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Knowledge recombination along the technology life cycle

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Abstract

Technological evolution is a dynamic process which is intimately related to the technology's knowledge base. A knowledge base shows certain dynamics and evolves over time. This study aims to understand how recombination of different kinds of knowledge influences the knowledge base along the technology life cycle. For this purpose, the [Anderson and Tushman \(1990\)](#) technology life cycle model is extended to account for the technology's knowledge base and proposes different kinds of knowledge which are relevant in the life cycle phases. This model is empirically tested for wind power and photovoltaics in Germany from 1970 until 2006. Patent's forward citations are considered as recombinatorial success and inventors' patenting experience proxies different kinds of knowledge. Negative binomial regressions as well as rolling-window regressions are used to capture 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. Here, rolling-window regressions prove to be a useful analytical tool to reveal nuanced changes over time. The results have several policy and management implications, especially 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, O32, O33, Q42

1 Introduction

Technologies evolve 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., 2015](#)), the influence of knowledge recombination on the technology knowledge base and its evolution over time is so far neglected. 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 it comes from, 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 ([Murmman 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 are so far 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 is 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 wind power (WP) and photovoltaics (PV) in Germany for the period from 1970 until 2006. After the oil crisis in the 1970s both technologies were considered as means to reduce the dependency on fossil fuels and to combat 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 them ideal cases to analyze how technologies evolve and mature over a life cycle. The period covers several TLC phases and allows 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's 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, 2016](#)). Negative binomial regressions are run for the overall period as well as for the different TLC phases to estimate the effect

of different sources of knowledge. Furthermore, rolling-window regressions are introduced as a novel approach to capture dynamics over time.

The results show that different sources of knowledge matter for technological evolution in general but differently in the phases of the TLC, mostly in line with the theoretical model. For the overall technological development, inventors which possess specialized knowledge are most influential. In WP also de-novo inventors matter, who induce knowledge which 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 relevant over time.

These results contribute to a deeper understanding of the evolution of a technology's knowledge base and which dynamics 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 right actors as well as for management to pursue the right 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 more holistic approach to understand technological development along the technology's life cycle. From an methodological point of view, the utilization of previous patents of inventors to distinguish different sources of knowledge allows to analyze long term developments, which can not 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 over time.

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 evolved over time. Section 4 presents the data, econometric approach and the results. The last Section discusses findings and concludes.

2 Knowledge recombination along the technology life cycle

2.1 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, 2006](#); [Cantner et al., 2010](#)) and the country level (e.g. [King, 2004](#); [Leydesdorff et al., 2006](#)). 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 regimes (Maleki and Rosiello, 2014), a general understanding how the knowledge base evolves and how the respective technologies are shaped is missing.

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., 2015). For example, the previous or stock of knowledge which the firm possess is of importance (Liyanaage 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 which can be integrated in the knowledge base is relevant (e.g. labor mobility, hiring specific labor, acquisitions, collaboration, suppliers, customers, ...; see Savino et al. (2015) for an overview).

Knowledge recombination takes place across the knowledge space. A technology can be viewed as a specific area of the knowledge space which constitutes its knowledge base. If knowledge is recombined within such a knowledge base, it can be considered specialized, since it combines parts of knowledge which if familiar already. The relation between a technology and knowledge which 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 approach, [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 evolution. [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 modelled by a technology life cycle (TLC) similar to the product or industry life cycle. In the TLC neither the actual product is of importance, nor the structure of the firms in the industry, but 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 to understand how different kinds of knowledge expand 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 cyclical models based on the [Anderson and Tushman \(1990\)](#) model presenting a macro view on the technology and models using a S-curve depicting the 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 in which state a specific technology is ([Haupt et al., 2007](#)). In the cyclical model by [Anderson and Tushman \(1990\)](#), 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.¹ 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.

While the TLC has been studied frequently in general, so far the underlying knowledge dimension which shapes the technological evolution has been widely neglected. However, with a focus on the knowledge base which constitutes a technology, there might be differences in the kind of knowledge which is 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 how different kinds of knowledge influences technological development over the TLC. There is the general concept

¹While [Anderson and Tushman \(1990\)](#) rather see the emergence of a dominant design and a new discontinuity as a point in time, its more 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 \(1993\)](#) or [Kaplan and Tripsas \(2008\)](#) who talk about the convergence towards a dominant design.

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 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, 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.² The result is summarized in Figure 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., 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

²The 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 approaches of a TLC.

from different fields and experimenting with new ways of applications and characteristics are possible. 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 which are influential as well (Suarez, 2004), such as the emergence of institutions which 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 which 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 so a single trajectory emerges and development focuses along this trajectory (Metcalf, 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 along the technological trajectory takes place (Dosi, 1982; Sahal, 1985; Anderson and Tushman, 1990). Here, 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 direction of search (Kaplan and Tripsas, 2008). Social, political and organizational routines are established as well (Tushman and Rosenkopf, 1992). Nevertheless, certain dynamics still exists 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 allow 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 researchers, 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 which provide detailed training in the field, this new knowledge can come up 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 which 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.

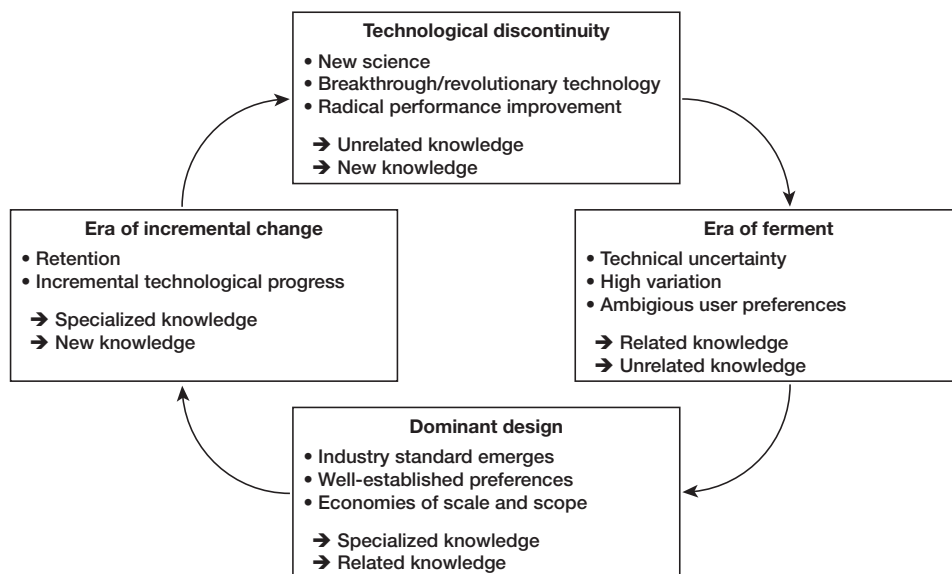


Figure 1: Technology life cycle phases and respective relevant knowledge.

Source: Extention based on Tushman and Rosenkopf (1992); Kaplan and Tripsas (2008); Taylor and Taylor (2012).

2.3 Inventors and knowledge recombination

To understand the evolution of a technology, it is crucial to determine which factors influence the evolution of the underlying knowledge base. Since the 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, also the breadth and depth of the knowledge the inventor possess has an influence, as shown by [Boh et al. \(2014\)](#), while [Conti et al. \(2014\)](#) find that the previous inventive activity positively influences new inventions. In addition to that, [Mohammadi and Franzoni \(2014\)](#) show that for scientists knowledge relatedness influences the technological value of inventions. [Meyer \(2006\)](#) demonstrate that scientists in nanotechnology who invent at the same time are more effective than non-inventing scientists. [Scandura \(2013\)](#) shows that the success of inventors is influenced by the type of knowledge they use. She shows based on survey data, that combining scientific and market knowledge enhances inventive output.

While the characteristics of the inventor are of importance, the origin in the knowledge space may also play a role. Mobile inventors, which enter a technology from outside the technologies' 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 they move into. It can be assumed that during the process of invention, the knowledge an inventor holds is recombined with knowledge present in the technology that the inventor moves to 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 may develop ([Schoenmakers and Duysters, 2010](#)). Here, the distance in the knowledge space plays a role again, since these inventors can originate from related technologies, which 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 they move into.

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 may have no inventive experience, which implies that their first invention contributes to the technologies 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 be customers which want specific features or characteristics of a technology and introduce them on their own ([von Hippel, 1976, 1988](#); [Bogers](#)

et al., 2010) or the classical tinkerer (Bettioli 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 which gives them a deep understanding of the technology (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 a technological field which is related to the technology they move to. They have previously invented in fields related to the technology or underlying technological principles. These inventors are familiar with the technological field 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 which is related to the technology's knowledge base. 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 which 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 carrier 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 new knowledge which 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 energy technologies

