	0.123	0.186 ***
	(0.055)	(0.180)	(0.166)	(0.060)	(0.055)	(0.075)	(0.072)
Related Inventors alt.	0.088	0.071	−0.049	0.148 **	0.092 **	0.174 **	0.060
	(0.054)	(0.199)	(0.121)	(0.062)	(0.038)	(0.069)	(0.047)
Unrelated Inventors alt.	0.073	0.377 ***	−0.258 *	0.025	0.004	0.030	−0.001
	(0.054)	(0.135)	(0.140)	(0.060)	(0.040)	(0.069)	(0.048)
PV Modules					−0.046	−0.179	0.022
					(0.072)	(0.110)	(0.093)
Silicon Wafer Cells					−0.935 ***	−1.708 ***	−0.829 **
					(0.342)	(0.458)	(0.383)
Thin-Film Cells					−0.234 **	−0.351 **	−0.139
					(0.098)	(0.155)	(0.129)
Emerging Cells					−0.039	−0.400	0.103
					(0.151)	(0.318)	(0.168)
Foreign Inventors	0.142 ***	−1.181 *	−0.670 *	0.170 ***	0.007	0.034	−0.016
	(0.041)	(0.648)	(0.373)	(0.042)	(0.058)	(0.086)	(0.073)

Table 10 (continued)

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power				Photovoltaics		
	Model 4 Full Period 1970-2006	Model 5 Era of Ferment 1970-1995	Model 6 Dominant Design 1996-2000	Model 7 Era of incremental change 2001-2006	Model 4a Full Period 1970-2006	Model 5a Era of Ferment 1970-1997	Model 6a Dominant Design 1998-2006
Number of IPCs	0.092 ***	0.120	0.085 *	0.084 ***	0.135 ***	0.147 ***	0.110 **
	(0.024)	(0.076)	(0.044)	(0.032)	(0.025)	(0.027)	(0.044)
Backward Citations	0.012 ***	0.021	0.025	0.011 ***	0.016 ***	0.024 ***	0.012 **
	(0.002)	(0.022)	(0.016)	(0.002)	(0.004)	(0.008)	(0.005)
New Combination	−0.139	−0.123	−0.192	−0.130	−0.212 **	−0.270 **	−0.167
	(0.086)	(0.205)	(0.149)	(0.121)	(0.098)	(0.119)	(0.152)
Family Size	0.068 ***	0.149 ***	0.053 ***	0.074 ***	0.126 ***	0.113 ***	0.131 ***
	(0.005)	(0.024)	(0.009)	(0.006)	(0.008)	(0.014)	(0.010)
PCT Patent	0.128	−0.584	−0.511	0.117	−0.027	−30.337 ***	0.212
	(0.225)	(0.977)	(0.339)	(0.228)	(0.415)	(0.533)	(0.406)
Granted Patent	0.320 ***	0.315 **	0.617 ***	0.137	0.060	0.088	0.058
	(0.067)	(0.147)	(0.136)	(0.090)	(0.064)	(0.092)	(0.092)
USPTO	1.034 ***	1.945 ***	0.734 *	1.025 ***	1.129 ***	1.186 ***	1.108 ***
	(0.159)	(0.518)	(0.403)	(0.166)	(0.205)	(0.218)	(0.280)
Year Dummies	yes	yes	yes	yes	yes	yes	yes
N	1984	827	332	825	1691	782	909
df	1936	790	315	807	1638	738	884

Table 10 (continued)

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power				Photovoltaics		
	Model 4 Full Period 1970-2006	Model 5 Era of Ferment 1970-1995	Model 6 Dominant Design 1996-2000	Model 7 Era of incremental change 2001-2006	Model 4a Full Period 1970-2006	Model 5a Era of Ferment 1970-1997	Model 6a Dominant Design 1998-2006
loglik	−3462.770	−830.673	−673.111	−1926.998	−3342.420	−1304.780	−2023.636
AIC	7023.541	1737.347	1382.222	3891.996	6792.841	2699.559	4099.271
McFadden R^2	0.146	0.084	0.074	0.096	0.078	0.076	0.062

