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Inventor Networks in Renewable Energies: The Influence of the Policy Mix in Germany

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Abstract

Technological change and gains in efficiency of renewable power generation technologies are to a large extent driven by governmental support. Various policy instruments that can broadly be categorized as technology push, demand pull or systemic constitute part of the policy mix for renewable energies. Our goal is to gain insights into the influence of this policy mix on the intensity and organization of inventive activities for wind power and photovoltaics in Germany since the 1980s. We examine the effect of different instruments on the size and structure of co-inventor networks based on patent data. Our results indicate notable differences between the technologies: the network size for wind power is driven by technology push and systemic instruments, while in photovoltaics, demand pull is decisive for network growth. By and large, the instruments complement each other and form a consistent mix of policy instruments. The structure of the networks is driven by demand pull for both technologies. Systemic instruments increase interaction, especially in the wind power network, and are complementary to demand pull in fostering collaboration.

Keywords: Renewable Energy, Inventor Network, Policy Mix, Systemic Instrument, Technology Push, Demand Pull

JEL classification: Q42, Q55, L14, O31, O34, O38

1 Introduction

During the last decades, the global capacity for electric power generation by renewable sources (excluding hydropower) increased substantially from 85 GW in 2004 to 657 GW in 2014 (REN21 2015). In Germany, the share of renewable energies in electric power production reached 27% in 2014 (BMWi 2015). This development is mainly driven by political support and technological progress in the specific technologies. Several studies have shown that policies and environmental regulations are important drivers of innovative activities in environmental technologies, especially in renewable energies (Johnston et al. 2010, Grau et al. 2012, Peters et al. 2012, Wangler 2013, Dechezleprêtre and Glachant 2014, Costantini et al. 2015a). In particular, inventive activities, largely induced by policies for wind power (WP) and photovoltaic (PV) technologies, increased tremendously over the last decades.

Policies have been implemented in an attempt to influence the development and diffusion of renewable power generation technologies (RPGT), especially PV and WP, from different directions. Demand pull instruments affect innovative activities indirectly by creating demand for RPGT, e.g. through feed-in tariffs (FIT) or investment support, and thus increase market size. Technology-push instruments directly affect inventive and innovative activities by means of R&D subsidies or through performing public R&D in research institutes. Systemic instruments, such as cooperative R&D programs, clusters or infrastructure provisions, provide support for collaboration and knowledge transfer (Smits and Kuhlmann 2004). The combination of these policies constitutes an instrument mix[1], which needs to be consistent to support fully innovative activity.

With respect to technology push policies, while their influence on investments in R&D is quite clear, two important aspects of policy impact are less obvious. First, while demand pull instruments increase incentives to invest in production facilities, do they also increase incentives for innovation and investment in R&D? And if so, is it an immediate effect or rather a consequence of the change in market size and structure? Regarding the second aspect, it is common knowledge that internal investments in R&D are only one input in the innovation process. External knowledge, captured through technological spillovers, increases the knowledge-base of innovative actors and therefore has a positive influence on innovation output (Cassiman and Veugelers 2006). Several channels of technological spillovers have been

[1] The terms instrument mix and policy mix are not clearly defined and sometimes are used interchangeably. Here we rely on the distinction by Rogge and Reichardt (2015), where the instrument mix is an essential part of a broader policy mix.

identified in the economics of innovation, with personal contact through cooperation or job mobility being one of the most important (Singh 2005, Breschi and Lissoni 2009, Edler et al. 2011). These modes of interaction constitute a network of actors, being either organizations or individuals. Networks of knowledge exchange are widely viewed as a central driver for inventive activity and it is most likely that they are affected by different policies as well (Cantner and Graf 2011, Phelps et al. 2012, Broekel et al. 2015). What we do not know is how the mix of policies influences the structure of these networks.

The aim of this research is to understand how the different instruments of the policy mix as well as the consistency of this mix influence the process of invention and innovation in WP and PV. We focus on Germany because of the strong political support for renewable energies and the high share of German inventors in these specific industries. In addition, Germany represented a good fraction of the world market for RPGTs in our observation period (1978–2012). This is especially true for PV, where Germany represented between 30 and 60 per cent of the world market from 2001 to 2010 (IEA 2010). Our approach adds three important aspects to the existing literature. First, in addition to the level of inventive activity, we put the focus on the structure of relations within the network of collaboration. Second, regarding policy instruments, we distinguish between R&D subsidies that are granted to single organizations and research grants aimed at fostering collaboration and which can, therefore, be regarded as systemic (Smits and Kuhlmann 2004). Third, we test for the consistency of a set of instruments within a policy mix. Here, the effects of single policy instruments as well as of changes in the policy mix on networks of cooperation are studied by mapping co-inventor networks in the PV and WP industries in Germany.

We use patent applications in WP and PV by German inventors to reconstruct co-inventor networks and estimate the effects of several policies as well as their mix on the size and structure of these networks. By and large, the size of the networks is increased by technology push as well as systemic instruments, whereas demand pull policies seem especially effective in PV. The structure of the co-inventor networks is driven by systemic instruments, especially in WP. For both technologies, surprisingly, demand pull policies are very important in facilitating collaboration. The mix of these instruments shows strong consistency in most cases.

The remainder of this paper is organized as follows: in the following section, we give a short review of the literature on innovation networks and innovation policy and derive respective hypotheses. In section 3, a short overview of relevant policy instruments in Germany is provided. Section 4 describes the data and our empirical approach. Section 5 presents our results and discusses their robustness. In the last section, we discuss our findings and conclude.

2 Policy influence on innovation, collaboration and networks

2.1 The innovation - network nexus

Inventive activity, and innovative activity in general, is an interactive process of knowledge creation and accumulation (Kline and Rosenberg 1986) in which novelty is created by combining knowledge from a diverse set of actors (Kogut and Zander 1992). This knowledge re-combination is especially successful in teams that are able to combine diverse sets of knowledge (Wuchty et al. 2007, Bercovitz and Feldman 2011). Corresponding networks of knowledge transfer and learning constitute one important driver of innovation (Dosi 1988, Powell et al. 1996, Ahuja 2000). These networks can be studied by the use of social network analysis, which maps actors and their relations in the context of innovation and knowledge transfer[2]. Knowledge transfer can be traced through different types of networks, such as co-authorship networks (e.g. Barabasi et al. 2002, Newman 2004, Moody 2004, Acedo et al. 2006), co-invention (e.g. Balconi et al. 2004, Fleming and Frenken 2007, Casper 2013), university-industry research collaborations (e.g. Balconi et al. 2004, Ponds et al. 2010, Guan and Zhao 2013) and industry collaborations (e.g. Ahuja 2000, Hagedoorn 2002, Schilling and Phelps 2007).

The motives to engage in collaborations and to exchange knowledge are manifold (Cantner and Graf 2011) and the objective is to increase the inventive and innovative performance. Indeed, as empirical research finds, collaboration and networking in R&D in general lead to a higher research output than individual R&D activities (e.g. Czarnitzki et al. 2007, Fornahl et al. 2011). While there are relatively few studies on the relation between network structure and its performance, theoretical as well as empirical results suggest a positive influence of increased interaction (Powell and Grodal 2005, Fritsch and Graf 2011, Phelps et al. 2012). The speed of information diffusion increases with the connectivity of the network and the probability of knowledge transfer between individuals decreases the longer the paths connecting them (Singh 2005). Average innovative performance is higher in well-connected networks (Fleming et al. 2007). Analyzing these networks helps us to understand how knowledge is generated and distributed and the way in which it affects the actors in the networks.

[2] See Borgatti and Foster (2003) for a general overview of social network analysis and Cantner and Graf (2011) for an overview and application in the context of innovation networks.

2.2 Policy instruments fostering innovation and collaboration

2.2.1 Rationale for policy intervention

Due to the costly and uncertain nature of inventive and innovative activity, policy intervenes to enhance and increase research and development activities. Furthermore, there are several market failures that hamper inventive and innovative activity, such as knowledge externalities or technological lock-ins and path dependencies (Arthur 1989, Griliches 1992, Cecere et al. 2014).

Concerning cooperation in R&D, the implied knowledge transfer between the actors and the underlying network structures tends to be affected by system failures of complementarity (Do the diverse piece of knowledge and hence the actors behind fit together?), reciprocity (Is the network based exchange of knowledge governed by trust and reciprocity?) and intermediation (Are the eventual network partners aware of all potential cooperation partners?). Answering a "no" to any one of these questions leads to a rationale for policy intervention in order (i) to reduce the monetary risk of non-complementarity and/or non-reciprocity and (ii) to bear the costs of searching for appropriate partners (Carlsson and Jacobsson 1997, Klein-Woolthuis et al. 2005, Cantner et al. 2011). In this context, various types of policies may have different influences on network formation, thereby affecting the rate of knowledge transfer and consequently influencing the speed at which technologies are developed. For example, R&D subsidies are frequently and increasingly awarded only if actors collaborate on these projects to overcome such failures and incentivize joint research efforts (Broekel and Graf 2012).

Furthermore, environmentally friendly innovations generate positive externalities for society by reducing emissions and resource extraction that cannot be fully internalized. Therefore, these eco-innovations are subject to a double or multiple externality problem (Rennings 2000, Jaffe et al. 2005, Cecere et al. 2014).

To deal with these externalities, and to directly or indirectly foster inventive activity various instruments originating from different policy fields can be implemented. The main fields are *innovation policy*, where policy needs to address the underinvestment in R&D due to spillovers and non-excludability of new knowledge, path dependency, lock-ins and network effects; *environmental policy*, which deals with the negative external effects concerning emissions from conventional technologies; and *climate policy* which focuses especially on the adverse effects of greenhouse gas emissions.[3] A broad set of instruments from these fields supports and induces environmental innovations to overcome these externalities and increases

[3] Of course, other policy fields also influence inventive activity, such as energy policy in general, industrial policy or trade policy.

innovation and the diffusion of clean technologies (Jaffe et al. 2002, Kemp and Pontoglio 2011, Costantini and Crespi 2013, Groba and Breitschopf 2013). These sets of instruments can be conventionally classified in technology push and demand pull instruments. Furthermore, there is an increasing attention towards instruments affecting the above mentioned failures related to the systemic nature of the innovation process (Smits and Kuhlmann 2004, Wieczorek and Hekkert 2012), so called systemic instruments.

On this basis, we are interested in how the mix of these instruments influences inventive activities in environmentally friendly technologies. Taking into account the importance of cooperation in those activities, we focus on networks of inventive activity and formulate hypotheses regarding their size and structure. The former reflects the attractiveness of the system in terms of the number of inventive actors, while the structure is of particular importance for the potential knowledge transfer within networks (Cowan and Jonard 2004, Schilling and Phelps 2007).