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

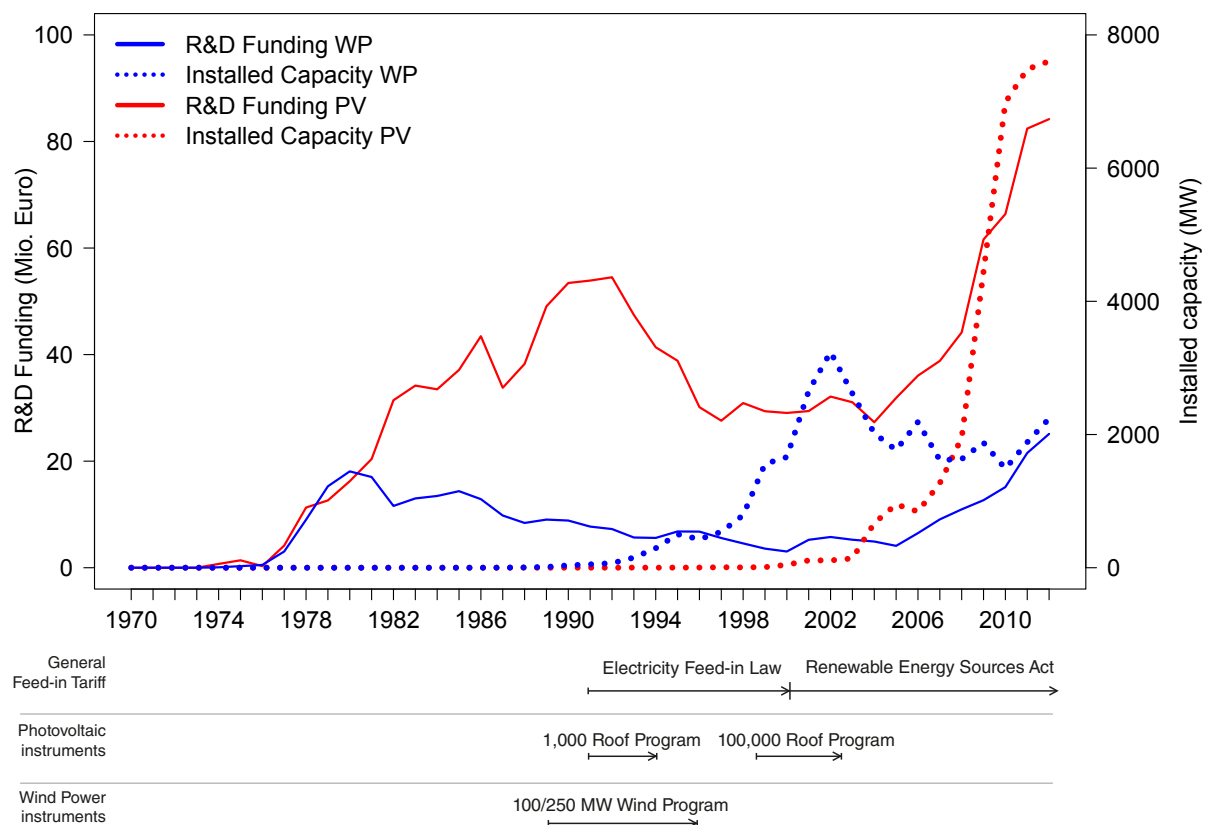


Figure 2: Wind power and photovoltaics policy instruments in Germany.

Source: Adapted from [Cantner et al. \(2016\)](#).

rising energy consumption, alternative energy technologies are demanded. Since the oil crisis in the seventies, renewable energy technologies, especially WP and PV, emerge and diffuse 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 base 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 policies. Over time, there is a shift from direct R&D subsidies to demand inducing policies which create a niche market for the technologies and supported their diffusion. This favorable environment helped the technologies to develop and the different instruments had tremendous 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 extent 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 in the end of the 1980s, variation and experimentation is 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 emerges already in the late 1980s. Since then WP is 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 is 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 takes place.

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 follows a mass-produced goods life cycle ([Abernathy and Utterback, 1988](#)) and a dominant design emerges in the early 1990s. Since then, PV is 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 which allowed first larger scale tests. From 1994 till 1998 there was a phase of slow down and uncertainty, followed by a breakthrough phase from 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](#)).³ For this purpose especially the 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

³Since 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. [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.

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.⁴ 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, 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 which 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 until 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 are developed and installed, however they do not substantially differ from onshore turbines and a discontinuity seems not to emerge yet.

In the case of PV⁵, the era of ferment covers the years from 1970 until 1997 and is characterized by massive R&D subsidies and first experimental demand policies which create a niche market (Jacobsson et al., 2004). 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 (Jacobsson et al., 2004; Herrmann and Töpfer, 2016). The emergence of a dominant design lasts from 1998 until about 2006 and covers the tremendous 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 lead to severe cost reductions and economies of scale. From 2007 onwards the era of incremental change begins 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

⁴In the case of WP it is hard to track a discontinuity which opened up the trajectory. The underlying technological principle is 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).

⁵The photovoltaic effect was discovered already in 1839, but the first conventional photovoltaic cell was developed in 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, PV was seriously considered for large scale electricity production.

PV subtechnologies. For example, dye-sensitized solar cells were discovered in 1991 (O'Regan and Grätzel, 1991) and the underlying principle is severely different from silicon based cells and their efficiency is far from conventional cells. These subtechnologies 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).⁶

Table 1: Summary of the TLC phases

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

4 Econometric approach

In the following, the extended TLC model is applied to the TLC of wind power and photovoltaics. Using negative binomial regression the effect of different sources of knowledge on the success of knowledge recombination is tested. Next data as well as variables and the econometric approach are explained. Descriptive statistics and correlations can be taken from Appendix A.2, 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 base can be observed in patent data. Patents are, despite their 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 (Cohen et al., 2000; Arundel and Kabla, 1998), 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 IPC (International Patent Classification) classes and keywords (see Appendix A.1 for details). All priority application filings 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. Since the database contains missing information on the inventor's country code, the country code was manually added if conclusive evidence is provided (e.g. German address). The overall data set comprises 3,765 WP patents and 3,589 PV patents. However, for the following analysis, only a subset until 2006 is considered, since the patents need some time to receive forward citations. For the set until 2006, there are 1,984 WP patents and 1,691 PV patents which are the units of observation.

⁶It could also be argued that the presence of subtechnologies indicates that no dominant design emerged yet. But these subtechnologies 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. For large scale, mass market applications silicon cells are the most frequent ones (Huenteler et al., 2016b).

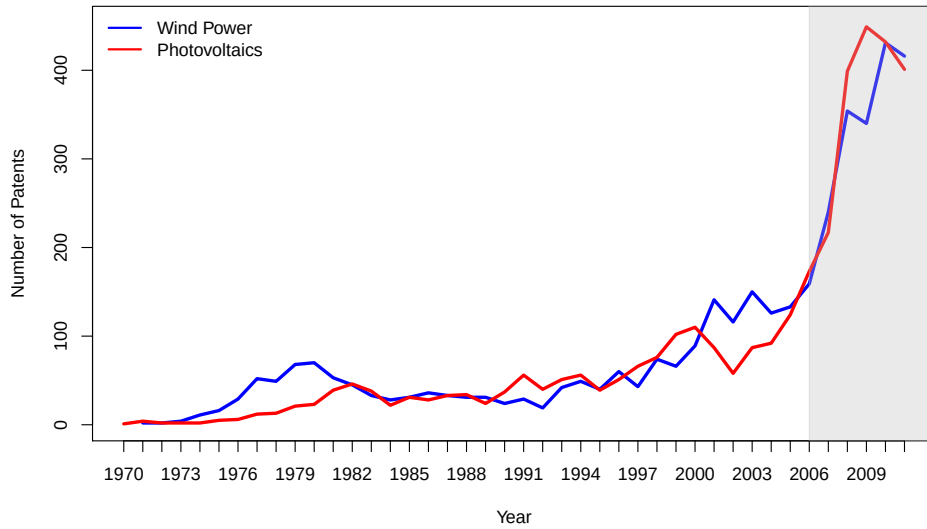


Figure 3: Wind power and photovoltaics patents by German inventors.

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, 2016). 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 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 indicate higher importance of the cited patent (Alcácer and Gittelman, 2006; Yasukawa and Kano, 2014). Figure 4 displays the number of forward patent citations. The number is highly skewed and about 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 in the sample.

4.1.3 Independent variables: Type of inventor

To understand the influence of different sources of knowledge on the technological evolution, 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

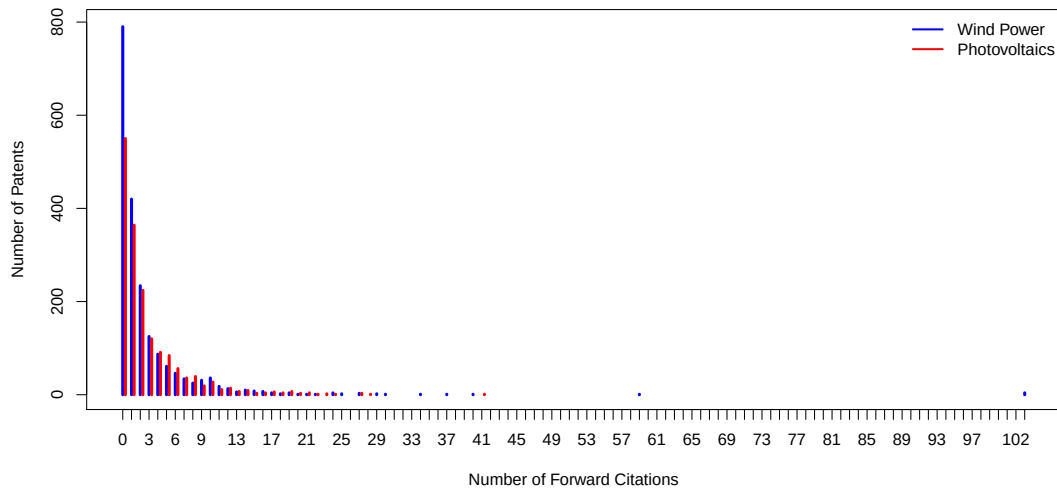


Figure 4: Distribution of forward citations per patent.

data is necessary. The inventor names were manually harmonized by correcting obvious typos⁷, academic titles or name order, controlling for patent applicant, address and year of application, to avoid inflating the number of inventors.⁸ In total there are 1,675 unique inventors on WP patents and 2,203 unique inventors on PV patents.

All filed patents for each inventor are collected from PATSTAT to construct the inventor's patenting history (similar to Jones, 2009). This patenting history is used to determine the type of inventor. The inventors can be assigned to the four different groups. The first group, *New Inventors*, are those without previous patenting experience, so there is no patenting history. The second group of inventors, *Specialized Inventors*, contains inventors who patented previously only in the respective technology. For the third and fourth group 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 his previous patents are assigned to. The inventor is considered to be related to the technology, so a *Related Inventor*, if one of the IPCs in the personal portfolio has also been used in the respective technology before, if not, the inventor is considered an *Unrelated Inventor*.⁹ The IPCs of all previous patents in WP or PV are collected over time and compared to the inventor's patenting history.¹⁰ If any of the inventor's patents coincides with an IPC which is already used in the technology, the inventor belongs to *Related Inventors*. 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.¹¹

⁷There 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.