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

Table 11 Regression results for inventor interactions

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power				Photovoltaics		
	Model 4 Full Period	Model 5 Era of Ferment	Model 6 Dominant Design	Model 7 Era of incremental change	Model 4a Full Period	Model 5a Era of Ferment	Model 6a Dominant Design
	1970-2006	1970-1995	1996-2000	2001-2006	1970-2006	1970-1997	1998-2006
New Inventors	0.202 ***	0.252 **	0.100	0.179 ***	0.081 *	0.109 *	0.020
	(0.052)	(0.114)	(0.158)	(0.069)	(0.047)	(0.063)	(0.065)
New Inventors x Specialized Inventors	−0.098 *	−0.641	−0.195 **	−0.138 **	−0.026	−0.038	0.008
	(0.052)	(0.601)	(0.098)	(0.061)	(0.043)	(0.057)	(0.063)
New Inventors x Related Inventors	0.057	−0.893 **	0.288	0.065 *	−0.022	0.002	−0.006
	(0.035)	(0.429)	(0.225)	(0.037)	(0.019)	(0.049)	(0.022)
New Inventors x Unrelated Inventors	−0.166 **	−0.041	−0.147	−0.246 *	−0.191 ***	−0.174	−0.172 *
	(0.082)	(0.187)	(0.209)	(0.127)	(0.069)	(0.106)	(0.099)
Specialized Inventors	0.524 ***	0.307	0.218	0.617 ***	0.207 ***	0.119	0.258 ***
	(0.073)	(0.237)	(0.261)	(0.079)	(0.075)	(0.110)	(0.086)
Specialized Inventors x Related Inventors	−0.168 **	−0.433	0.885 ***	−0.231 ***	0.015	0.131	−0.100
	(0.076)	(0.334)	(0.333)	(0.082)	(0.061)	(0.098)	(0.071)
Specialized Inventors x Unrelated Inventors	−0.155	−0.226	−37.941 ***	0.075	−0.176	−0.112	−0.219
	(0.170)	(0.358)	(0.805)	(0.180)	(0.112)	(0.182)	(0.154)
Related Inventors	0.098	0.291	−0.563 **	0.134 **	0.074 *	0.081	0.041
	(0.062)	(0.200)	(0.251)	(0.059)	(0.042)	(0.073)	(0.053)
Related Inventors x Unrelated Inventors	−0.061	0.928 **	0.479 **	−0.164	0.047	0.066	0.071

Table 11 (continued)

Negative binomial regressions: Dependent variable: Forward citations per patent.							
	Wind Power				Photovoltaics		
	Model 4 Full Period	Model 5 Era of Ferment	Model 6 Dominant Design	Model 7 Era of incremental change	Model 4a Full Period	Model 5a Era of Ferment	Model 6a Dominant Design
	1970-2006	1970-1995	1996-2000	2001-2006	1970-2006	1970-1997	1998-2006
	(0.074)	(0.431)	(0.188)	(0.101)	(0.061)	(0.126)	(0.079)
Unrelated Inventors	0.213 **	0.385 **	−0.353	0.195	0.259 **	0.285 **	0.188
	(0.090)	(0.180)	(0.277)	(0.126)	(0.107)	(0.130)	(0.179)
PV Modules					−0.032	−0.187 *	0.030
					(0.072)	(0.110)	(0.092)
Silicon Wafer Cells					−0.917 ***	−1.592 ***	−0.790 **
					(0.331)	(0.456)	(0.374)
Thin-Film Cells					−0.232 **	−0.358 **	−0.124
					(0.100)	(0.157)	(0.132)
Emerging Cells					−0.009	−0.342	0.119
					(0.151)	(0.322)	(0.167)
Foreign Inventors	0.137 ***	−1.138 *	−0.940 ***	0.164 ***	0.020	0.054	−0.002
	(0.042)	(0.643)	(0.324)	(0.043)	(0.058)	(0.085)	(0.074)
Number of IPCs	0.093 ***	0.139 *	0.065	0.084 ***	0.132 ***	0.152 ***	0.103 **
	(0.024)	(0.076)	(0.045)	(0.032)	(0.025)	(0.027)	(0.046)
Backward Citations	0.012 ***	0.027	0.017	0.011 ***	0.015 ***	0.021 ***	0.012 **
	(0.002)	(0.022)	(0.015)	(0.002)	(0.004)	(0.008)	(0.005)

Table 11 (continued)

Negative binomial regressions: Dependent variable: Forward citations per patent.