2.2.2 Technology push instruments

There are several measures directly targeted at overcoming the above mentioned externalities and enhancing inventive activity. The most prominent instruments directly influencing inventors' activity are R&D subsidies or other means, such as tax incentives, to reduce the private costs of R&D activities. In his seminal report, Bush (1945) addressed the necessity to fund directly R&D activities to increase the knowledge stock and to increase research cooperation between actors. Since then, there has been a long debate about the effectiveness of direct R&D support and its benefits for inventive activity (cf. David et al. 2000, García-Quevedo 2004). Growing empirical evidence indicates that direct R&D funding increases inventive output (e.g. Czarnitzki and Hussinger 2004, Alecke et al. 2012), despite frequent concerns regarding crowding-out of private R&D investments (see Zúñiga-Vicente et al. (2014) for a review).

Several empirical studies have analyzed the effect of direct R&D subsidies in environmentally friendly technologies, especially renewable energies. Most of them use patent data as an output of the R&D process and estimate how R&D subsidies influence patenting activity. Johnston et al (2010) estimate for a panel of 25 countries that public R&D expenditure fosters inventive activity, especially in WP and PV. Wangler (2013) as well as Böhringer et al. (2014) focus their analyses on inventive activity in Germany and find that public R&D expenditure has a positive effect on inventive activity. Costantini et al. (2015a) find no positive effect for mature biofuel technologies, but a positive effect for less mature technologies that are still in the early stage of development. Costantini et al. (2015b) show for a panel of 23 OECD countries that technology push policies increase inventive performance in energy efficiency technologies. However, Nesta et al. (2014) find no significant effect of public R&D expenditure on green patents.

With our focus on collaboration and networking in R&D, we extend these analyses by looking at the effects of technology push instruments on inventor networks. First, since patents are the basis for the size of the co-inventor network, we expect that technology push instruments foster inventive activity and thereby increase the size of the network.

H1a: Technology push instruments increase the size of the co-inventor network

Second, concerning the structure of inventor networks, we do not expect an effect of individual funding. Technology push instruments are not designed to influence connectivity within the network, since by its very nature individual R&D funding does not aim at encouraging cooperation. In addition, inventors working for private companies may be concerned about secrecy and may prefer not to cooperate to inhibit an outflow of knowledge. This leads us to the following hypothesis:

H1b: Technology push instruments have no effect on cooperation within the co-inventor network

2.2.3 Systemic instruments

Systemic instruments are designed to provide support at the systemic level of inventive activity and reduce system failures (Chaminade and Edquist 2006, Wieczorek and Hekkert 2012). This includes the provision of infrastructure, especially to facilitate learning and knowledge exchange, to enhance cooperation, for example by cluster initiatives, or to foster cooperation between inventive actors (Smits and Kuhlmann 2004). The aim of such policies is to connect different actors, such as firms, universities and research institutes, to create a network of knowledge transfer, encourage learning processes and open up possibilities of resource and capability sharing. The most common systemic instrument is subsidizing research collaboration with the requirement to involve different actors in a R&D project. Such cooperative grants lead to higher inventive output compared to individual grants (e.g. Czarnitzki et al. 2007, Fornahl et al. 2011).

Concerning the effect of systemic instruments on inventive activity, Branstetter and Sakakibara (1998, 2002), Czarnitzki and Fier (2003) and Czarnitzki et al. (2007) find that firms that participate in publicly funded R&D consortia have a higher inventive output than non-funded or non-participating firms. Fornahl et al. (2011) find that R&D funding for German biotech firms has only a minor effect on inventive output, while collaborative R&D funding increase inventive output to some extent. Falck et al. (2010) show that a cluster initiative in Bavaria, Germany, increased the amount of innovation and eased the access to foreign knowledge for participating firms. Indirect support of networking within a Japanese cluster policy has been shown to be effective in increasing innovative output (Nishimura and Okamuro 2011).

In view of this evidence and parallel to the analysis of technology push instruments, we are interested in the effects of systemic instruments on co-inventor networks. Since many types of systemic instruments provide financial support for joint R&D activity, they should increase inventive activity similar to technology push instruments. Furthermore, by providing incentives to form cooperation with (often) previously unknown partners, they could increase the size of the network by attracting new actors to these technologies. Hence, we suggest the following hypothesis:

H2a: Systemic instruments increase the size of the co-inventor network

The instruments at the systemic level are especially designed to increase the connectivity inside the network. They attract new actors to the network and integrate them by providing incentives to establish linkages. Even though evidence on the link between systemic instruments and network formation is scarce, some studies find positive effects of collaborative R&D funding or cluster policies on collaboration (Giuliani and Pietrobelli 2011, Nishimura and Okamuro 2011, Cantner et al. 2014). In view of this evidence, we propose the following hypothesis:

H2b: Systemic instruments increase cooperation inside the co-inventor network

2.2.4 Demand pull instruments

The notion of a demand effect on inventive and innovative activity was introduced by Schmookler (1962, 1966), who postulates that markets with high expected profitability provide incentives to engage in inventive activity. This relationship has been widely discussed in the literature (e.g. Mowery and Rosenberg 1979, Kleinknecht and Verspagen 1990) with recent empirical evidence indicating that market demand induces inventive output in general (Peters et al. 2012) and especially fosters process innovations (Fontana and Guerzoni 2008).

Environmentally friendly technologies compete with incumbent technologies that have cost-advantages due to negative externalities and path-dependencies and are therefore left with sub-optimal market shares from a societal perspective. To establish demand for these technologies, a protected niche marked is required that allows the technologies to emerge and improve (Kemp et al. 1998, Nill and Kemp 2009). Demand pull instruments can create such niche markets and provide incentives for firms to enter the market or to innovate and expand production capacity. With revenues generated on this market, firms can grow to appropriate economies of scale and learning effects that allow the development of more efficient production processes or investment in new machinery (Arrow 1962, Peters et al. 2012, Lindman and Söderholm 2012); thereby they reduce production costs and generate revenues, which can be re-invested in R&D (Nemet 2009, Hoppmann et al. 2013). Different demand inducing policies can be thought of, such as public procurement, demand subsidies, deployment policies, and fiscal incentives, or soft instruments such as standards and labels or initiatives to reduce information asymmetries (Edler 2010).

The effect of niche markets for environmentally friendly technologies has been observed in case studies and broader empirical settings. For energy efficiency technologies, Costantini et al (2015b) find that a general energy tax, which induces demand for energy efficiency applications, increase inventive output. In a case study on PV module producers, Hoppmann et al. (2013) show that an increase in market size also increases the innovative investments, with gained revenues being partly reinvested. Nemet (2009) finds the opposite effects for WP in California, where demand policies did not trigger non-incremental inventions. In an econometric framework, Johnston et al (2010) show that feed-in tariffs have only a significant effect for solar technologies and a negative effect for WP on inventive output, while certificates and obligations increase inventions in general. Costantini et al. (2015a) show that demand induces innovation and, especially for less-mature technologies, price-based demand instruments enhance invention more than quantity-based ones. Peters et al. (2012) consider domestic and foreign demand policies for PV and find that both have an effect on inventive output. Wangler (2013) finds that an increase in market size has a positive effect on inventive activity in Germany.

As stated above, the evidence for the effect of demand pull instruments on invention is inconclusive and apparently technology dependent. We assume that demand pull instruments may have an indirect effect on the size of co-inventor networks. First and foremost, they establish markets and/or increase market size. Furthermore, with a larger market, more actors will see an opportunity to serve that market. Hence, with inventive activity being a prerequisite for survival in the market, due to the increased competition, indirectly more inventions are induced. Hence, for the size of inventor networks we suggest:

H3a: Demand pull instruments increase the size of the co-inventor network

Demand pull instruments increase the number of actors, but we have no good reason to expect that they change cooperative behavior within the network. While an increasing number of actors positively affects the number of potential partners, it might at the same time increase the fear of unintended knowledge spillovers if competition becomes fiercer. Therefore we hypothesize for the structure of inventor networks:

H3b: Demand pull instruments have no effect on cooperation in the co-inventor network

2.3 Consistency of the Instrument Mix

All the above mentioned instruments seem relevant for increased inventive activity and are frequently implemented simultaneously, thereby constituting an instrument mix for innovation. In the literature, it is acknowledged for quite some time that such a mix of instruments is necessary to increase inventive activity, especially for eco-innovations (Mowery and Rosenberg 1979, Kemp et al. 1992).

Recently, the interaction, interdependency and possible coordination failures within the instrument mix for innovation have caught the attention of researchers. Several theoretical contributions argue that the optimal reduction of emissions is achieved by emission control policies combined with the direct support of inventive activity (see Lehmann 2012 for a survey). Concerning the interaction of implemented instruments to support inventive activity, the evidence is scarce.[4] Buen (2006) shows for WP in Denmark and Norway that supply and demand subsidies should be implemented at the same time and be predictable over time to create an environment in which actors can successfully engage in inventive activity. Bérubé and Mohnen (2009) show for a sample of Canadian firms that the presence of tax credits as well as R&D subsidies increase inventive output more than tax credits alone. Guerzoni and Raiteri (2015) find for a sample of European firms that, if supply and demand side policies positively interact, innovation expenditures are highest.

Various conceptualizations of a broader policy mix have been proposed. Within the innovation system approach, Borrás and Edquist (2013) suggest how an instrument mix with systemic characteristics should be designed. Flanagan et al. (2011) emphasize several dimensions (policy space, governance space, geographical space and time) of innovation policy mix interactions on various levels. A recent conceptualization of the policy mix is proposed by Rogge and Reichardt (2015), who argue that the instrument mix is part of a wider policy mix for innovation. This policy mix consists of different elements that capture the policy strategy to define certain objectives, the instruments used to achieve the strategies' objectives, and the

[4] There is distinct stream of literature focusing on instrument mixes in environmental policy in general (e.g. OECD 2007) and the interaction of the EU ETS and the diffusion policies for renewable energies and their emission reduction in particular (e.g. Sorrell et al. 2003, del Río 2007, del Río 2010, Lehmann 2012).

mix of these instruments. These elements furthermore have certain characteristics. A particularly important one is the consistency of the elements in the policy mix that includes, among others, the consistency between the instruments and their interaction.

According to Rogge and Reichardt (2015), the consistency of the instrument mix can be assessed by interaction analysis and can have three degrees of interaction: strong, if the instruments reinforce each other, weak, if the interaction is neutral, and inconsistent if the interaction effect is negative. They argue that due to the conflicting objectives, perfect consistency may not be possible (Flanagan et al. 2011), and may sometimes not even be desirable (Quitzow 2015). Costantini et al (2015b) show how an inconsistent mix of instruments, characterized by an excess of implemented instruments, can deter inventive performance in energy efficiency technologies. They find that if too many policies are implemented, complexity increases and inconsistencies emerge that reduce inventive performance. Guerzoni and Raiteri (2015) find strong consistency for the interaction between public procurement and direct subsidies. Inventive expenditures of firms are found to be higher if the instruments interact compared with the sum of the individual effects of both instruments.