⁸Technically, the different person-IDs from the PATSTAT database for one person are attributed to one unique identifier used to describe the inventor.

⁹If an inventor has patented in related and unrelated fields, the inventor is assigned to the *Related Inventors*.

¹⁰Patents from 1965 until 1969 are used to create an initial set of ICP classes, otherwise the first inventors would be unrelated by default.

¹¹Since this is a rather strong assumption, a robustness test is done where the inventor is assigned to the related and unrelated group if the patent belongs to a similar technology field or not. See section 4.4.

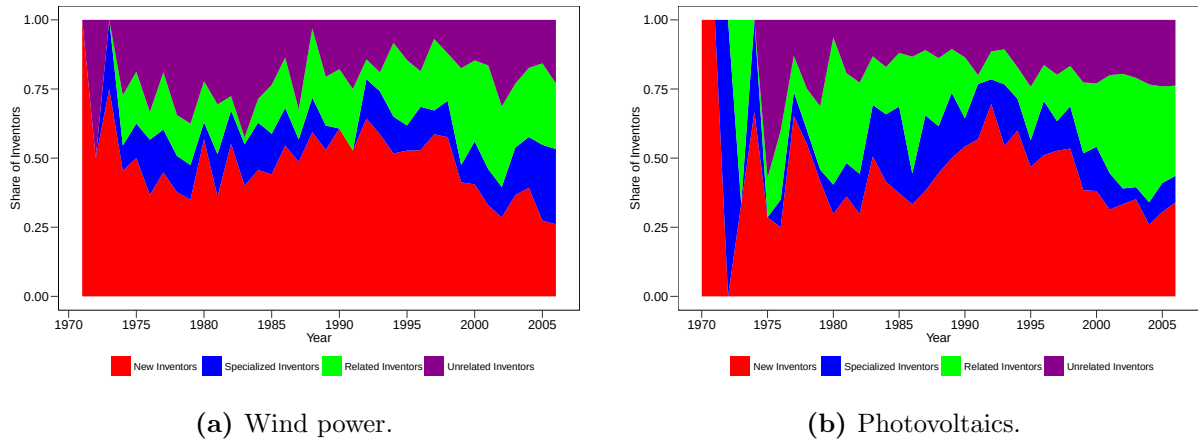


Figure 5: Inventor types per technology over time

The distinction between *Related Inventors* and *Unrelated Inventors* is influenced how detailed the technological relatedness is constructed. The minuteness of detail of the technological relatedness can be proxied by the hierarchical nature of the IPC classification. The IPC classes consists of 8 different fields, e.g. physics or electricity. These fields have several classes and subclasses (about 640, usually referred to as four-digit IPC class). Several studies use these four-digit IPC class to distinguish between different technological fields (e.g. [Nemet and Johnson, 2012](#)). There are furthermore also groups (about 7,000) and subgroups (more than 70,000) which 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.

The share of the different kinds of inventors over time is presented in Figure 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 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 on 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 better understand the effect of separating different kinds of inventors, intermediate groups are created to see the effect if the inventors are separated into the 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, *Knowledable 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, the relevant control variables are discussed.¹²

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 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 aggregation 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, 2015](#)). Patents might be invented in international teams and inventors from other countries are counted.

IPC Classes: 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 a patent comprises is counted.

Family Size: The size of the patent family the patent belongs to 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 calculated ([Martínez, 2011](#)).

Backward Citations: The previous knowledge the inventor used to create the patent may influence the technological value of a patent ([Harhoff et al., 2003](#)). However, it can be the case that patents with many backward citations are rather incremental compared to patents with no or only a few backward citations ([Lanjouw and Schankerman, 1999](#)).

Granted Patent: If the patent is granted is usually a good indicator for 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 class into the knowledge base which has not been used in the technology. This might be a new combination which can be of higher value. [Arts and Veugelers \(2015\)](#) use a similar idea to capture previously uncombined technologies. The dummy variable is constructed by comparing all previous IPCs used in the technology and the patent under consideration.

USPTO: Patents filed at the United States Patent and Trademark Office (USPTO) receive usually a higher number of forward citations, since the USPTO requires to indicate all prior art which 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](#)

¹²Besides the variables presented, there are several other which 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 has hardly any such references and is according to [Harhoff et al. \(2003\)](#) only relevant in 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.

et al., 2010).

Year Effects: Year dummies capture time variant effects such as macroeconomic changes, political support, patent legislation changes or other factors which 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 which could cite them.

PV Subtechnologies: For PV, the technology is more complex and consists of different components, 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 to produce electricity while nowadays also thin film materials and very recently organic and nanomaterials are used. Since they emerge in 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 deal with the overall construction and installation of the cell, and the actual *PV Cells*, which can be further distinguished based on their material into *Silicon Cells*, *Thin Film Cells* and *Organic Cells*. However, not all patents could be attributed to a specific technology and the distinction serves only as a rough indicator. A detailed elaboration how they can be distinguished in patent data is explained in Kalthaus (2016).

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. Since forward citations are a rare event, the count data is over-dispersed (the variance exceeds the mean of the data). This requires a negative binomial regression model (Cameron and Trivedi, 1986; Hilbe, 2011). These models are commonly used for patent data. Since the patent is the object of analysis (i), the data set is cross sectional but has time information. The stylized regression model looks like:

$$Forward\ Citation_i = \beta_1 Inventor\ Types_i + \beta_2 Controls_i + \epsilon_i \quad (1)$$

In the following, there are seven models for WP and six models for PV to estimate the effect of the different types of inventors on the 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 if 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 if previous knowledge is present. The third model separates the *Experienced Inventors* into *Specialized Inventors* which only invent in the respective technology and *Knowledgeable Inventors* which have experience in other fields. Model four furthermore separates the *Knowledgeable Inventors* into *Related Inventors* and *Unrelated Inventors* to estimate if the kind of previous knowledge has an effect. In the case of PV, two alternatives are estimated as well, which distinguishes PV in subtechnologies. Model 4a controls for patents which belong to *PV Modules* and *PV Cells*. Model 4b separates the

PV Cells further into *Silicon 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, distinction between the PV module and different cell technologies 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 if 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, so 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 which 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 provided in Section 4.4.

4.3 Results

4.3.1 Overall influence of different inventor types

The regression results for the influence of different types of inventors for wind power and photovoltaic can be taken from 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 is not significant. However the negative effect of *New Combination* is surprising. The introduction of a new IPC class into the technology seems to have a negative effect on the contribution to the knowledge base. This indicates that the extension of the knowledge base by bringing in new principles seems not to contribute. This is however in line with the argumentation by 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 strong positive effect, indicating that both sources of knowledge are relevant. This effect sustains if the *Experienced Inventors* are 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* are weakly significant, while the *Related*

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	Model 4b Full Period
Team Size	0.160 *** (0.025)				0.049 *** (0.019)					
New Inventors		0.157 *** (0.040)	0.163 *** (0.039)	0.166 *** (0.039)		0.032 (0.030)	0.032 (0.030)	0.033 (0.030)	0.037 (0.030)	0.033 (0.030)
Experienced Inventors		0.170 *** (0.033)				0.069 *** (0.027)				
Specialized Inventors			0.424 *** (0.055)	0.424 *** (0.055)			0.154 *** (0.056)	0.155 *** (0.056)	0.167 *** (0.057)	0.169 *** (0.055)
Knowledgeable Inventors			0.080 ** (0.041)				0.049 * (0.029)			
Related Inventors				0.069 (0.047)			0.042 (0.030)	0.042 (0.030)	0.058 * (0.030)	0.056 * (0.029)
Unrelated Inventors				0.114 * (0.066)			0.117 (0.076)	0.117 (0.076)	0.117 (0.075)	0.116 (0.075)
PV Modules							-0.027 (0.072)	-0.027 (0.072)	-0.027 (0.072)	-0.045 (0.072)
PV Cells							-0.215 ** (0.088)	-0.215 ** (0.088)		
Silicon Cells										-0.933 *** (0.326)
Thin Film Cells										-0.236 ** (0.099)
Organic Cells										-0.010 (0.151)
Foreign Inventors		0.152 *** (0.040)	0.142 *** (0.041)	0.141 *** (0.041)		0.017 (0.059)	0.021 (0.059)	0.023 (0.060)	0.016 (0.059)	0.013 (0.058)
IPC Classes	0.081 *** (0.025)	0.081 *** (0.025)	0.092 *** (0.024)	0.093 *** (0.024)	0.135 *** (0.026)	0.134 *** (0.026)	0.138 *** (0.026)	0.140 *** (0.026)	0.139 *** (0.026)	0.135 *** (0.025)
Backward Citations	0.012 *** (0.002)	0.012 *** (0.002)	0.012 *** (0.002)	0.012 *** (0.002)	0.017 *** (0.004)	0.017 *** (0.004)	0.016 *** (0.004)	0.016 *** (0.004)	0.016 *** (0.004)	0.016 *** (0.004)
New Combination	-0.145 * (0.087)	-0.146 * (0.088)	-0.139 (0.086)	-0.143 * (0.085)	-0.212 ** (0.100)	-0.213 ** (0.100)	-0.204 ** (0.099)	-0.206 ** (0.100)	-0.214 ** (0.101)	-0.217 ** (0.100)
Family Size	0.066 *** (0.005)	0.066 *** (0.005)	0.068 *** (0.005)	0.069 *** (0.005)	0.132 *** (0.008)	0.131 *** (0.008)	0.129 *** (0.008)	0.130 *** (0.008)	0.128 *** (0.008)	0.126 *** (0.008)
PCT Patent	0.267 (0.234)	0.266 (0.235)	0.127 (0.225)	0.127 (0.225)	-0.094 (0.400)	-0.085 (0.404)	-0.097 (0.420)	-0.126 (0.411)	-0.113 (0.408)	-0.061 (0.398)
Granted Patent	0.359 *** (0.066)	0.359 *** (0.067)	0.319 *** (0.067)	0.321 *** (0.067)	0.056 (0.065)	0.056 (0.065)	0.057 (0.065)	0.057 (0.065)	0.057 (0.065)	0.062 (0.065)
USPTO	1.146 *** (0.165)	1.154 *** (0.161)	1.033 *** (0.159)	1.028 *** (0.159)	0.979 *** (0.175)	1.035 *** (0.192)	1.031 *** (0.194)	1.038 *** (0.194)	1.141 *** (0.202)	1.137 *** (0.205)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1984	1984	1984	1984	1691	1691	1691	1691	1691	1691
df	1940	1938	1937	1936	1646	1644	1643	1642	1640	1638
loglik	-3478.858	-3478.796	-3462.796	-3462.620	-3356.730	-3356.106	-3354.165	-3353.734	-3350.518	-3343.702
AIC	7047.715	7051.591	7021.592	7023.240	6805.459	6808.211	6806.330	6807.468	6805.035	6795.403
McFadden R ²	0.142	0.142	0.146	0.146	0.074	0.074	0.074	0.075	0.075	0.077