	Wind Power				Photovoltaics		
	Model 4 Full Period	Model 5 Era of Ferment	Model 6 Dominant Design	Model 7 Era of incremental change	Model 4a Full Period	Model 5a Era of Ferment	Model 6a Dominant Design
	1970-2006	1970-1995	1996-2000	2001-2006	1970-2006	1970-1997	1998-2006
New Combination	−0.140 *	−0.220	−0.155	−0.123	−0.212 **	−0.299 **	−0.146
	(0.084)	(0.203)	(0.146)	(0.119)	(0.100)	(0.123)	(0.154)
Family Size	0.070 ***	0.147 ***	0.063 ***	0.077 ***	0.127 ***	0.113 ***	0.133 ***
	(0.005)	(0.024)	(0.009)	(0.006)	(0.008)	(0.014)	(0.010)
PCT Patent	0.135	−0.737	36.429 ***	0.110	−0.113	−31.327 ***	0.124
	(0.227)	(1.024)	(0.798)	(0.236)	(0.391)	(0.535)	(0.386)
Granted Patent	0.322 ***	0.323 **	0.658 ***	0.135	0.065	0.083	0.059
	(0.067)	(0.142)	(0.137)	(0.092)	(0.064)	(0.092)	(0.091)
USPTO	1.030 ***	1.858 ***	1.019 **	1.035 ***	1.150 ***	1.239 ***	1.099 ***
	(0.163)	(0.505)	(0.406)	(0.172)	(0.206)	(0.228)	(0.281)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1984	827	332	825	1691	782	909
df	1930	784	309	801	1632	732	878
loglik	−3457.785	−827.086	−667.408	−1921.658	-3339.656	−1303.689	−2021.261
AIC	7025.570	1742.172	1382.817	3893.315	6799.311	2709.377	4106.523
McFadden R^2	0.147	0.088	0.082	0.099	0.078	0.077	0.063

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

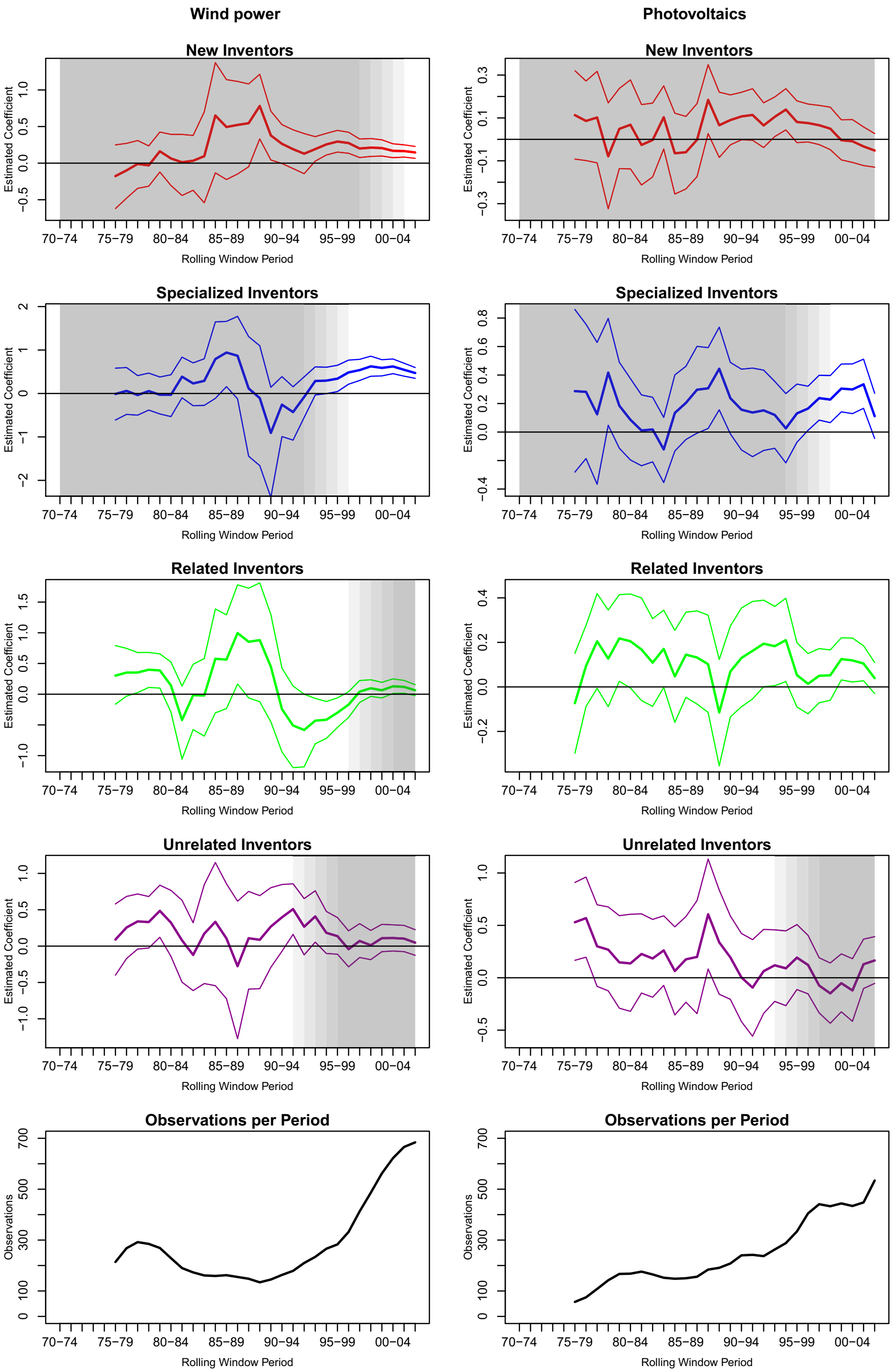

Fig. 8 Five year long rolling-window regression results for wind power and photovoltaics