Based on the previous empirical findings, we argue that market demand must be present to encourage inventors to engage in R&D activity. Here, we expect that demand pull interacts with technology push instruments and enhances the size of the network. Both policies create incentives: demand pull instruments promise customers for products based on each technology and technology push instruments lower barriers to the pursuit of R&D activities. Expecting strong consistency, we can formulate the following hypothesis:

H4a: The size of the co-inventor network is positively affected by the interaction of demand pull and technology push instruments

A similar line of reasoning can be put forward regarding the structure of the network. Market demand is required for actors to engage in R&D activity. Systemic instruments provide incentives to collaborate on R&D, especially between previously unknown partners. We expect that the interaction between the two instruments increases the connectivity inside the network and therefore shows strong consistency.

H4b: Collaboration within the co-inventor network is positively affected by the interaction of demand pull and systemic instruments

3 Policies for renewable energy in Germany

The development of RPGT and especially WP and PV received broader attention in the 1970s in reaction to the oil crisis and due to the growing awareness of resource depletion and environmental concerns in society. Governmental support of R&D in these technologies started in Germany in 1974 (Lauber and Mez 2004). This development has been accompanied and pushed by various policy initiatives. They are designed to aim at technological improvement and cost competitiveness directly via subsidizing R&D activities leading to cost reduction, or indirectly via feed-in-tariffs, i.e. guaranteeing a cost covering price that induces demand and allows reaping scale and learning economies by increased production. The rationale for such policies is seen in the initially low competitiveness of the new compared to incumbent technologies as well as in the external effects associated with these infant technologies (Painuly 2001).

While both technologies were at an infant stage when policy support in Germany started, there are noteworthy differences between them. Windmills as a source of mechanical energy have long been known and even though modern WP installations differ greatly from traditional windmills, the concept of using wind as a source of energy was familiar (see Shepherd 1994 for a historical review). Furthermore, many auxiliary technologies that were used to develop wind turbines could be adapted from other fields (e.g. wind tunnels in aviation), which may ease technological progress. The first photovoltaic cell was only introduced in 1954 and provided a new way of utilizing solar energy. While there was not much previous knowledge to build on, photovoltaic applications benefitted from simultaneous developments within the emerging semiconductor industry (Sze 1981). This leads to differences in efficiencies and production costs, which partly explains political support patterns described below.

3.1 Technology push instruments

For RPGTs in Germany, the main technology push instrument is R&D funding by the German federal government. Federal R&D spending is documented in the German Förderkatalog (2014), a database containing all federal granted research projects from 1968 until today (see Broekel and Graf 2012 for a detailed description of the database). We identify research projects relevant for the technologies under concern by conducting a keyword search[5].

[5] The keywords used are: “wind”, “pv”, “photovoltai*”, “solar”. We remove projects not directly relevant for inventive activity, such as energy related educational programs, as well as projects that focus on upstream technologies, but not on WP and PV directly, manually from the dataset. Furthermore, funding for demand pull instruments, especially the 100/250 MW wind program, are removed as well.

Overall, funding can be divided into funding for individual research projects at an institute or a company and collaborative research projects. We separate these two kinds of funding since they have different effects and select for the technology push instrument only projects attributed to one recipient. We collect the data from 1978 until 2011, which covers 259 research projects with a total amount of €283.4 million in WP and 590 projects with a total of €934.9 million in PV (in 1995 Euros).[6]

Overall funding as well as its breakdown into individual and cooperative funding is depicted in figure 1. Regarding the respective overall funds, we observe similar patterns for both technologies with an early first maximum around 1980 (WP) and 1990 (PV), followed by a decline that lasts for several years and a sharp increase during the 2000s.

Individual funding in both technologies follows the same pattern most of the years but the upsurge during the last years is not as pronounced as in overall funding due to a policy shift towards cooperative funding. However, between the two technologies, there are also some notable differences with respect to the timing and the amount of funding. Spending for PV reaches its maximum ten years later than WP which reflect differences in the maturity of these technologies. The Government also seems to perceive a greater need for funding or puts higher expectations in PV, since the maximum level of spending on PV is about five times higher than on WP. In general, spending for PV is more volatile than for WP.

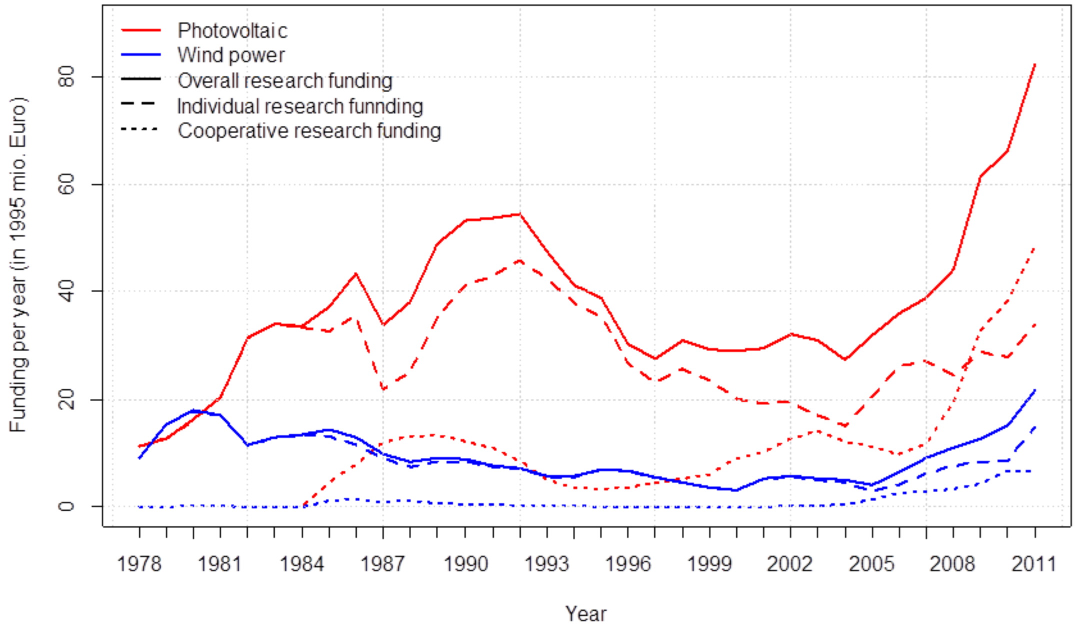

Figure 1: Federal funding of research projects in wind power and photovoltaics.
Source: Own calculation based on Förderkatalog (2014).

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[6] The project grants are equally distributed over the project duration to account for the length of the project. This means, if €1 million is granted to a research project running for five years, we allocate €0.2 million per year.

3.2 Systemic instruments

Systemic instruments support the research infrastructure by facilitating learning and knowledge exchange, enhancing cooperation, or fostering cooperation between inventive actors (Smits and Kuhlmann 2004). In Germany, institutional funding for research institutes such as the Fraunhofer Institute for Solar Energy Systems ISE or the establishment of dedicated chairs at universities are examples of this type of instrument. Furthermore, cooperative research projects ("Verbundforschung") are widely used to connect public actors with partners from industry and also among each other. Cluster policies such as the funding of the SolarValley fall into this category as well.

We select grants for cooperative research also from the Förderkatalog (2014).[7] There are 216 cooperative research projects for PV and 55 for WP in the timespan from 1978 until 2011. The amount of funding for the projects was €35.1 million for WP and €344.2 million for PV, respectively (see figure 1). Cooperative research grants were introduced in WP and PV at the beginning of the 1980s, and especially in PV it had a substantial and increasing share in the following years with a short period of decline during the early 1990s. By 2011, more than half of overall funding in PV was granted to cooperative projects. In WP, the systemic instrument was not frequently applied until 2000. Afterwards, cooperative funding increased and by 2011 it accounted for one third of total funding in WP.

3.3 Demand pull instruments

In the beginning of the development of RPGT in the 1970s, demand pull instruments did not play a major role. Only some local demonstration programs were in place, trying to overcome the cost disadvantages especially faced by PV (Jacobsson and Lauber 2006). These agreements, most of the time between municipal services and the installation owner, granted a payment per electricity unit in relation to production costs. With the Electricity Feed-in Law ("Stromeinspeisungsgesetz"), the first German FIT, a profound demand side policy was introduced in 1991. This national law granted renewable energy producers a fixed feed-in tariff of 90% of the regular customer's electricity price (computed on the price two years before the granting year) for WP and PV. This fixed price permitted RE producers to sell their electricity to the grid operators, which were obliged to purchase. This removed market and price uncertainty for RPGT. The incentives were sufficient for WP to diffuse, but did not create high demand for PV, due to the low FIT compared to the high system costs of PV

[7] We identify collaborative grants by the term "Verbundforschung" in the project title, which is specifically used to describe these cooperative grants. This also includes funding for clusters.

(Jacobsson and Lauber 2006). This overarching policy was continued by the Renewable Energy Sources Act ("Erneuerbare Energien Gesetz", EEG) in 2000, which extended the FIT and distinguished further between different kinds of technologies and increased the support for PV and other technologies (see Hoppmann et al. 2014 for the development of the EEG, especially for PV). The EEG was amended several times to differentiate further between technologies and to adjust for unexpected cost reductions.

Besides these main instruments, which created a stable environment for investments in RPGT, other demand inducing policies were in place. For WP, the 100/250 MW wind program supported the diffusion of WP as well. The program started in 1989 and granted the owner of a wind turbine either an investment support or an additional payment for each unit of electricity feed into the grid. This could be combined with the Electricity Feed-in Law and created strong incentives to invest in WP. In 1996, the program ended, covering about 1,500 installations with 350 MW installed capacity (see Durstewitz et al. 2000 for an evaluation).

Similar demand supporting programs were in place for PV. In 1991, the 1,000 roof program was enacted, which provided PV installations support of 70% of installation costs. Until 1994, 2,250 installations were installed and created the biggest market for PV installations in Europe (Kiefer and Hoffmann 1994). In 1999, a second program to support the diffusion of PV was introduced, the 100,000 roof program. The program also granted investment subsidies, but only up to 30% of the investment costs, and provided interest reduced loans for PV installations. The program was a big success and was amended to keep up with the demand for support (Bruns et al. 2009). Eventually, the program ended in 2003 and was integrated in the amended version of the EEG in 2004. An overview of the most important demand pull instruments and their amendments is provided in figure 2.

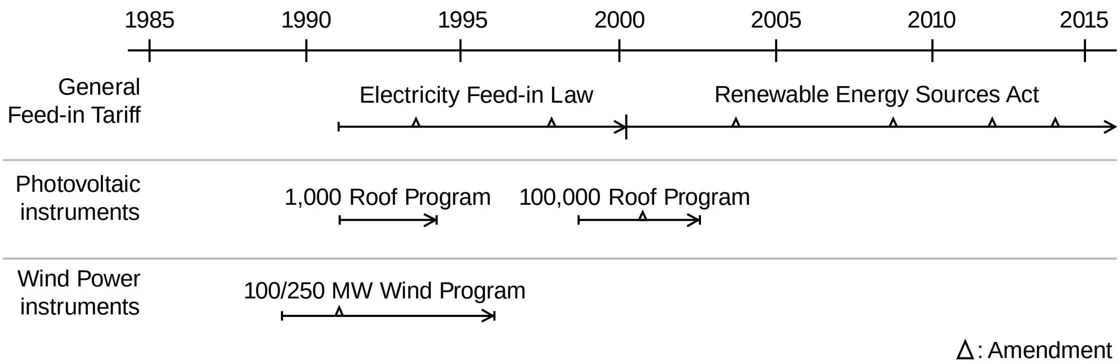

Figure 2: Main demand pull instruments for wind power and photovoltaics in Germany.
Source: Own elaboration based on Bruns et al. (2009).