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

Inventors do not play a significant role in WP. In all models also *Foreign Inventors* contribute, indicating that international knowledge spillover 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* is also not significant. Again, *New Combination* is negative 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* seem not to play a role, but *Experienced Inventors*. 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 significant, but especially the *Specialized Inventors* are of importance, indicating that knowledge accumulation seems to matter more than a diverse set of knowledge. In model 4 we see that only *Specialized Inventors* contribute to the technological development and the distinction between *Related Inventors* and *Unrelated Inventors* seems not to explain recombinatorial success. However, controlling for different subtechnologies in model 4a and 4b reveals that *Related Inventors* have a weak significant effect, indicating that subtechnologies interfere with each other and that the relevance of related knowledge is conditioned on the subtechnology. Contrary to WP, *Foreign Inventors* do not matter 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 influences recombinatorial success. There are differences between the technologies as well. While in WP *New Inventors* have a significant effect, they do not matter in PV. Also the kind of knowledge from domains external to the technology's knowledge base matters. While in WP *Unrelated Inventors* are able to provide useful recombinations, in PV *Related Inventors* are successful. Also the difference concerning *Foreign Inventors* is remarkable. However, the systemic difference between WP and PV on the technological level has also been shown by Cantner et al. (2016) and Huenteler et al. (2016b), but not with respect to the relevant knowledge.

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* and especially *Unrelated Inventors* play a significant role. While it was proposed in the extended TLC model that *Related Inventors* and *Unrelated Inventors* are decisive in this phase, only *Unrelated Inventors* seem 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 which 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, *IPC Classes* and *Backward Citations* lose their significance as well as the negative effect of *New Combination* compared to the full model. Interestingly, *Foreign Inventors* have a negative effect, indicating that knowledge from other countries lead to a reduction in recombinatorial success. Here, it could be that German inventors follow their

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 5b Era of Ferment 1970-1997	Model 6 Dominant Design 1998-2006	Model 6a Dominant Design 1998-2006	Model 6b Dominant Design 1998-2006
New Inventors	0.163 * (0.091)	0.275 *** (0.065)	0.146 *** (0.053)	0.084 * (0.044)	0.086 ** (0.043)	0.085 * (0.044)	-0.007 (0.039)	-0.003 (0.040)	-0.008 (0.040)
Specialized Inventors	0.080 (0.175)	0.485 *** (0.165)	0.499 *** (0.060)	0.120 (0.077)	0.138 * (0.075)	0.132 * (0.076)	0.174 ** (0.075)	0.181 ** (0.076)	0.190 *** (0.072)
Related Inventors	0.236 (0.176)	-0.170 (0.113)	0.091 * (0.049)	0.084 (0.055)	0.092 * (0.055)	0.110 ** (0.056)	0.030 (0.036)	0.041 (0.036)	0.036 (0.035)
Unrelated Inventors	0.337 ** (0.141)	-0.042 (0.149)	0.082 (0.098)	0.170 (0.110)	0.178 (0.110)	0.177 (0.110)	0.070 (0.108)	0.076 (0.108)	0.074 (0.107)
PV Modules					-0.189 * (0.111)	-0.196 * (0.110)		0.048 (0.093)	0.026 (0.093)
PV Cells					-0.481 *** (0.144)			-0.085 (0.109)	
Silicon Cells						-1.665 *** (0.450)			-0.833 ** (0.368)
Thin Film Cells						-0.371 ** (0.155)			-0.136 (0.130)
Organic Cells						-0.368 (0.311)			0.126 (0.169)
Foreign Inventors	-1.130 * (0.641)	-0.764 ** (0.342)	0.172 *** (0.042)	0.087 (0.085)	0.034 (0.087)	0.043 (0.086)	-0.006 (0.074)	-0.007 (0.074)	-0.011 (0.074)
IPC Classes	0.125 (0.078)	0.086 ** (0.043)	0.087 *** (0.032)	0.158 *** (0.028)	0.156 *** (0.027)	0.155 *** (0.027)	0.116 ** (0.046)	0.118 ** (0.046)	0.108 ** (0.045)
Backward Citations	0.025 (0.022)	0.024 (0.015)	0.011 *** (0.002)	0.021 *** (0.008)	0.022 *** (0.008)	0.023 *** (0.008)	0.012 ** (0.005)	0.012 ** (0.005)	0.012 ** (0.005)
New Combination	-0.194 (0.204)	-0.190 (0.146)	-0.132 (0.120)	-0.256 ** (0.125)	-0.297 ** (0.123)	-0.301 ** (0.123)	-0.167 (0.154)	-0.165 (0.156)	-0.163 (0.154)
Family Size	0.147 *** (0.024)	0.057 *** (0.008)	0.076 *** (0.006)	0.121 *** (0.013)	0.112 *** (0.014)	0.111 *** (0.014)	0.134 *** (0.010)	0.135 *** (0.010)	0.132 *** (0.010)
PCT Patent	-0.595 (0.983)	-0.821 *** (0.306)	0.110 (0.225)	-32.345 *** (0.526)	-31.298 *** (0.536)	-31.321 *** (0.534)	0.108 (0.404)	0.122 (0.405)	0.188 (0.393)
Granted Patent	0.342 ** (0.147)	0.640 *** (0.136)	0.131 (0.091)	0.065 (0.094)	0.081 (0.092)	0.076 (0.093)	0.064 (0.094)	0.056 (0.094)	0.065 (0.092)
USPTO	1.895 *** (0.511)	0.741 * (0.404)	1.016 *** (0.166)	1.104 *** (0.212)	1.272 *** (0.236)	1.214 *** (0.226)	1.041 *** (0.266)	1.103 *** (0.271)	1.107 *** (0.279)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	827	332	825	782	782	782	909	909	909
df	790	315	807	742	740	738	888	886	884
loglik	-832.361	-673.535	-1928.075	-1314.259	-1307.914	-1305.916	-2029.824	-2029.360	-2024.069
AIC	1740.723	1383.071	3894.151	2710.518	2701.829	2701.833	4103.649	4106.719	4100.139
McFadden R ²	0.082	0.073	0.096	0.070	0.074	0.075	0.059	0.059	0.062

Robust standard errors in parenthesis. Sig. at *** 0.01, ** 0.5, * 0.1 level

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. Here, *New Inventors* as well as *Specialized Inventors* are decisive. It was however supposed 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 need further knowledge from related fields. Concerning the control variables, *Foreign Inventors* still have a negative coefficient, but the size of the effect decreases. Interestingly, *PCT Patent* shows a significant negative effect.

In the era of incremental change, presented in model 7, again *New Inventors* and *Specialized Inventors* play a significant role, which is in line with the proposed model. Additionally, *Related Inventors* are able to integrate knowledge from adjacent technologies into the WP knowledge base. 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* are positive and significant, 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* contribute to technological development. However, controlling for different subtechnologies in model 5a and 5b reveals that also *Specialized Inventors* and *Related Inventors* have a positive effect. *Unrelated Inventors*, as proposed, do not matter, but *New Inventors* as well as *Specialized Inventors* do. 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). This diverse areas of application could explain the different sources influencing the technology, especially at the subtechnology 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 subtechnologies. Similar to the overall results, *Foreign Inventors* have no influence.

During the emergence of the dominant design, only *Specialized Inventors* contribute to the technological development, irrespectively controlling for subtechnologies or not. Contrary to the theoretical expectation, *Related Inventors* do not matter. 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 effect of *New Combinations* is not significant anymore.

Overall it is eminent that the knowledge relevant to advance the technologies 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 do not matter in both cases. The era of ferment 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* become 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 more fine grained by rolling-window regressions. They allow to analyze changes in the effect of different types of inventors over time. The rolling-window regressions here use an eight-year window 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. For WP, model 4 is used and for PV model 4b to estimate the rolling-window regressions. Figure 6 presents the results for WP and PV graphically.¹³ The coefficients for the different inventors of the regressions are plotted along with the 10% confidence intervals for each eight-year period.¹⁴ To test the proposed TLC model, the time periods in which the respective inventor type should have an effect are non-shaded in Figure 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 however a significant effect already from the end of the 1980s onward which is persistent until the end of the observation period, indicating 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 *New Inventors* do not matter for about the first 15 years, but have a substantial effect 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. Since this large scale wind turbine failed, focus was put on small

¹³The variation in the plotted graph is the result of 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. This implies that each period can be considered on its own, but changes from one period to another should be interpreted with caution.

¹⁴Sensitivity tests for five and eleven years are discussed in Section 4.4.