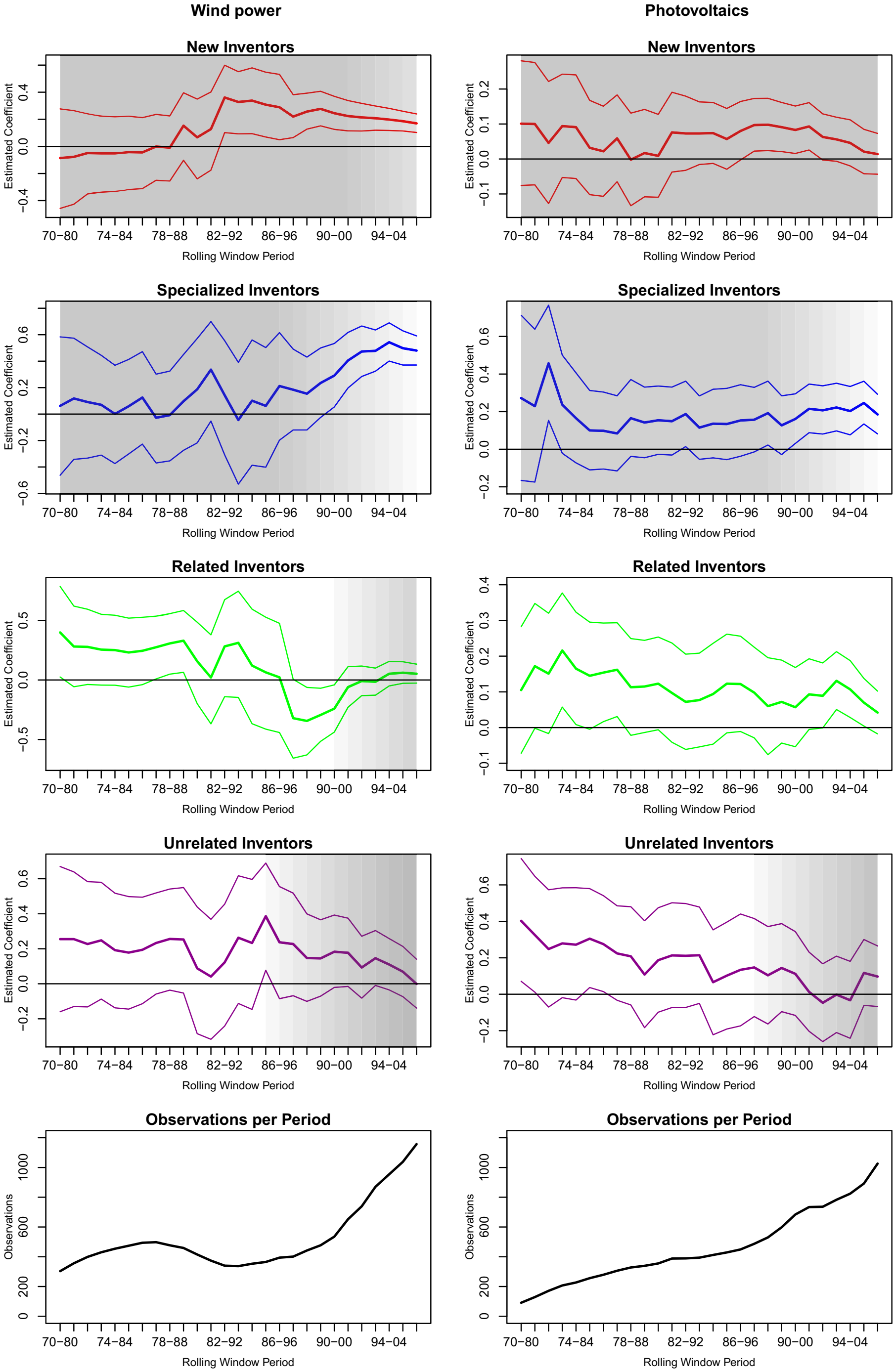

Fig. 9 Eleven year long rolling-window regression results for wind power and photovoltaics

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