4 Data and empirical strategy

To test our hypotheses, we run a set of OLS time series regressions, which estimate the effect of different of policy instruments and their mix on the development of the size and the structure of co-inventor networks. In the following, we explain how the networks for WP and PV are derived from patent data, continue with the policy instruments and control variables (see table 1), and describe our empirical strategy.

4.1 Dependent variables: co-inventor networks

4.1.1 Reconstructing co-inventor networks from patent data

We use patent data to identify cooperation at the inventor level. The dataset for the analysis is retrieved from the Worldwide Patent Statistical Database (PATSTAT) (EPO 2014). Subsets for WP and PV are extracted by a combination of technology specific IPC (International Patent Classification) classes and keywords (see appendix 1 for the selection criteria). We consider all priority applications in the timespan from 1980 to 2011. The dataset consists of 3,985 patents for WP and 3,763 patents for PV invented by German inventors. A patent is selected if at least one of its inventors resides in Germany. After extensive manual cleaning of the dataset, controlling for patent applicant, address and year of application, the final dataset consists of 3,603 unique WP and 4,761 PV inventors. The development of the patents and inventors over time can be seen in figure 3.

We use a social network approach to reconstruct and analyze the structure and evolution of the undirected inventor networks in the two technologies. For the reconstruction of inventor networks, we link inventors via joint patents. If two or more inventors are named on the same patent (co-invention), we assume that they have collaborated and exchanged knowledge during the process of invention (Breschi and Lissoni 2004). The technology specific networks are constructed using 3-year moving windows to account for persistence, while also allowing for decay of the linkages (Fleming et al., 2007; Schilling and Phelps, 2007). These moving windows help to map the invention process, because the patent is just the point in time when the result occurs, while the inventive process itself is continuous and interaction between the actors takes place before filing the patent and might persist afterwards.

4.1.2 Development of network structures over time

Based on the inventor networks, different properties can be observed concerning their size and structure (figure 3). Looking at the size of the networks based on the underlying patent data, we can observe a steady increase in patents over time, rather exponentially during the last years. The nodes in the network, which represent the individual inventors, show a similar pattern. The edges in the network, which represent the number of connections between the inventors, increase as well. Average team size, i.e. the number of inventors per patent, shows a significant difference between the technologies. The average team in PV is larger than in WP by about one inventor per patent throughout most of the periods. The gap becomes smaller during the last observations, but still accounts for 0.5. This could partly be caused by the existence of very successful individual inventors in WP, for example, the founder of the German wind turbine company Enercon, Aloys Wobben, who filed about 3.5% of all WP patents in the observed time period on his own.

The change of the network structure over time can be described by statistics that measure characteristics of the network as a whole or describe the individual position of network actors. A broad overview of these measurements and detailed calculations can be found in Wasserman and Faust (1994). Concerning network structure, the mean degree, which is the average number of edges per node, shows an upward development, indicating an increase in cooperative behavior over time. However, in both networks, density, i.e. the share of active links in all possible links, decreases over time. Since density is a function of network size, this fact is not surprising, because the size of the network, in terms of nodes, is increasing over time as well. In the first years of observation, density is much higher in the PV-network than in the WP-network, but, by the end of our observation period, both are equal. Degree centralization, which accounts for the concentration of edges across the nodes, is in both technologies quite volatile but has no trend, indicating that no actor is important or dominates the network. The largest component in the network, which represents the largest group of connected inventors, has a surprisingly low share and is quite volatile in both technologies. However, in both networks, the share of the largest component increases over time, indicating an increased potential for knowledge diffusion in the network.

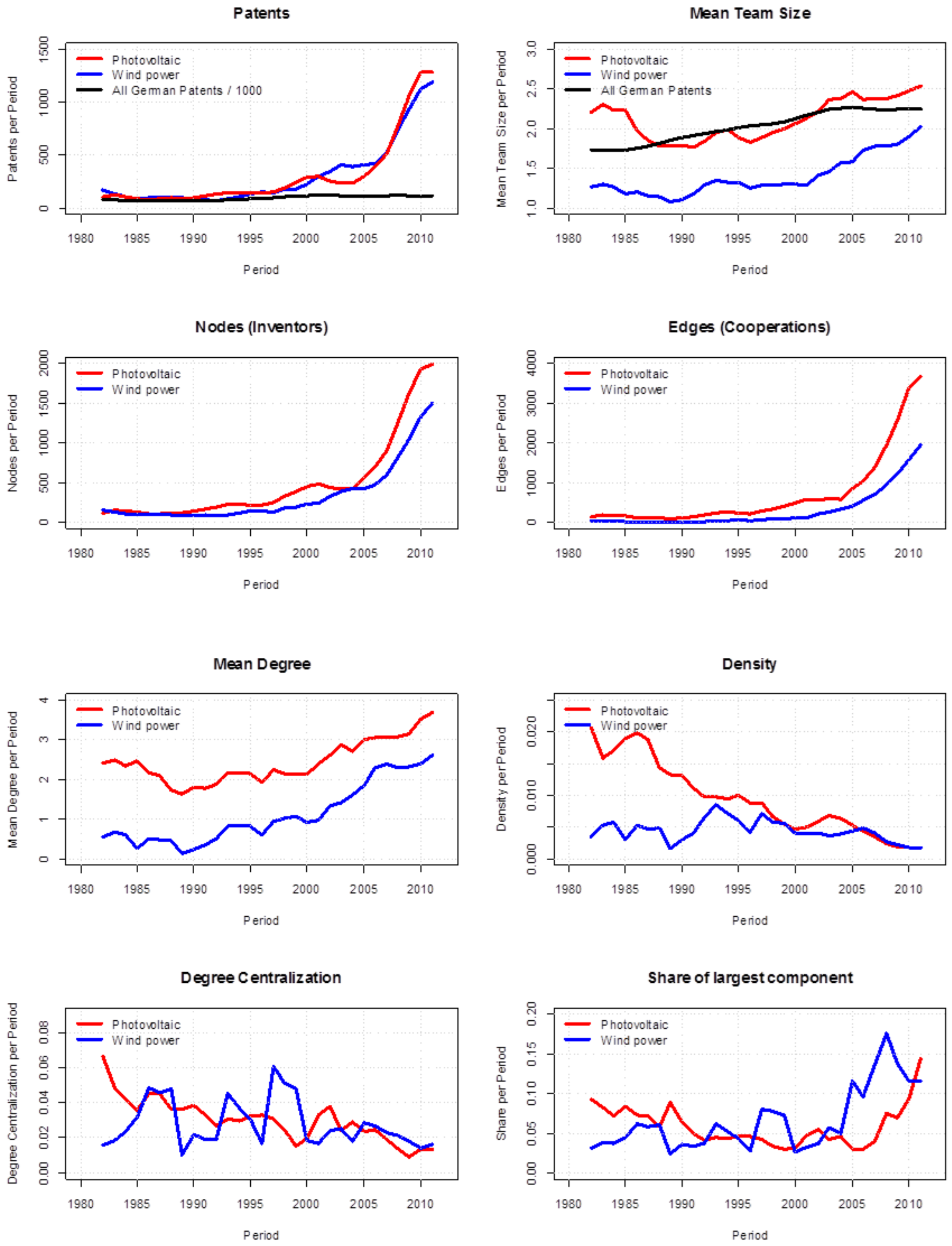

Figure 3: Structural properties of co-inventor networks in wind power and photovoltaics.

4.1.3 Operationalization

For the econometric analysis we use two network measures as dependent variables. The size of the network is given by the number of nodes, i.e. the number of distinct inventors, which indicates the intensity and variety of inventive activity in the respective fields. Since the time series for WP and PV show an exponential trend, we use the first difference of network size, Δ *Nodes*.

We use *Mean Degree*, calculated as the average number of collaboration partners, as a very simple and easy to interpret measure of network structure. Since it is independent of network size, it is superior to density and many other measures of network structure in the context of our study.

4.2 Policy Variables

The operationalization of technology push (*TP*) and systemic instruments (*SYS*) is straightforward, since they are provided as monetary values (see sections 3.1 and 3.2). We aggregate annual funding to three-year moving windows to account for the duration of the inventive process, with some projects taking more time to produce patentable output than others. We take first differences of the three-year moving windows to estimate the effect of changes in the funding policy.

To operationalize demand pull instruments (*DP*), we use the logarithm of annually installed capacity in Germany in MW per year. Since neither of the technologies analyzed was cost competitive with fossil fuel technologies during the observed time period, we assume that investments in installed capacity are only undertaken because of an effective demand pull instrument (Klaassen et al. 2005, Peters et al. 2012, Wangler 2013, Dechezleprêtre and Glachant 2014). Data on installed capacity is taken from Bergek and Jacobsson (2003) for the period before 1990 for WP and for PV from Jacobsson et al. (2004) and for 1990 onwards from BMWi (2015) for both technologies (see figure 4). This approach, however, does not differentiate between different possible causes for an increase in installed capacity.