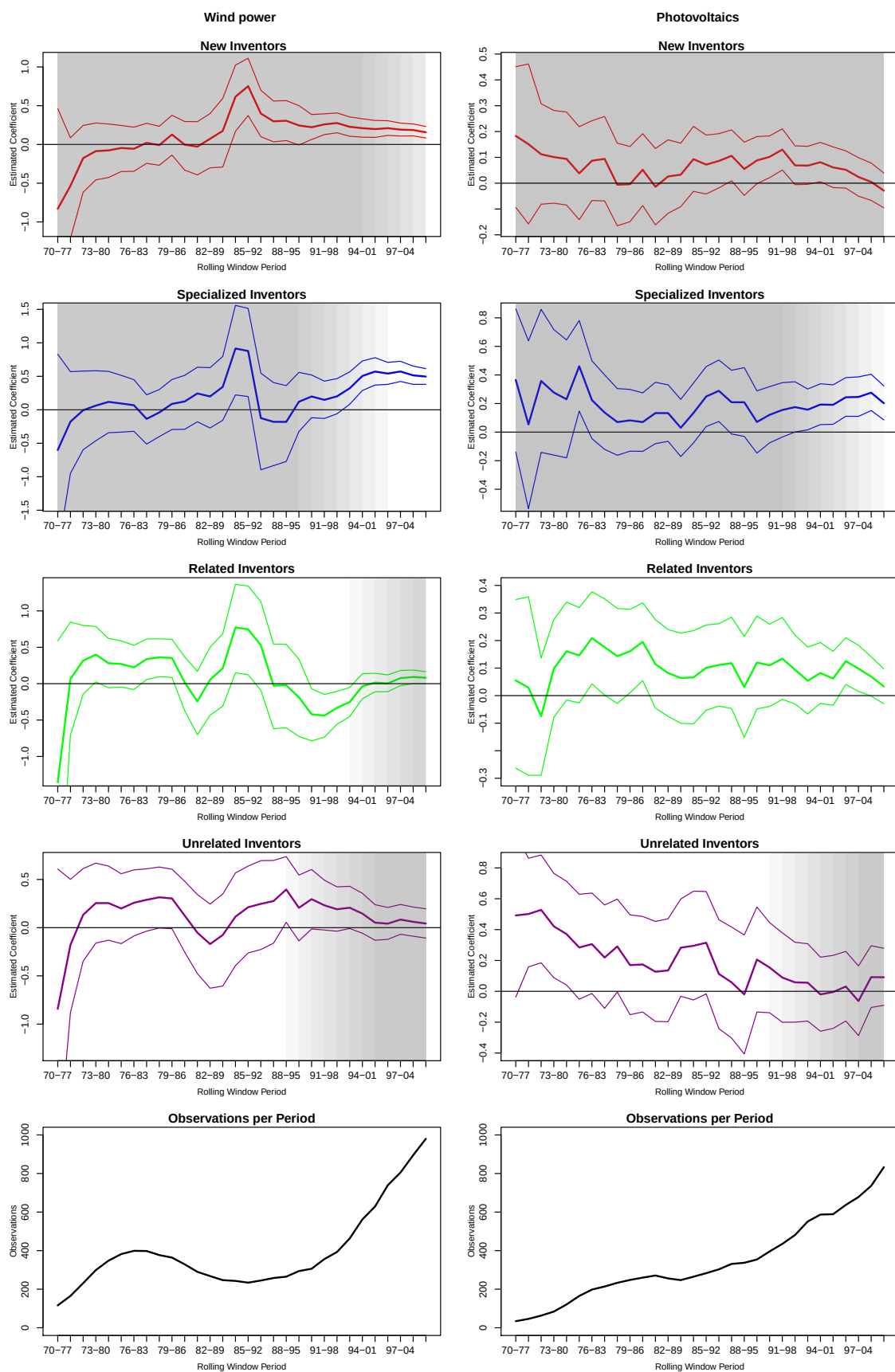


Figure 6: Eight year long rolling window regression results for wind power and photovoltaics.

scale turbines and new actors entered the technology (Bergek and Jacobsson, 2003). *Specialized Inventors* are supposed to be relevant in the emergence of the dominant design and the era of incremental change. The results nicely show how these inventors become relevant 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 relevant 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 effect 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, the *Related Inventors* become slightly significant and seem to play a role again, which is also shown in the TLC regression. The rolling-window regressions reveal a significant negative effect in some periods which is unnoticed in the TLC regressions. *Unrelated Inventors* are supposed to have an effect in the era of ferment. The results show basically no effect at all. Only in some periods in the era of ferment, the coefficient is close to significant. This contrasts the results from the regression for the era of ferment, which finds an effect. However, the number of observations are quite low in these rolling-window regressions which could explain that a significant effect does not show up. Towards the end of the observation period, there is no effect of these inventors at all, indicating that knowledge from outside the technology's domain does not matter and *Unrelated Inventors* seem not to disrupt the technology until then.

In PV, only the first two stages can be analyzed in which *New Inventors* are 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 there is a significant positive effect. This small effect is also present in the TLC regression conducted earlier. *Specialized Inventors* are supposed to matter while the dominant design emerges. Here, we can see an increase of the effect in this period in line with the model. In the earlier periods, there are only a few periods in which these inventors are relevant as well.

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

Overall, the rolling-window regression provide further insights into the technological development. In both technologies we see shifts of relevance of different inventors over time. For WP, we can observe that *New Inventors* and *Specialized Inventors* become relevant, *New Inventors* even much earlier than expected. Also 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* have a negative effect while the dominant design emerges. In PV the results

are in general not that pronounced, but partially in line with the model. *New Inventors* play basically no role, as expected, and *Specialized Inventors* only have a significant effect while the dominant design emerges. *Related Inventors* should have an effect along the whole observation period, but show only a significant effect in some periods. *Unrelated Inventors* show as expected an effect 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 length (see Appendix A.5). 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 which 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 9 shows the results for WP and PV for model 4 and the TLC phases. For WP, we see in model 4 that the *Unrelated Inventors* are no longer significant. In the first phase of the TLC, the effect of *Unrelated Inventors* becomes stronger, but surprisingly *New Inventors* are no longer significant. In the second phase, the *Unrelated Inventors* become significant again, however, with a negative coefficient. In the last phase, no changes occur. In PV, Model 4b shows basically no differences, while in the era of ferment *Specialized Inventors* loose their 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 10. 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 Figure 8. For WP, accounting for different interactions does not change the results in the 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 neither, but here 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 fosters technological development. The phase in which the dominant design emerges shows deviating results. *New Inventors* and *Specialized Inventors* are no longer significant and *Related Inventors* are 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 the model 4b. Here, *New Inventors* and *Unrelated Inventors* become significant as well. Concerning the interactions, there is a negative, significant effect 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 effect. In the era of ferment, we observe that *Specialized Inventors* and *Related Inventors* are no longer significant, but *Unrelated Inventors* become 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 effect.

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 inventors. In most cases heterogeneous teams exhibit a negative effect which is contrary to the previous findings of these stream of literature. Especially in PV controlling for team composition reveals effects for *New Inventors* and *Unrelated Inventors* in the full model. Furthermore, there are some hints that also the effect 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 over time. However, the effects might be dependent on the length of the time window. Shorter time periods should increase the volatility, since the number of observation 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 observation 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 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 extends the knowledge base of a technology along its life cycle. For this purpose, from a theoretical perspective, 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 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 partly in line with the theoretical elaborations. 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 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. In the era of ferment, WP requires unrelated knowledge as expected, however, not related knowledge. In PV its the opposite: related knowledge is relevant, but unrelated not. 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 which it can benefit from, 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 this phase. 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. 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.

Rolling-window regressions, introduced as a new method in this stream of literature, reveal a finer grained picture of the relevance of different kinds of knowledge along the TLC. They allow to observe the effect of different sources of knowledge in a continuous way and 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. However, the rolling-windows reveal some differences. 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 periods later on. New knowledge becomes relevant from the 1990s onwards and some years later specialized knowledge as well. These time nuances cannot be observed in the normal regressions. In PV, new knowledge matters hardly 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.

These 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 which is used for technological advancement. 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 driving force and specialization on 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 technological concepts are present and developing 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 these 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 further research is necessary to provide a more fine grained understanding how knowledge is relevant for technical progress in different subtechnologies or components.

From a theoretical perspective, integrating a knowledge related 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 and knowledge recombination along the TLC 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 have 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 on industrial dynamics. The dynamics in a sector's underlying technology allow to infer towards the life cycle of the sector as well, since here actors transform the knowledge into products. This knowledge is however generated by a diverse set of actors, such as research institutes, universities, users, tinkers and knowledge is not bound to the firm. Integrating the overall TLC in studies on industrial dynamics helps to understand how technologies and the related sector and firms evolve. Third, the personal characteristics of inventors seem to be relevant for knowledge recombination. This dimension was absent in previous studies on knowledge recombination and the actual persons involved in the recombinatorial process need further research. Fourth, the chosen technologies provide new cases besides the commonly used biotech 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 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 for 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, 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 however a difficult task for policy making.

The analysis faces certain shortcomings and limitations which 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. Applying this approach to technologies which faced a discontinuity would shed light on this phase as well. 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 which could not be explored in more detail, such as the team composition which seems to matter partly and changes along the TLC. Subtechnologies 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 only and not all inventions are patented. 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.

Acknowledgment: Previous drafts of the paper have been presented at the European Meeting on Applied Evolutionary Economics 2013 in Sophia Antipolis, the 2014 SPRU DPhil Day in Brighton and the 15th International Conference of the International Joseph A. Schumpeter Society in Jena. The Paper benefited from discussions by and with Stephan B. Bruns, Uwe Cantner, Alex Coad, Holger Graf, Johannes Herrmann, Max-Peter Menzel, Francesco Quatraro, Giorgio Triulzi, Susanne Walter. The usual caveats apply.

A Appendix

A.1 Patent selection approach

The WP and PV patents were queried from Patstat ([EPO, 2014](#)) by combining IPC classes and keywords. The title and abstract of patent documents are searched for the keyword while restricted to the specific IPC class. 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 derived in [Kalthaus \(2016\)](#). The keywords and IPCs are grouped for specific subtechnologies and fields to reduce the overlap with other adjacent technologies. The `_` and the `%` symbol are used as single and multiple wildcards.

Table 4: List of IPC and keywords for patent selection.

Tech.	Subtechnology	IPC Class	Keyword combination
WP		F03D%	
		H02K 7/18 B63B 35/00 E04H 12/00	((%wind% + (%turbine% %power% %mill% %energ%)))
PV	Silicon Cells	H01L 21% H01L 31% C30B 15%	((%monocrystalline_silicon% %monocrystal_silicon% %crystal_silicon% %silicon_crystal% %silicon_wafer%) + (%photovoltaic% %solar%)) %back_surface_passivation% (%pyramid% + %etching% + %silicon%)
		C01B 33% C30B 15% C30B 29% H01L 21% H01L 31%	((%polycrystalline_silicon% %multicrystalline_silicon% %poly-Si% %polysilicon%) + (%photovoltaic% %solar%)) (%ribbon% + (%photovoltaic% %solar% %silicon%)) (%Edge_defined_film_fed_growth% + %silicon%) %Metal_wrap_through% %Emitter_wrap_through% %Ribbon-growth%
		C23C 14% C23C 16% H01L 21% H01L 27% H01L 29% H01L 31%	((%chemical_vapour_deposition% %PECVD% %Physical_vapour_deposition% %PVD% %solid_phase_crystallization% %laser_crystallization% %Nanocrystalline% %microcrystalline%) + (%photovoltaic% %solar% %silicon%)) ((%tandem% %amorphous_silicon% %silicon_substrate% %silicon_film%) + (%photovoltaic% %solar%)) %Staebler_wronski%
		C23C 14% C23C 16% H01L 21% H01L 25% H01L 27% H01L 29% H01L 31%	((%Cadmium_Telluride% %CdTe% %Copper_Indium_diselenide% % CIS % %CuInSe% %indium_tin_oxide% %gallium_arsenide% %GaAs% %roll_to_roll% %surface_textur% %thin_film% %thinfil%) + (%photovoltaic% %solar%)) %Copper_indium_gallium_diselenide% %CuInGeSe% %CIGS% %Copper_zinc_tin_sulfide% %CZTS% %Kesterite%
	Thin Film Cells	C23C 14% C23C 16% H01L 21% H01L 25% H01L 27% H01L 29% H01L 31%	((%Cadmium_Telluride% %CdTe% %Copper_Indium_diselenide% % CIS % %CuInSe% %indium_tin_oxide% %gallium_arsenide% %GaAs% %roll_to_roll% %surface_textur% %thin_film% %thinfil%) + (%photovoltaic% %solar%)) %Copper_indium_gallium_diselenide% %CuInGeSe% %CIGS% %Copper_zinc_tin_sulfide% %CZTS% %Kesterite%
		C23C 14% C23C 16% H01L 21% H01L 25% H01L 27% H01L 29% H01L 31%	((%Cadmium_Telluride% %CdTe% %Copper_Indium_diselenide% % CIS % %CuInSe% %indium_tin_oxide% %gallium_arsenide% %GaAs% %roll_to_roll% %surface_textur% %thin_film% %thinfil%) + (%photovoltaic% %solar%)) %Copper_indium_gallium_diselenide% %CuInGeSe% %CIGS% %Copper_zinc_tin_sulfide% %CZTS% %Kesterite%
		C23C 14% C23C 16% H01L 21% H01L 25% H01L 27% H01L 29% H01L 31%	((%Cadmium_Telluride% %CdTe% %Copper_Indium_diselenide% % CIS % %CuInSe% %indium_tin_oxide% %gallium_arsenide% %GaAs% %roll_to_roll% %surface_textur% %thin_film% %thinfil%) + (%photovoltaic% %solar%)) %Copper_indium_gallium_diselenide% %CuInGeSe% %CIGS% %Copper_zinc_tin_sulfide% %CZTS% %Kesterite%
		C23C 14% C23C 16% H01L 21% H01L 25% H01L 27% H01L 29% H01L 31%	((%Cadmium_Telluride% %CdTe% %Copper_Indium_diselenide% % CIS % %CuInSe% %indium_tin_oxide% %gallium_arsenide% %GaAs% %roll_to_roll% %surface_textur% %thin_film% %thinfil%) + (%photovoltaic% %solar%)) %Copper_indium_gallium_diselenide% %CuInGeSe% %CIGS% %Copper_zinc_tin_sulfide% %CZTS% %Kesterite%
	Organic Cells	C08K 3% C08G 61% H01B 1% H01G 9% H01L 21% H01L 31% H01L 51% H01M 14%	((%Dye_sensiti% %titanium_oxide% %titanium_dioxide% %TiO2% %Organic% %polymer%) + (%photovoltaic% %solar%)) %Gr_tzel% %Graetzel% %hybrid_solar_cell%
		H01G 9% H01L 31% H01L 51% H01M 14%	((%Quantum_dot% %perovskite% %organic_inorganic% %Plasmon% %Nanowire% %nanoparticle% %nanotube%) + (%photovoltaic% %solar%))
		H01G 9% H01L 31% H01L 51% H01M 14%	((%Quantum_dot% %perovskite% %organic_inorganic% %Plasmon% %Nanowire% %nanoparticle% %nanotube%) + (%photovoltaic% %solar%))
		H01G 9% H01L 31% H01L 51% H01M 14%	((%Quantum_dot% %perovskite% %organic_inorganic% %Plasmon% %Nanowire% %nanoparticle% %nanotube%) + (%photovoltaic% %solar%))
	PV Modules	H01L 21% H01L 25% H01L 27% H01L 31% H01R 13% H02N 6% H02S 20% H02S 30% B64G 1% E04D 13%	((%anti_reflection% %encapsulat% %back_contact% %buried_contact% %bypass_diode% %rear_surface_protection% %back_sheet% %building_integrat% %mounting_system%) + (%photovoltaic% %solar%)) %solar_panel% %photovoltaic_panel% %solar_modul% %solar_cell_modul% %photovoltaic_modul% %solar_cable% %Photovoltaic_Wire% %solar_array% %photovoltaic_array% %BIPV% %solar_park% (%spacecraft% + (%photovoltaic% %solar_cell%))
		H01L 21% H01L 25% H01L 27% H01L 31% H01R 13% H02N 6% H02S 20% H02S 30% B64G 1% E04D 13%	((%anti_reflection% %encapsulat% %back_contact% %buried_contact% %bypass_diode% %rear_surface_protection% %back_sheet% %building_integrat% %mounting_system%) + (%photovoltaic% %solar%)) %solar_panel% %photovoltaic_panel% %solar_modul% %solar_cell_modul% %photovoltaic_modul% %solar_cable% %Photovoltaic_Wire% %solar_array% %photovoltaic_array% %BIPV% %solar_park% (%spacecraft% + (%photovoltaic% %solar_cell%))
		H01L 21% H01L 25% H01L 27% H01L 31% H01R 13% H02N 6% H02S 20% H02S 30% B64G 1% E04D 13%	((%anti_reflection% %encapsulat% %back_contact% %buried_contact% %bypass_diode% %rear_surface_protection% %back_sheet% %building_integrat% %mounting_system%) + (%photovoltaic% %solar%)) %solar_panel% %photovoltaic_panel% %solar_modul% %solar_cell_modul% %photovoltaic_modul% %solar_cable% %Photovoltaic_Wire% %solar_array% %photovoltaic_array% %BIPV% %solar_park% (%spacecraft% + (%photovoltaic% %solar_cell%))
		H01L 21% H01L 25% H01L 27% H01L 31% H01R 13% H02N 6% H02S 20% H02S 30% B64G 1% E04D 13%	((%anti_reflection% %encapsulat% %back_contact% %buried_contact% %bypass_diode% %rear_surface_protection% %back_sheet% %building_integrat% %mounting_system%) + (%photovoltaic% %solar%)) %solar_panel% %photovoltaic_panel% %solar_modul% %solar_cell_modul% %photovoltaic_modul% %solar_cable% %Photovoltaic_Wire% %solar_array% %photovoltaic_array% %BIPV% %solar_park% (%spacecraft% + (%photovoltaic% %solar_cell%))
	Other	B64G 1% C01B 33% C08K 3% 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%	(%photovoltaic% %solar_cell%)
		B64G 1% C01B 33% C08K 3% 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%	(%photovoltaic% %solar_cell%)
		B64G 1% C01B 33% C08K 3% 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%	(%photovoltaic% %solar_cell%)
		B64G 1% C01B 33% C08K 3% 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%	(%photovoltaic% %solar_cell%)

A.2 Decriptives

Table 5: Descriptive Statistics for Wind power and Photovoltaic

	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
	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
Knowledable 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
IPC Classes	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	0,29	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
PV Cells	PV	0	0	0,167	1	0,373
Silicon Cells	PV	0	0	0,021	1	0,142
Thin Film Cells	PV	0	0	0,100	1	0,300
Organic Cells	PV	0	0	0,054	1	0,227

A.3 Correlations

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 IPC Classes	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: Correlation for Photovoltaics