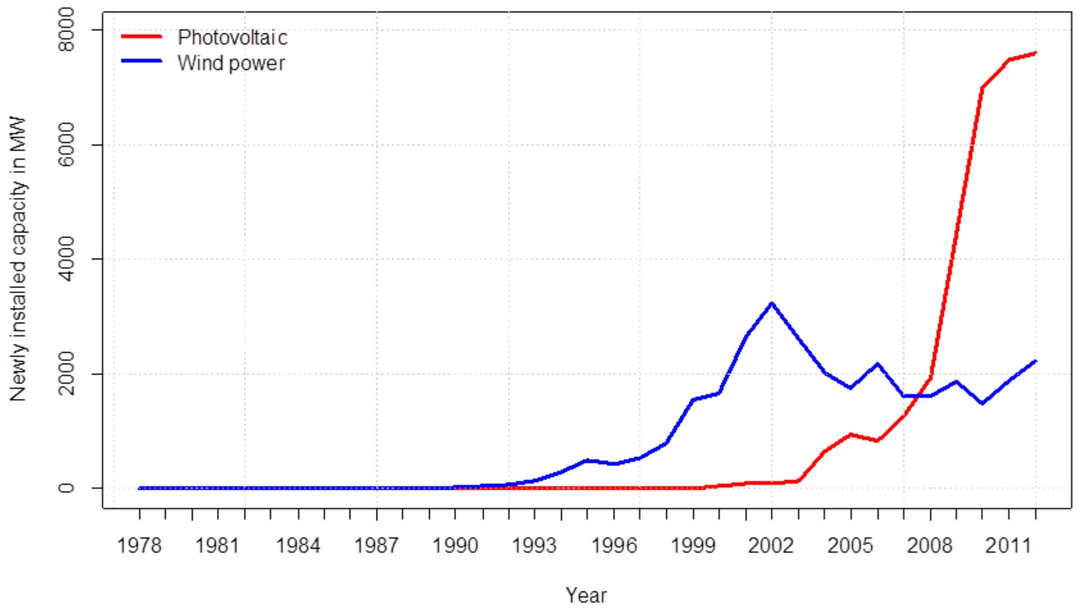

Figure 4: Annually installed capacity in wind power and photovoltaics in MW.
Data sources: Bergek and Jacobsson (2003), Jacobsson et al. (2004) and BMWi (2015)

4.3 Control Variables

We control for other factors than policy measures that could influence inventive activity in RPGT. To account for a general increasing trend in patenting, we collect all patents filed at the German patent office and take the first differences (Δ *Patents*). We also account for the overall, increasing trend in cooperation (Wuchty et al. 2007) by calculating mean *Team Size* for all German patents[8]. Furthermore, we use inflation adjusted changes in the crude oil price index (Δ *Oilprice*) provided by the Federal Statistical Office of Germany (Destatis 2014) to account for an induced innovation effect by increasing fuel prices (see Popp 2002). We also control for the size of (potential) *Export Markets* and thereby also capture effects of foreign policies (Peters et al. 2012, Dechezleprêtre and Glachant 2014, Costantini et al. 2015b). To be precise, we take the logarithm of the global annual installations of WP in MW and the global annual production of PV in MW (Earth Policy Institute 2014a, b) and subtract the respective new installed capacities in Germany.

[8] We use mean team size instead of mean degree since the latter is impossible to calculate due to the large number of German inventors and the related issues with name disambiguation. We also calculated the mean degree of a co-inventor network based on a random sample of 5% of all German patents. The correlation between the two is 0.99 so that we believe this is a viable proxy.

Table 1: Variables and descriptive statistics

Variable	Description	RPGT	Min.	Median	Mean	Max.	SD	Observations (Period)
Δ *Nodes*	First differences of the number of distinct inventors in the network	WP	-32.00	15.00	46.10	271.00	80.70	29
		PV	-45.00	29.00	64.62	364.00	109.75	29
								(1981-1983 until 2009-2011)
Mean Degree	Average number of cooperations in the co-inventor network	WP	0.14	0.87	1.11	2.62	0.76	30
		PV	1.63	2.30	2.44	3.68	0.54	30
								(1980-1982 until 2009-2011)
TP+SYS	First differences of overall R&D funding	WP	-5.97	-0.45	0.23	10.58	4.06	31
		PV	-17.30	5.00	5.49	38.25	12.91	31
								(1979-1981 until 2009-2011)
TP	First differences of individual R&D funding	WP	-5.81	-0.80	-0.33	7.94	3.35	31
		PV	-15.90	1.24	1.63	19.38	10.01	31
								(1979-1981 until 2009-2011)
SYS	First differences of collaborative R&D funding	WP	-0.69	0.00	0.56	3.70	1.15	31
		PV	-7.47	1.85	3.86	28.86	8.84	31
								(1979-1981 until 2009-2011)
DP	Logarithm of annually installed capacity in MW	WP	0.00	6.06	4.58	8.08	3.20	35
		PV	0.00	1.10	2.88	8.94	3.27	35
								(1978 until 2012)
Export Market	Logarithm of annually installed capacity (WP) / production (PV) outside Germany in MW	WP	0.00	6.67	6.55	10.66	2.92	35
		PV	1.25	4.34	5.03	10.30	2.44	35
								(1978 until 2012)
Δ *Oilprice*	First differences in oil price		-42.64	-0.79	1.60	27.84	14.74	31
								(1981 until 2011)
Δ *Patents*	First differences in the overall number of patents in Germany		-52.68	-0.57	12.70	77.73	33.57	29
								(1981-1983 until 2009-2011)
Team Size	Average number of inventors per patent in Germany		1.73	2.05	2.03	2.27	0.20	30
								(1980-1982 until 2009-2011)

4.4 Econometric approach

4.4.1 Estimation strategy

We use OLS time series regressions to estimate the effect of the different policy instruments and their interaction on the size and structure of the network. We estimate ten different models to test the effect of the policy instruments on the two dependent variables in two technologies. The general functional form is as follows:

$$\left.\begin{array}{r}\Delta\, Nodes_t \\ Mean\ Degree_t\end{array}\right\} = \alpha + \boldsymbol{\beta}\, policies_{t-x} + \boldsymbol{\gamma}\, controls + \varepsilon$$

We add variables to see their effect and apply different lags, denoted by t-x (see 4.4.2 for a discussion of the lag structure). The first three models test whether funding in general affects inventive activity, *policies* is just the aggregate of *TP* and *SYS,* and *DP* is included with different lags to replicate the setup of previous studies (e.g. Johnstone et al. 2010, Peters et al. 2012, Nesta et al. 2014).

The fourth and all subsequent models use *TP* and *SYS* individually. In models 5 and 7, we again include *DP* with the respective lag structure. In models 6 and 8, we account for the export market instead of domestic demand. Due to problems of multicollinearity, we cannot include *DP* and *export market* in the same model.

We explicitly model the instrument mix in the last two models by including an interaction term between single instruments. The interaction term is supposed to grasp the type of consistency of the instrument mix. Model 9 introduces an interaction between *TP* and *DP*, while the last model employs an interaction between *DP* and *SYS*.

The correlation between the variables is not critical (see appendix 2) except for *Team Size, DP* and *Export Market,* which can therefore not be used in the same models. Also, the variance inflation factors show no critical values, except for the interaction term in model 10.

According to the Breusch-Pagan test (Breusch and Pagan 1979), we have heteroscedasticity in the error terms in most models. In addition, the Durban-Watson test (Fox 2008) reveals autocorrelation in the error terms. To account for this, we use heteroscedasticity and autocorrelation consistent covariance matrices (HAC) (Newey and West 1987, Andrews 1991) to calculate standard errors.

Due to the time series nature of our variables, we apply a unit root test (Elliott et al. 1996) to test for non-stationarity. We cannot reject non-stationary in the dependent variables and DP. For the dependent variables, we provide alternative specifications that are stationary in section 5.3. They show that non-stationarity does not bias our general results. While it would be possible to transform the *DP* variable in a way that is stationary (e.g. the growth rate of newly installed capacity), we would lose a lot of valuable information. Apart from that, we believe that the explosive growth in demand is what is particular about this instrument and is the basis for its effectiveness. Due to its very nature, it is not possible to model the effect of the *DP* variable as a one-time shock to the time series. However, this has to be considered while interpreting the results.

4.4.2 Lag structures

Analyzing the influence of a specific policy instrument on inventive activity requires considering time lags between the introduction of the instrument and the realization of an inventive output (see Hall et al. 1986 for a general discussion). Were this not the case, the policy instrument would rather influence the propensity to patent already existing inventions, instead of incentivizing inventive activity (Scherer 1983).

Various lag structures have been proposed in the context of environmental innovations and RPGTs in particular. Brunnermeier and Cohen (2003) use no lag structure to estimate the effect of R&D expenditures on inventive output in environmental innovation, yet their results are robust to one and two years lags as well. Johnstone et al. (2010) also use no lags in their analysis. Peters et al. (2012) use one, three and five year lags for R&D spending, but abandon lags since their initial model provides the best fit. Wangler (2013) employs no lag for public R&D spending and a positive lag for installed capacity. A positive lag means that actors either anticipate future policies or have expectations regarding the future impact of existing policies and adjust their inventive activities accordingly. Böhringer et al. (2014) use a one year lag for R&D investments and no lag for installed capacity.

We decided to lag *TP* and *SYS* by one year. Most *DP* instruments were intensively discussed in the public before introduction (e.g. Hoppmann et al. 2014), so that the actors could anticipate policies well before their introduction and change their inventive behavior (*anticipation effect*). Therefore, for *DP*, we introduce a foresight of one year, which has also been used by Wangler (2013). In addition, a long term effect of a *DP* instrument, such as a FIT, would be generation of profits, which can be invested in inventive activity that shows success only some years later (*resource effect*).[9] Therefore, we assume four years to be a reasonable time span for new research projects to result in patentable output. For the interaction terms, we consider only the resource effect and lag *DP* by four years[10]. While thinking about optimal lag structures, one has to consider that any specification of a lag structure is subject to noise. This is especially so in the case of inventive activities and somewhat accounted for by our reconstruction of networks with three-year moving windows. It is therefore unlikely that we find a single lag structure which clearly outperforms all other options. We provide robustness checks accounting for a series of lag structures in section 5.3.

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[9] Nemet (2009) as well as Hoppmann et al. (2013) provide detailed evidence for the existence of both types of effects.

[10] We also considered interactions between *TP* and *DP* with the one year negative lag (anticipation), but overall, these models had a poorer fit.

5 Results: policy impact on network size and structure

5.1 Size of the network

The size of the network is given by the number of nodes, which represent individual inventors and could be interpreted as the attractiveness of the research field.[11]

In the first three models for WP (table 2), we observe that an increase in overall funding (*TP+SYS*) is associated with an increase in the number of nodes in the network. More effective *DP* policies, however, do not seem to be important for the stimulation of inventive activities, independent of the lag structure. The differential impact of the instrument mix on innovation in different technologies becomes clear by comparing the results for WP with those for PV (table 3). Network size in PV is largely explained by effective *DP*, whereas we find almost no effect of funding. Comparing the two different lags shows that the *resource effect* provides a better model fit than the *anticipation effect*.

The individual effects of *TP* and *SYS* in model 4 are positive and significant in WP, while in PV only *SYS* increases network size. Also, the overall fit of the model is nearly zero for PV, indicating that R&D subsidies do not contribute significantly to the technological development. This confirms the hypotheses H1a and H2a for WP but not for PV. Including *DP* with different lags in models 5 and 7 shows similar coefficients as in models 2 and 3 but the *anticipation effect* for *DP* turns significant in WP. In PV, *TP* becomes significant, indicating that conventional R&D funding needs to be accompanied by *DP*. Here we can confirm the hypothesis H3a for PV but not for WP.

Comparing the models that differentiate between *TP* and *SYS* with the ones that do not shows that the model fit improves especially in WP but to a lesser extent in PV, which is due to the dominance of DP instruments in PV. In models 6 and 8, we account for the fact that firms in both industries are engaged on international markets and include the size of export markets. Again, the *anticipation effect* and the *resource eff*ect are strong predictors of network size in PV, but only the *anticipation effect* proves significant in WP. It is worth noting that including international demand instead of national demand (*DP*) leads to a better model fit in WP. In PV, comparing the models with *anticipation effect* (5 and 6), explanatory power is higher when we control for the *export market*. When it comes to the *resource effect* (models 7 and 8), the domestic market (*DP*) has a higher explanatory power than the *export market*.