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
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	0.005	—												
10 IPC Classes	0.083	0.018	-0.097	0.081	0.015	0.036	0.030	0.084	-0.001	—											
11 Backward Citations	0.076	0.015	0.058	-0.048	-0.022	0.017	-0.022	-0.054	0.070	-0.005	—										
12 New Combination	-0.015	0.021	-0.069	-0.001	0.075	0.004	-0.011	0.025	-0.006	0.532	-0.010	—									
13 Family Size	0.378	0.041	0.088	0.180	-0.014	0.227	0.208	0.171	0.115	0.124	0.042	0.056	—								
14 PCT Patent	0.011	-0.022	0.061	-0.033	0.002	-0.008	0.001	-0.032	0.020	-0.029	0.025	-0.049	-0.009	—							
15 Granted Patent	0.051	0.064	0.047	-0.003	-0.023	0.079	0.014	-0.011	0.070	0.044	0.248	0.041	0.105	-0.068	—						
16 USPTO	0.122	-0.024	0.025	-0.031	-0.048	0.077	-0.032	-0.047	0.364	-0.046	0.265	-0.008	-0.020	-0.012	0.105	—					
17 PV Modules	-0.052	-0.060	-0.012	-0.097	-0.055	-0.151	-0.115	-0.115	-0.058	-0.038	0.041	-0.117	-0.158	0.000	-0.038	-0.084	—				
18 PV Cells	-0.029	0.039	0.067	0.162	-0.027	0.179	0.176	0.148	0.048	-0.013	0.016	-0.029	-0.039	0.029	0.132	0.132	-0.084	—			
19 Silicon Cells	-0.056	-0.007	0.064	0.105	-0.019	0.095	0.125	0.096	0.011	-0.024	-0.016	-0.029	-0.014	0.078	-0.020	-0.076	0.324	—			
20 Thin Film Cells	-0.052	0.021	0.076	0.036	0.021	0.086	0.079	0.043	0.028	-0.069	0.049	-0.048	-0.055	-0.030	0.101	0.149	-0.059	0.743	—		
21 Organic Cells	0.048	0.076	-0.032	0.163	-0.059	0.160	0.116	0.139	0.050	0.105	-0.036	0.052	0.028	0.036	-0.081	0.027	-0.024	0.535	-0.017	-0.019	—

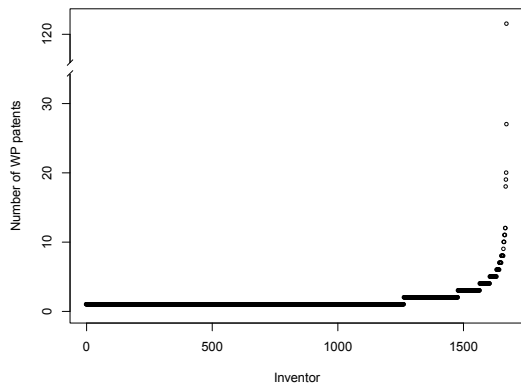
A.4 Inventor Types

In this section, more 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.

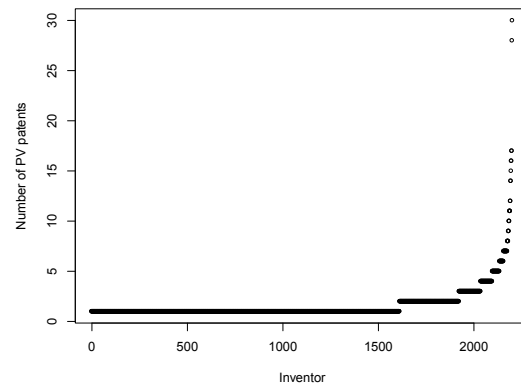
Table 8: Number of inventors

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

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 of patents to the type of inventor. Related and Unrelated Inventors can have only one patent or inventors which start and continue their inventive activity have more than one patent. Remarkably is the WP inventor with 127 patents. This inventor is Aloys Wobben, founder of the German wind turbine manufacturer Enercon.



(a) Wind power patents per inventor.



(b) Photovoltaics patents per inventor.

Figure 7: Number of Wind power and Photovoltaics patents each inventor possess.

Figure 8 depicts the team composition in WP and PV. A edge between two different kinds of inventor is established if they are present on the same patent. The loops for each inventor consists of patents invented by only one type of inventor, regardless of the amount (patents with only one inventor are included in the loop as well). 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.

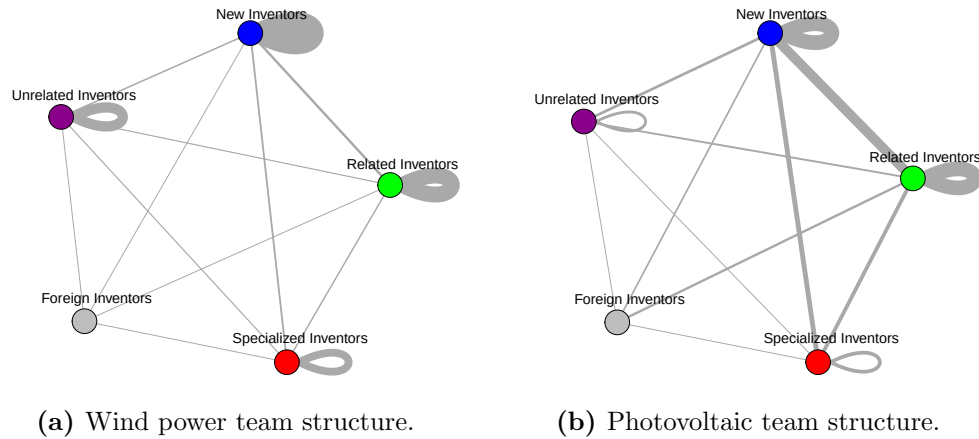


Figure 8: Team structures in WP and PV.

A.5 Robustness tests

Table 9: 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 4b Full Period	Model 5b Era of Ferment	Model 6b Dominant Design
	1970-2006	1970-1995	1996-2000	2001-2006	1970-2006	1970-1997	1998-2006
New Inventors	0.163 *** (0.039)	0.142 (0.094)	0.269 *** (0.067)	0.146 *** (0.053)	0.033 (0.030)	0.083 * (0.044)	-0.007 (0.040)
Specialized Inventors	0.425 *** (0.055)	0.052 (0.180)	0.489 *** (0.166)	0.508 *** (0.060)	0.164 *** (0.055)	0.123 (0.075)	0.186 *** (0.072)
Related Inventors alt.	0.088 (0.054)	0.071 (0.199)	-0.049 (0.121)	0.148 ** (0.062)	0.092 ** (0.038)	0.174 ** (0.069)	0.060 (0.047)
Unrelated Inventors alt.	0.073 (0.054)	0.377 *** (0.135)	-0.258 * (0.140)	0.025 (0.060)	0.004 (0.040)	0.030 (0.069)	-0.001 (0.048)
PV Modules					-0.046 (0.072)	-0.179 (0.110)	0.022 (0.093)
Silicon Cells					-0.935 *** (0.342)	-1.708 *** (0.458)	-0.829 ** (0.383)
Thin Film Cells					-0.234 ** (0.098)	-0.351 ** (0.155)	-0.139 (0.129)
Organic Cells					-0.039 (0.151)	-0.400 (0.318)	0.103 (0.168)
Foreign Inventors	0.142 *** (0.041)	-1.181 * (0.648)	-0.670 * (0.373)	0.170 *** (0.042)	0.007 (0.058)	0.034 (0.086)	-0.016 (0.073)
IPC Classes	0.092 *** (0.024)	0.120 (0.076)	0.085 * (0.044)	0.084 *** (0.032)	0.135 *** (0.025)	0.147 *** (0.027)	0.110 ** (0.044)
Backward Citations	0.012 *** (0.002)	0.021 (0.022)	0.025 (0.016)	0.011 *** (0.002)	0.016 *** (0.004)	0.024 *** (0.008)	0.012 ** (0.005)
New Combination	-0.139 (0.086)	-0.123 (0.205)	-0.192 (0.149)	-0.130 (0.121)	-0.212 ** (0.098)	-0.270 ** (0.119)	-0.167 (0.152)
Family Size	0.068 *** (0.005)	0.149 *** (0.024)	0.053 *** (0.009)	0.074 *** (0.006)	0.126 *** (0.008)	0.113 *** (0.014)	0.131 *** (0.010)
PCT Patent	0.128 (0.225)	-0.584 (0.977)	-0.511 (0.339)	0.117 (0.228)	-0.027 (0.415)	-30.337 *** (0.533)	0.212 (0.406)
Granted Patent	0.320 *** (0.067)	0.315 ** (0.147)	0.617 *** (0.136)	0.137 (0.090)	0.060 (0.064)	0.088 (0.092)	0.058 (0.092)
USPTO	1.034 *** (0.159)	1.945 *** (0.518)	0.734 * (0.403)	1.025 *** (0.166)	1.129 *** (0.205)	1.186 *** (0.218)	1.108 *** (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
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 parenthesis. Sig. at *** 0.01, ** 0.05, * 0.1 level