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[11] The results for changes in the number of patents instead of nodes are very similar. Respective results are available upon request.

The interaction of different instruments, especially between *TP* and *DP*, are used to evaluate the complementarity between the instruments, i.e. the consistency of the instrument mix. Acknowledging this interrelation between policies strongly improves the model fit in all cases analyzed. The interaction between *TP* and *DP* is significant for both technologies, which indicates that both policy instruments complement each other in attracting inventive activities, which is in line with hypothesis H4a. We also find a significant positive effect of the interaction between *DP* and *SYS* in model 10 in WP, while in PV, this effect is negative. This negative effect in PV could indicate that the combination of demand pull and systemic instruments mainly strengthens already existing actors and therefore makes entry into the industry more difficult.

Table 2: OLS-Regression results for Δ *Nodes* Wind Power as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	54.736***	8.405	19.304	32.572***	-12.751	-94.680	6.017	-13.541	-25.186	14.563
	(13.012)	(28.261)	(18.528)	(11.711)	(26.028)	(58.940)	(20.045)	(35.632)	(18.438)	(13.691)
$(TP + SYS)_{t-1}$	19.437***	15.259**	14.030**							
	(5.105)	(5.883)	(6.106)							
TP_{t-1}				13.084***	9.040*	8.101**	9.387*	10.410**	-3.642	10.208**
				(4.228)	(4.713)	(3.877)	(4.729)	(4.200)	(3.025)	(3.893)
SYS_{t-1}				45.549***	41.183***	29.082**	37.966***	36.583***	38.120***	-17.656
				(9.704)	(11.228)	(13.472)	(13.391)	(12.705)	(11.944)	(12.936)
DP_{t+1}		8.820			8.670*					
		(5.458)			(4.503)					
DP_{t-4}			8.540				7.040		9.836**	2.869
			(5.425)				(4.919)		(3.746)	(3.508)
$DP_{t-4} \times TP_{t-1}$									3.168***	
									(0.792)	
$DP_{t-4} \times SYS_{t-1}$										9.839***
										(2.337)
Δ $Oilprice_{t-1}$	-0.033	-0.400	-0.544	-0.296	-0.654	-0.992	-0.686	-0.430	-0.370	-1.400**
	(0.707)	(0.578)	(0.559)	(0.972)	(0.867)	(0.619)	(0.819)	(0.917)	(0.686)	(0.642)
Δ $Patents_{t}$	-0.067	-0.391	-0.300	0.246	-0.076	0.064	0.016	0.133	0.388	0.168
	(0.278)	(0.398)	(0.373)	(0.251)	(0.308)	(0.287)	(0.324)	(0.236)	(0.385)	(0.237)
Export $Market_{t+1}$						17.740*				
						(8.949)				
Export $Market_{t-4}$								8.117		
								(5.742)		
Adj. R^2	0.627	0.662	0.674	0.697	0.735	0.771	0.727	0.720	0.809	0.822
Obs.	29	29	29	29	29	29	29	29	29	29
Max. VIF	1.134	1.942	2.095	1.742	1.942	2.696	2.157	2.224	4.313	9.970
F-Value	16.663	14.692	15.453	17.115	16.537	19.837	15.924	15.382	20.737	22.483
AIC	314.087	312.041	310.993	308.829	305.718	301.510	306.571	307.346	296.9732	294.970

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

Table 3: OLS-Regression results for Δ *Nodes* Photovoltaics as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	33.258	-63.286**	-49.289**	19.979	-61.190*	-213.692***	-44.431*	-197.662***	-25.034*	-68.097***
	(23.620)	(30.442)	(22.496)	(32.867)	(32.659)	(59.256)	(21.624)	(66.072)	(12.127)	(19.628)
$(TP + SYS)_{t-1}$	4.644	4.627**	3.257***							
	(3.339)	(1.808)	(1.044)							
TP_{t-1}				4.255	4.888**	4.122**	3.480**	5.095*	1.501*	4.794***
				(2.824)	(2.323)	(1.858)	(1.298)	(2.515)	(0.831)	(1.349)
SYS_{t-1}				7.558***	2.664	0.029	0.678	1.786	1.960	7.818**
				(2.095)	(2.559)	(2.811)	(2.459)	(2.662)	(2.188)	(3.350)
DP_{t+1}		25.363***			27.162***					
		(6.950)			(8.993)					
DP_{t-4}			39.487***				42.552***		29.595***	49.017***
			(6.901)				(8.649)		(5.784)	(7.510)
$DP_{t-4} \times TP_{t-1}$									2.344***	
									(0.519)	
$DP_{t-4} \times SYS_{t-1}$										-1.303***
										(0.420)
Δ Oilprice $_{t-1}$	1.168	-0.867	-1.101*	1.328	-1.119	-1.446**	-1.412*	-0.937	-0.742	-1.229
	(1.214)	(0.552)	(0.545)	(1.170)	(0.714)	(0.649)	(0.777)	(0.875)	(0.961)	(0.745)
Δ $Patents_t$	0.936	1.589**	1.631***	1.301**	1.389*	1.043*	1.376***	1.070*	1.247***	1.872***
	(0.700)	(0.768)	(0.528)	(0.577)	(0.759)	(0.544)	(0.431)	(0.623)	(0.242)	(0.553)
Export $Market_{t+1}$						46.048***				
						(10.980)				
Export $Market_{t-4}$								54.108***		
								(17.020)		
Adj. R^2	0.046	0.575	0.725	0.045	0.572	0.677	0.737	0.518	0.826	0.796
Obs.	29	29	29	29	29	29	29	29	29	29
Max. VIF	2.064	2.146	2.138	2.444	2.445	2.698	2.579	2.580	2.683	7.131
F-Value	1.451	10.472	19.436	1.327	8.475	12.760	16.701	7.020	23.097	19.261
AIC	359.120	336.488	323.887	359.980	337.480	329.261	323.327	340.902	312.131	316.617

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

5.2 Structure of the network

To analyze changes in the structure of the networks, we focus on the mean degree, which accounts for the intensity of collaboration. In this section, we test the effect of different policy instruments on the mean degree.

The first three models show in the case of WP (table 4) and PV (table 5) that both an increase of overall R&D funding (*TP* + *SYS*) and of *DP* increase the mean degree. From models 1 and 4, we can infer that changes in the network structures are not independent from the overall trend towards increased collaboration but controlling for this trend still leaves room for unexplained variation of the mean degree.

Models 4 to 8 differentiate between *TP* and *SYS*. As in the regressions in the previous section, this increases the explanatory power of our models only for WP but not for PV. The results for WP strongly support our hypotheses H1b and H2b, since *SYS* is always positive and significant, while *TP* shows no influence on the mean degree. In PV, these relationships are not robust and strongly depend on the model specification. Overall, demand plays an important role in both technologies for stronger interaction in R&D. These findings are contrary to our expectations in H3b, where we assumed that DP has no effect on network structure.

The joint effect of *SYS* and *DP* in model 10 is positive and significant for both technologies. This supports hypothesis H4b, indicating that these instruments complement each other and form a consistent policy mix fostering collaboration in R&D. Concerning the interaction of *TP* and *DP* in model 9, we find no significant effect in WP but a significant negative one for PV. This result is somehow puzzling, but may indicate that an increase in *TP* provides companies with sufficient resources to perform R&D on their own, thereby reducing the incentive to engage in R&D collaboration.

Table 4: OLS-Regression results for *Mean Degree* Wind Power as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-4.411***	0.336***	0.405***	-3.754***	0.220	-1.071***	0.350***	0.192	0.335***	0.400***
	(0.725)	(0.026)	(0.025)	(0.768)	(0.197)	(0.186)	(0.091)	(0.263)	(0.091)	(0.080)
$(TP + SYS)_{t-1}$	0.065***	0.096**	0.061**							
	(0.023)	(0.036)	(0.027)							
TP_{t-1}				0.012	0.023	0.014	0.010	0.034	-0.007	0.014
				(0.020)	(0.028)	(0.014)	(0.018)	(0.036)	(0.017)	(0.014)
SYS_{t-1}				0.350***	0.437***	0.193***	0.336***	0.319***	0.317***	0.061
				(0.045)	(0.065)	(0.033)	(0.046)	(0.103)	(0.051)	(0.077)
DP_{t+1}		0.147***			0.131***					
		(0.024)			(0.034)					
DP_{t-4}			0.175***				0.149***		0.151***	0.131***
			(0.014)				(0.021)		(0.020)	(0.021)
$DP_{t-4} \times TP_{t-1}$									0.006	
									(0.005)	
$DP_{t-4} \times SYS_{t-1}$										0.046***
										(0.013)
Δ $Oilprice_{t-1}$	0.000	0.002	0.000	0.002	0.004	0.000	0.002	0.008	0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.002)	(0.004)	(0.007)	(0.003)	(0.003)
Team $Size_t$	2.729***			2.322***						
	(0.389)			(0.375)						
Export $Market_{t+1}$						0.284***				
						(0.026)				
Export $Market_{t-4}$								0.133***		
								(0.048)		
Adj. R^2	0.765	0.609	0.791	0.902	0.825	0.943	0.918	0.745	0.920	0.940
Obs.	30	30	30	30	30	30	30	30	30	30
Max. VIF	1.238	1.115	1.257	1.344	1.253	1.820	1.365	1.642	2.201	9.725
F-Value	32.443	16.071	37.475	67.669	35.172	121.080	82.087	22.175	68.116	91.142
AIC	30.803	46.040	27.339	5.395	22.769	-10.920	0.048	34.065	-0.115	-8.348

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

Table 5: OLS-Regression results for *Mean Degree* Photovoltaics as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-1.617	1.941***	2.049***	-1.500	1.938***	1.300***	2.048***	1.378***	2.001***	2.075***
	(1.030)	(0.119)	(0.096)	(0.979)	(0.095)	(0.261)	(0.097)	(0.316)	(0.090)	(0.093)
$(TP + SYS)_{t-1}$	0.023***	0.013*	0.007							
	(0.007)	(0.006)	(0.006)							
TP_{t-1}				0.021**	0.013*	0.012	0.007	0.017*	0.013*	0.006
				(0.009)	(0.007)	(0.008)	(0.007)	(0.009)	(0.007)	(0.007)
SYS_{t-1}				0.026***	0.011	0.007	0.005	0.014**	0.000	-0.009
				(0.006)	(0.008)	(0.007)	(0.008)	(0.007)	(0.006)	(0.012)
DP_{t+1}		0.130***			0.132***					
		(0.023)			(0.020)					
DP_{t-4}			0.183***				0.186***		0.225***	0.171***
			(0.031)				(0.034)		(0.033)	(0.029)
$DP_{t-4} \times TP_{t-1}$									-0.007***	
									(0.002)	
$DP_{t-4} \times SYS_{t-1}$										0.003*
										(0.002)
Δ $Oilprice_{t-1}$	0.004	0.003	0.003	0.004	0.002	0.003	0.002	0.006	0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
Team $Size_t$	1.947***			1.886***						
	(0.490)			(0.463)						
Export $Market_{t+1}$						0.197***				
						(0.040)				
Export $Market_{t-4}$								0.231***		
								(0.063)		
Adj. R^2	0.667	0.786	0.807	0.657	0.779	0.758	0.800	0.663	0.829	0.809
Obs.	30	30	30	30	30	30	30	30	30	30
Max. VIF	1.070	1.078	1.164	1.252	1.343	1.422	1.435	1.334	2.441	4.568
F-Value	20.339	36.604	41.391	14.866	26.552	23.679	29.997	15.253	29.179	25.614
AIC	20.476	7.120	4.105	22.193	8.978	11.728	5.982	21.647	2.001	5.327

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

5.3 Robustness checks

There might be concerns about endogeneity, especially reverse causality in the models explaining the size of the networks. It could be possible that policy makers react to an exogenous growth of the number of inventors by investing more into the specific technologies,[12] or that both phenomena are influenced by an unobserved variable that is exogenous to our model. We partly account for this issue by imposing a lag structure on our models, which implies a distinct direction of causality (Nesta et al. 2014). In addition, we check if any of our explanatory variables are correlated with the error term of our regressions, which could indicate endogeneity issues (Hayashi 2000). This is not the case in any of our models. An instrumental variables approach has been put forward as a method to deal with possible endogeneity (Angrist et al. 1996, Brynjolfsson et al. 2009, Peters et al. 2012, Nesta et al. 2014). Peters et al. (2012) use the funding for one technology as an instrument for the other technology. However, due to the low number of observations, instrumental variable estimations are not reliable in our case (Crespo-Tenorio and Montgomery 2013).

Concerning the imposed lag structure, we test the sensitivity of our results to different lags by estimating all possible lag combinations on the intervals [0, 3] for *TP* and *SYS* and [-1, 4] for *DP* (see appendix 3). In general, the estimated coefficients imply that our results would also hold for most other tested lag structures even though they do not always provide the best model fit.

With respect to the data’s time series nature, non-stationarity might be an issue. All variables except *Mean Degree* and *Team Size* enter our regressions as first differences[13]. Our dependent variables are non-stationarity and we create alternative, stationary dependent variables to investigate whether the non-stationarity biases our results: for Δ *Nodes*, we divide the number of inventors in each technology by the overall number of German inventors and take the first difference. This represents change in the share of inventors in this technology in all German inventors and captures the changing attractiveness of the respective technology relative to all technologies. We divide the *Mean Degree* by the *Team Size* of all German patents to capture the propensity to cooperate in WP and PV relative to all technologies in Germany.

[12] The reverse causality issue for mean degree is not that likely, since the cooperation intensity has only since recently been on the policy maker’s agenda.

[13] Recall that *DP* is operationalized as the log of annual installments, which is the first difference of cumulative installments.

Table 6: OLS-regression robustness results with new dependent variables

	Δ Share of Inventors				*Relative Mean Degree*			
	Wind power		Photovoltaics		Wind power		Photovoltaics	
	Model 5	Model 7	Model 5	Model 7	Model 5	Model 7	Model 5	Model 7
Intercept	-0.002	0.000	-0.003	-0.002	0.206**	0.239***	-0.054*	-0.038
	(0.002)	(0.002)	(0.002)	(0.001)	(0.079)	(0.044)	(0.032)	(0.026)
TP_{t-1}	0.000*	0.000*	0.000**	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SYS_{t-1}	0.000***	0.000***	0.000	0.000	0.000***	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DP_{t+1}	0.001***		0.002***		0.039***		0.016**	
	(0.000)		(0.001)		(0.013)		(0.007)	
DP_{t-4}		0.001		0.004***		0.046***		0.020**
		(0.000)		(0.001)		(0.009)		(0.009)
Δ $Oilprice_{t-1}$	0.000	0.000	0.000	0.000	0.001	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
Adj. R^2	0.799	0.784	0.550	0.693	0.791	0.869	0.156	0.122
Obs.	29	29	29	29	30	30	30	30
Max. VIF	1.697	1.814	1.427	1.525	1.253	1.365	1.427	1.525
F-Value	28.853	26.454	9.550	16.781	28.490	48.991	2.291	1.974
AIC	-236.157	-234.088	-197.466	-208.540	-32.906	-46.821	-48.472	-47.341

Δ *share of inventors* is the first difference of the ratio between the number of inventors in each technology and the overall number of German inventors. *Relative Mean Degree* is the ratio of *Mean Degree* in the respective technology and *Team Size* in Germany.
Robust standard errors (HAC) in parenthesis. Sig. at *** 0.01, ** 0.05, * 0.1 level

We re-estimate models 5 and 7 with our altered dependent variables. Models 5 and 7 were chosen because these models include all our explanatory variables with no interactions.[14] Table 6 shows that the results change very little, only in model 5 for *Relative Mean Degree* in PV is the *TP* variable insignificant and, for both models, the overall model fit is drastically reduced. However, since the new dependent variables do not have exactly the same meaning as the original ones, we consider these small deviations unproblematic. These results indicate that the non-stationarity of our dependent variable does not bias our general findings.

6 Discussion and Conclusions

This study attempts to shed light on the influence of the German policy mix with its constituting instruments and their consistency on the size and the structure of co-inventor networks in wind power (WP) and photovoltaics (PV) in Germany. We go beyond previous and related studies by focusing explicitly on co-inventor networks and not merely on the number of patents (e.g. Johnstone et al. 2010, Wangler 2013, Böhringer et al. 2014, Nesta et al. 2014). Such networks of knowledge transfer and learning have been identified as important drivers of innovation (Dosi 1988, Powell et al. 1996, Ahuja 2000). Several theoretical as well as empirical studies suggest a positive influence of increased interaction on innovation performance (Powell and Grodal 2005, Fritsch and Graf 2011, Phelps et al. 2012). Our main contribution in this respect is to analyze the effects of policy on interaction within co-inventor networks. For this purpose, we refer to the existing literature on technology push and demand pull policies, and extend the analysis by accounting for systemic instruments, specifically designed to foster cooperation and knowledge transfer. In addition, we provide insights regarding the consistency of the policy mix, by looking at the interaction of these policy instruments (Rogge and Reichardt 2015). While most related studies are based on a panel of several countries, we focus solely on Germany. The reason for this choice of study design lies in the availability of more fine grained funding data that allows for the identification of the systemic instrument.

Despite this different approach, our general results are in line with previous studies on policy effects of push and pull instruments in RPGT. As in Johnstone et al. (2010), Wangler (2013) and Böhringer et al. (2014), we find positive effects of technology push on innovation activities (contrary to the findings by Nesta et al. 2014). Similar to Wangler (2013) and Peters et al. (2012) and partly in line with Johnstone et al. (2010), we show that demand pull policies

[14] We do not include Δ *Patents* and *Team Size* in these regressions. Both are control variables meant to account for the general development in Germany, which are part of the dependent variables.

play an important role in facilitating inventive activity. However, the effect is technology dependent, and seems to be very influential in PV but less pronounced in WP (also in line with Johnstone et al 2010).

In particular, we find that the network size, i.e. the number of actors active in the technology, is positively affected by technology push and systemic instruments in WP, whereas in PV it is only technology push which shows an effect. Demand pull instruments, such as the EEG, have a strong positive effect in PV in creating resources for inventive activity (*resource effect*), but also by allowing the actors to anticipate policy effects, e.g. in terms of upcoming market opportunities for their products. In the case of WP, this *anticipation effect* seems to be relatively more important. This phenomenon has also been discussed by Nemet (2009) and Hoppman et al. (2013) and seems to be a relevant force for technological development. Considering the international context, export market dynamics are closely correlated with domestic demand in Germany. Such an apparently aligned behavior might be a response to international CO_2 reduction targets or result from international policy learning. In line with Peters et al. (2012) and Dechezleprêtre and Glachant (2014) these export market dynamics also play a role in WP and PV, where actors anticipate market opportunities abroad and increase their inventive activities. In the case of PV, our results indicate a resource effect via export markets.

Our hypothesis regarding the influence of systemic instruments on the structure of the networks finds support only in the case of WP, whereas in PV, the results are inconclusive. As expected, technology push policies do not increase cooperation in WP at all, while for PV, the effect is ambiguous. Concerning the effect of demand pull instruments on collaboration, we find a strong positive influence in both technologies. This is quite surprising, since demand pull policies are not designed to support collaboration. One possible explanation could be the presence of an increased number of potential cooperation partners with complementary knowledge and capabilities. In a similar vein, the increase in market size might allow for more specialization, thereby increasing the benefits of cooperation when combining different sets of knowledge (Cantner and Meder 2007).

Concerning the policy mix, we find that push and pull instruments work hand in hand in increasing network size, while pull and systemic instruments together spur cooperation. These results indicate the necessity of market demand to reap the full potential of technology push and systemic instruments. Our findings indicate strong consistency of the analyzed instruments in the policy mix. However, we also find some inconsistencies. Pull and systemic instruments interact in a way that seems detrimental to network size in PV. Apparently, this combination of instruments favors existing actors rather than attracting new ones. In a similar fashion, a combination of push and pull instruments works against collaboration in PV and rather favors individual research activities. Therefore, our results question the relevance of technology push to enhance cooperation. Since this instrument does not aim at fostering cooperation, but rather provides sufficient resources to conduct R&D without cooperation, this seems quite plausible. Apparently, we look at two, at least partly conflicting measures of system performance, since it might be difficult to sustain the level of average cooperation intensity in times of fast network growth. There might well be a tradeoff between policy goals that shows in the above mentioned inconsistencies, which is not necessarily to be judged negative (Quitzow 2015).

Based on our empirical findings, we can derive several suggestions for policy: First, implementing a mix of policies goes beyond a single instrument in fostering innovation, at least in infant technologies. Second, demand inducing policies should be designed to create resources for inventive actors to enlarge their research activities, but also provide stable perspectives regarding future market opportunities. Third, cooperation activity should be supported by specific instruments and existing instruments should be evaluated concerning their effect on cooperation – some policies affect cooperation, even though it is not their objective. Fourth, all these policies form a mix that ought to be consistent in providing incentives to engage in R&D and especially collaborative activities as well as in supporting market creation. However, our results are technology specific. These differences may be related to the technologies' state of development, their relative competitiveness, market dynamics and differences concerning the nature of these technologies, which need to be considered when implementing a certain policy instrument within a policy mix (Huenteler et al. 2015).

From a research perspective, we contribute the following insights: First, we bring together the literature on innovation networks and policy support in the context of environmental innovation. This helps to understand better the relationship between policy instruments and their effect on invention networks and the knowledge transfer in these networks. Second, we can show that certain policies do not only increase inventive activity, but also alter the underlying network structure. The effects of policies on network structure are still poorly understood and we provide first insights as to the types of policies that actually have an effect. Third, we demonstrate that public R&D funding can have different effects if it contains systemic components that successfully support network formation. Finally, with respect to the policy mix for innovation, we provide a simple approach to operationalize aspects of its consistency, which gives insights about how different policy instruments interact.