Table 10: Regression results for inventor interactions

	Wind Power						Photovoltaics		
	Negative Binomial Regressions: Dependent Variable: Forward Citations per Patent								
	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 4b Full Period 1970-2006	Model 5b Era of Ferment 1970-1997	Model 6b Dominant Design 1998-2006		
New Inventors	0.202 *** (0.052)	0.252 *** (0.114)	0.100 (0.158)	0.179 *** (0.069)	0.081 * (0.047)	0.109 * (0.063)	0.020 (0.065)		
New Inventors x Specialized Inventors	-0.098 * (0.052)	-0.641 (0.601)	-0.195 ** (0.098)	-0.138 ** (0.061)	-0.026 (0.043)	-0.038 (0.057)	0.008 (0.063)		
New Inventors x Related Inventors	0.057 (0.035)	-0.893 ** (0.429)	0.288 (0.225)	0.065 * (0.037)	-0.022 (0.019)	0.002 (0.049)	-0.006 (0.022)		
New Inventors x Unrelated Inventors	-0.166 ** (0.082)	-0.041 (0.187)	-0.147 (0.209)	-0.246 * (0.127)	-0.191 *** (0.069)	-0.174 * (0.106)	-0.172 * (0.099)		
Specialized Inventors	0.524 *** (0.073)	0.307 (0.237)	0.218 (0.261)	0.617 *** (0.079)	0.207 *** (0.075)	0.119 (0.110)	0.258 *** (0.086)		
Specialized Inventors x Related Inventors	-0.168 ** (0.076)	-0.433 (0.334)	0.885 *** (0.333)	-0.231 *** (0.082)	0.015 (0.061)	0.131 (0.098)	-0.100 (0.071)		
Specialized Inventors x Unrelated Inventors	-0.155 (0.170)	-0.226 (0.358)	-37.941 *** (0.805)	0.075 (0.180)	-0.176 (0.112)	-0.112 (0.182)	-0.219 (0.154)		
Related Inventors	0.098 (0.062)	0.291 (0.200)	-0.563 ** (0.251)	0.134 ** (0.059)	0.074 * (0.042)	0.081 (0.073)	0.041 (0.053)		
Related Inventors x Unrelated Inventors	-0.061 (0.074)	0.928 ** (0.431)	0.479 ** (0.188)	-0.164 (0.101)	0.047 (0.061)	0.066 (0.126)	0.071 (0.079)		
Unrelated Inventors	0.213 ** (0.090)	0.385 ** (0.180)	-0.353 (0.277)	0.195 (0.126)	0.259 ** (0.107)	0.285 ** (0.130)	0.188 (0.179)		
PV Modules									
Silicon Cells									
Thin Film Cells									
Organic Cells									
Foreign Inventors	0.137 *** (0.042)	-1.138 * (0.643)	-0.940 *** (0.324)	0.164 *** (0.043)					
IPC Classes	0.093 *** (0.024)	0.139 * (0.076)	0.065 (0.045)	0.084 *** (0.032)					
Backward Citations	0.012 *** (0.002)	0.027 (0.022)	0.017 (0.015)	0.011 *** (0.002)					
New Combination	-0.140 * (0.084)	-0.220 (0.203)	-0.155 (0.146)	-0.123 (0.119)					
Family Size	0.070 *** (0.005)	0.147 *** (0.024)	0.063 *** (0.009)	0.077 *** (0.006)					
PCT Patent	0.135 (0.227)	-0.737 (1.024)	36.429 *** (0.798)	0.110 (0.236)					
Granted Patent	0.322 *** (0.067)	0.323 ** (0.142)	0.658 *** (0.137)	0.135 (0.092)					
USPTO	1.030 *** (0.163)	1.858 *** (0.505)	1.019 ** (0.406)	1.035 *** (0.172)					
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		
Pseudo R ²	0.147	0.088	0.082	0.099	0.078	0.077	0.063		

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

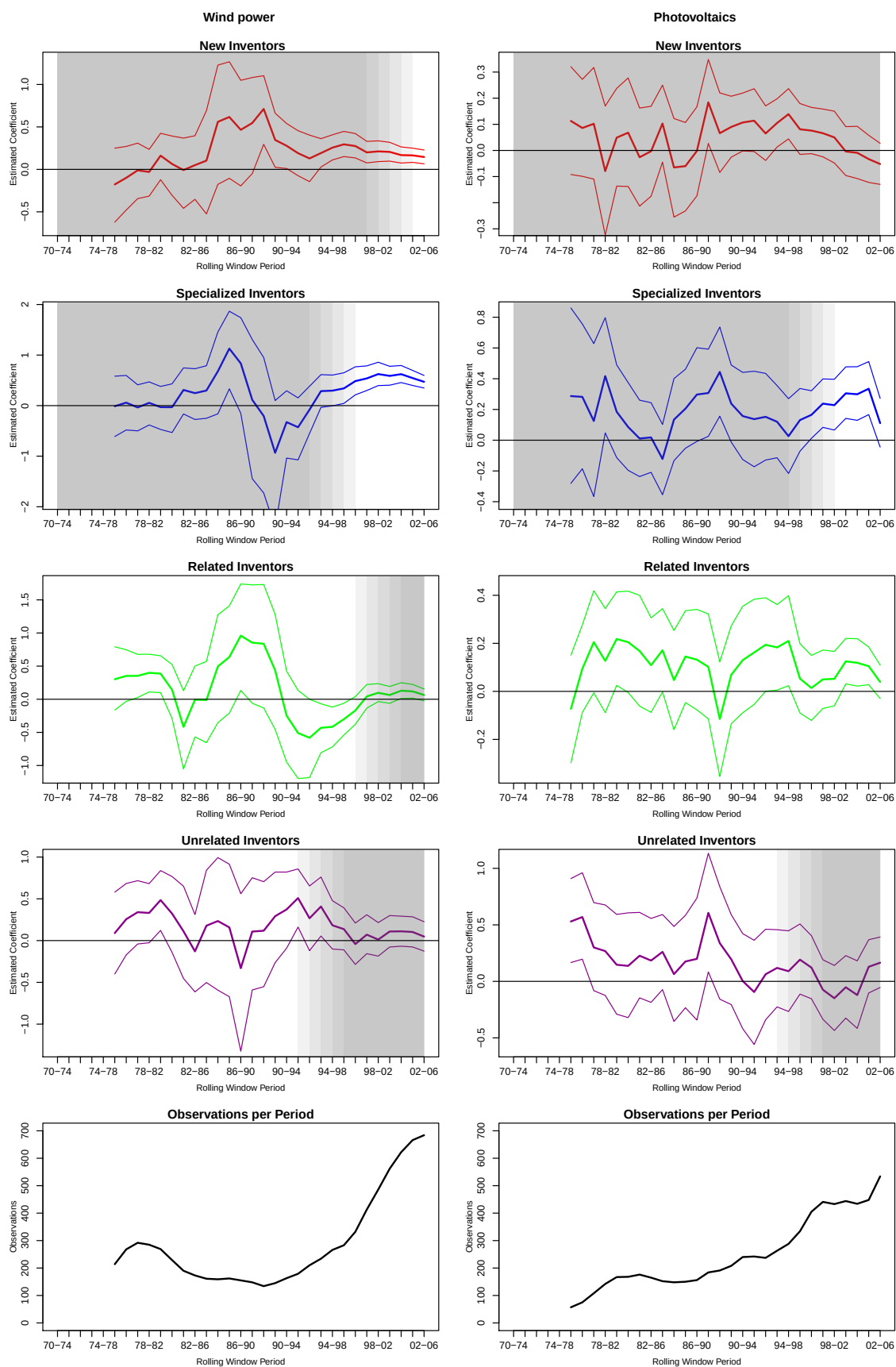


Figure 9: Five year long rolling-window regression results for wind power and photovoltaics.

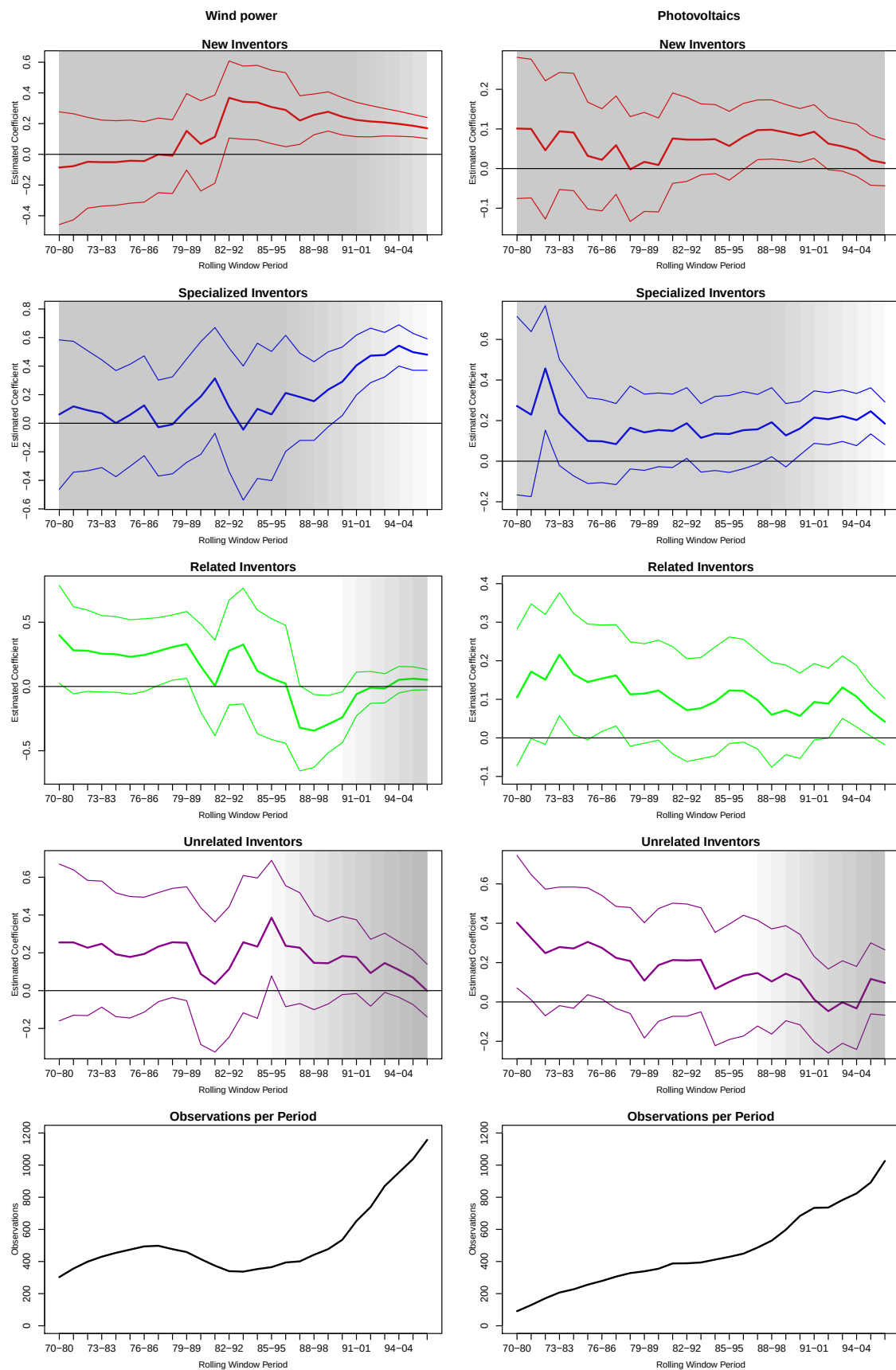


Figure 10: Eleven year long rolling-window regression results for wind power and photovoltaics.

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