However, this study leaves room for improvement and extension. We consider only the situation in Germany; extending the scope of the analysis for a panel of countries and/or a broader set of technologies may lead to further insights on the effect of the different policy instruments and their interaction. Unfortunately, more fine grained data that would allow us to identify funding as technology push or systemic is, to our knowledge, not readily available for other countries. Concerning the systemic instruments, institutional funding to public research institutes and universities is not included in our analysis, neither are non-monetary policy instruments such as changes in patent law, the education system, grid access or other market design instruments, which need to be taken into account to understand fully the effect of systemic instruments. Moreover, the role of potential export markets could be explored in more detail by accounting for interdependencies between national RPGT policies. Also, the consistency of the policy mix needs further empirical investigation. Here, more empirical applications in different countries and technologies are required to generalize our findings. From a methodological point of view, using instrumental variables would be desirable, which would be possible with a panel of countries.

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Appendix 1: Patent selection

The selection of the relevant patents was done by combining IPC classes and keywords. The abstract and title of the patent document are searched for the keyword. The selection criteria for WP is based on the suggestions from the WIPO Green Inventory and own elaboration. For PV, we rely on a detailed elaboration on keywords and IPCs derived in Kalthaus (2016). The keywords and IPCs are grouped for specific technologies and fields to reduce the overlap with other adjacent technologies:

	IPC Class	Keyword combination
Wind Power	F03D%	
	H02K 7/18 B63B 35/00 E04H 12/00	(%wind% + (%turbine% | %power% | %mill% | %energ%))
Photovoltaics	H01L 21% H01L 31% C30B 15%	((%monocrystalline_silicon% | %monocrystal_silicon% | %crystal_silicon% | %silicon_crystal% | %silicon_wafer%) + (%photovoltai% | %solar%)) | %back_surface_passivation% | (%pyramid% + %etching% + %silicon%)
	C01B 33% C30B 15% C30B 29% H01L 21% H01L 31%	((%polycrystalline_silicon% | %multicrystalline_silicon% | %poly_Si% | %polysilicon%) + (%photovoltai% | %solar%)) | (%ribbon% + (%photovoltai% | %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%) + (%photovoltai% | %solar% | %silicon%)) | ((%tandem% | %amorphous_silicon% | %silicon_substrate% | %silicon_film%) + (%photovoltai% | %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% | %thinfilm%) + (%photovoltai% | %solar%)) | %Copper_indium_gallium_diselenide% | %CuInGeSe% | %CIGS% | %Copper_zinc_tin_sulfide% | %CZTS% | %Kesterite%
	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%) + (%photovoltai% | %solar)) | %Gr_tzel% | %Graetzel% | %hybrid_solar_cell%
	H01G 9% H01L 31% H01L 51% H01M 14%	((%Quantum_dot% | %perovskite% | %organic_inorganic% | %Plasmon% | %Nanowire% | %nanoparticle% | %nanotube%)) + (%photovoltai% | %solar))

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%) + (%photovoltai% | %solar)) | %solar_panel% | %photovoltaic_panel% | %solar_modul% | %solar_cell_modul% | %photovoltaic_modul% | %solar_cable% | %Photovoltaic_Wire% | %solar_array% | %photovoltaic_array% | %BIPV% | %solar_park% | (%spacecraft% + (%photovoltai% | %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%	(%photovoltai% | %solar_cell%)

Appendix 2: Correlations

Table 6: Correlations Wind Power

	Δ Nodes	Mean	TP + SYS	TP	SYS	DP	Export	Δ Oilprice	Δ Patents	Team Size
Δ Nodes	---	0.820***	0.818***	0.737***	0.781***	0.537***	0.808***	0.266	-0.285	0.646***
Mean Degree	0.000	---	0.753***	0.639***	0.825***	0.701***	0.939***	0.369**	-0.244	0.841***
TP + SYS	0.000	0.000	---	0.982***	0.455***	-0.003	-0.095	0.345**	-0.360*	0.633***
TP	0.000	0.000	0.000	---	0.276	-0.083	-0.235	0.325*	-0.284	0.611***
SYS	0.000	0.000	0.006	0.108	---	0.370**	0.618***	0.229	-0.448**	0.505***
DP	0.003	0.000	0.987	0.637	0.028	---	0.839***	0.189	0.251	0.960***
Export Market	0.000	0.000	0.586	0.174	0.000	0.000	---	0.097	-0.158	0.909***
Δ Oilprice	0.163	0.045	0.046	0.061	0.193	0.285	0.584	---	0.057	0.402**
Δ Patents	0.134	0.202	0.055	0.135	0.015	0.189	0.412	0.769	---	0.025
Team Size	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.028	0.897	---

Upper triangle: Pearson correlation coefficient, lower triangle: p-values. Sig. at *** 0.01, ** 0.05, * 0.1 level

Table 7: Correlations Photovoltaics

	Δ Nodes	Mean	TP + SYS	TP	SYS	DP	Export	Δ Oilprice	Δ Patents	Team Size
Δ Nodes	---	0.633***	0.450**	0.185	0.451**	0.711***	0.740***	0.216	-0.056	0.539***
Mean Degree	0.000	---	0.510***	0.170	0.555***	0.878***	0.847***	0.358*	-0.441**	0.666***
TP + SYS	0.014	0.004	---	0.731***	0.625***	0.349**	0.326*	0.169	-0.706***	0.018
TP	0.335	0.369	0.000	---	-0.075	-0.064	-0.127	0.170	-0.467**	-0.213
SYS	0.014	0.001	0.000	0.669	---	0.584***	0.622***	0.053	-0.520***	0.267
DP	0.000	0.000	0.040	0.715	0.000	---	0.956***	0.287	-0.274	0.900***
Export Market	0.000	0.000	0.056	0.466	0.000	0.000	---	0.247	-0.254	0.876***
Δ Oilprice	0.260	0.052	0.340	0.335	0.765	0.100	0.159	---	0.057	0.402**
Δ Patents	0.772	0.017	0.000	0.011	0.004	0.150	0.183	0.769	---	0.025
Team Size	0.003	0.000	0.924	0.258	0.154	0.000	0.000	0.028	0.897	---

Upper triangle: Pearson correlation coefficient, lower triangle: p-values. Sig. at *** 0.01, ** 0.05, * 0.1 level

Appendix 3: Lag structure

Figure 5 shows for all four dependent variables overall model fit (AIC) and the effect of the respective policy instrument depending on different lag structures. For any given lag of the respective policy instrument, we perform regressions with all possible lag variations of the other instruments, thereby modifying the benchmark model 5 (tables 2-5). Positive coefficients are displayed with a '+', negative ones with a '-', and those insignificant with a '○' (the significance threshold is a p-value $\leq$ 10%). For example, in the case of *Δ Nodes* in WP, we see that TP is almost always positive for lags of 0 and 1, regardless of the lags of the other variables. However, TP is always insignificant for lags of 2 or 3. Furthermore, the model fit seems to be slightly better for lag of 0 according to the AIC.

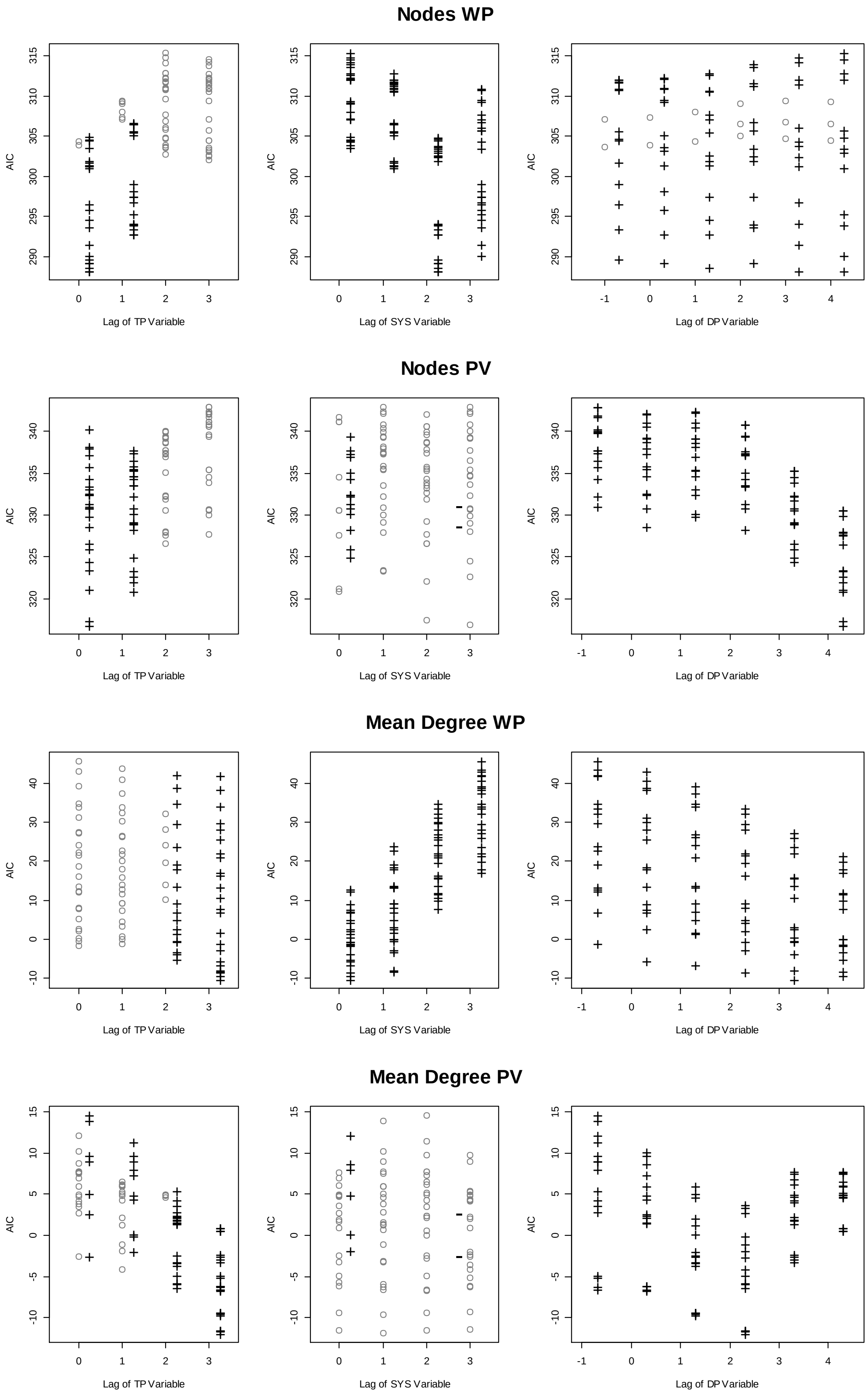

Figure 5: Sensitivity analysis of lag structures as variations of regression model 5.

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