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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 policies that can broadly be categorized as technology push, demand pull or systemic constitute a policy mix for renewable energies. Our goal is to gain insights on the influence of this policy mix on the intensity and organization of inventive activities within the technological innovation systems for wind power and photovoltaic 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 photovoltaic demand pull is decisive for network growth. The instruments complement each other and form a consistent policy mix. 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, O38

1 Introduction

During the last decades, global electric power generation by renewable sources increased constantly, especially in Germany (IEA 2010). In the last decade, from 2002 to 2012, the amount of energy globally generated from renewable sources (except hydropower) has increased by the factor four (BP 2013). This increase is mainly driven by political support and technological progress in the specific technologies. Several studies show 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). In particular, inventive activities, induced by policies for wind power (WP) and photovoltaic (PV) technologies, increased tremendously over the last decades.

This development is heavily driven by political intervention and support. Respective schemes attempt to influence the development and diffusion of renewable power generation technologies (RPGT), especially PV and WP, from different directions. Demand pull instruments (DP) 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 (TP) directly affect inventive and innovative activities by means of R&D subsidies or through performing public R&D in research institutes. Systemic instruments (SYS), such as cooperative R&D programs, clusters or infrastructure provisions provide support at the innovation system level (Smits and Kuhlmann 2004). These various policy instruments together constitute a policy mix (Rogge and Reichardt 2013), meant to commonly support the development and diffusion of RPGTs. This policy mix is changing over time in terms of the balance of the different instruments implemented.

While the positive influence of, especially TP policies, on investments in R&D is quite clear, two important aspects of policy impact are less obvious. First, DP instruments increase incentives to invest in production facilities, but do they also increase incentives for innovation and to invest 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, increase the knowledge-base of innovative actors and therefore have a positive influence on innovation output. Several channels of technological spillovers have been identified in the economics of innovation, with personal contact through cooperation or job mobility being one of the most important one. 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. 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 changes in that mix due to new instruments influence the process of invention and innovation in specific technologies. 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 that aim at fostering collaboration 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. Our focus is 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 represents a good fraction of the world market for RPGTs. 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), which was caused by extensive support schemes.

The remainder of this paper is organized as follows: First we give a short review of the literature and theoretical framework of our study in section 2. In section 3, a short summary of the policy instruments in Germany is provided. Section 4 describes the networks and their properties. In section 5, we derive hypotheses for the influence of different instruments and the policy mix on the inventor networks. In section 6, we present our methodological approach in more detail, followed by a presentation of the data and our econometric results. Section 7 concludes.

2 Literature review and theoretical framework

Systemic perspective and networks

Innovative activity and output depend not only on the quantity of inputs, but also on the institutional framework, knowledge related interactions and the resulting overall structure between the actors that constitute the technological innovation system (Carlsson and Stankiewicz 1991). Hekkert et al. (2007) derive seven central functions of a technological innovation system: entrepreneurial activity, knowledge development, knowledge diffusion through networks, guidance for search, market formation, resource mobilization and creation of legitimacy/counteract resistance to change. The interaction of these functions is crucial for the innovation process. In the following, especially the interaction between the market creation, which is the formation of a market niche by certain policy measures, and the creation and diffusion of knowledge through networks is elaborated in more detail.

The last decades saw a large increase in the number of studies developing and applying the technological innovation systems approach with many studies focusing on renewable energies (e.g. Jacobsson and Johnson 2000, Jacobsson and Bergek 2004, Verbong and Geels 2007, Dewald and Truffer 2011). They focus on the presence of network structures which support and enhance innovative activity and diffusion of technology. They also acknowledge the importance of a market creation mechanism, which supports the development of the technologies. Besides the mechanism for market creation, other mechanism aiming to directly support research and technological development are needed to strengthen inventive activity and to overcome market and system failures and barriers for the commercialization of technologies (Foxon et al. 2005).

These different instruments, which focus on cooperation and networks in a systemic context, foster a cumulative process of knowledge creation and innovations, in which novelty is created by combining knowledge from a diverse set of actors. Cooperation and the resulting 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 (SNA) that maps the different actors and their relations in the context of innovation and knowledge transfer (see Borgatti and Foster 2003 for a general overview of SNA and Cantner and Graf 2011 for an overview and application in the context of innovation networks). Knowledge transfer can take place in different kinds of networks, like co-authorship networks (e.g. Barabasi et al. 2002, Newman 2004, Moody 2004, Acedo et al. 2006) university-industry research collaborations (e.g. Balconi et al. 2004, Ponds et al. 2010, Guan/Zhao 2013), industry collaborations (e.g. Ahuja 2000, Schilling and Phelps 2007) or co-invention (e.g. Balconi et al. 2004, Fleming and Frenken 2007, Casper 2013). Analyzing these networks helps to understand how knowledge is generated, distributed and affects the actors in these networks. However, concerning cooperation in R&D, the implied knowledge transfer between the actors and the underlying network structures tend to be affected by the 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 rational for policy intervention in order (i) to reduce the monetary risk of non-complementarity and/or of non-reciprocity and (ii) to bear the costs of searching for appropriate partners. In this context, various types of policies may have a different influence on network formation, thereby affecting the rate of knowledge transfer and consequently influencing the speed at which technologies are developed.

Policy Mix

Concerning the RPGT innovation system, there are different policy instruments in place, affecting invention, innovation and diffusion. In the innovation system for RPGT, there are several market and system failures which are addressed by different instruments and policy fields. The three main fields concerning RPGT 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 refers to negative external effects concerning the production of electricity by conventional electricity production, and *climate policy* which focusses especially on the adverse effects of greenhouse gas emissions form conventional electricity generation. The problem arising from these externalities is summarized under the double or multiple externality problem (Rennings 2000, Jaffe et al. 2005). Policies trying to internalize these externalities interact and form a policy mix, affecting the processes of invention, innovation, and diffusion of RPGT. The interaction, interdependence and possible coordination failures within this policy mix caught the attention of researchers and first conceptual considerations on the instrument and policy mix level are derived. Sorrell et al. (2003) look at different kinds of interaction between instruments in the context of the EU emission trading system (EU ETS), del Río (2007) gives an overview of the interaction between emission trading and renewable electricity support schemes, while Flanagan et al. (2011) conceptualize a policy mix for innovation instruments and Lehmann (2012) reviews instrument mixes to cope with multiple market and governance failures in pollution control.

In the instrument mix, the interaction between the different instruments is a crucial factor for the effectiveness, especially with respect to climate and energy policy. Buen (2006) examines different instruments and their relationships supporting invention and diffusion of WP in Denmark and Norway. del Río (2010) looks at the interaction between the EU ETS, energy efficiency standards and renewable energy promotion. Walz (2005) investigates the interaction between the EU ETS and the German FIT and Rathman (2007) estimates these instruments' interaction effect on the electricity price. Böhringer and Rosendahl (2010) show analytically that in the presence of two interacting quota instruments an adverse effect on pollution control emerges. While the effect of climate and environmental policy on innovation is well known (e.g. Jaffe et al. 2002, Requate 2005, Johnstone et al. 2010) the interaction between innovation policy and environmental and climate policy instruments is, to our best knowledge, not studied in detail so far.

Since the interaction of different instruments in an instrument mix captures only a part of the picture, a higher level of policy concordance in terms of a policy mix must be considered. At this level, which includes the instrument mix, further characteristics constituting a policy mix must be considered as well. While Flanagan et al. (2011) already emphasize several dimensions (policy space, governance space, geographical space and time) in which an innovation policy mix interacts with the same or different groups of actors or itself, Borrás and Edquist (2013) look how different instruments should be chosen and form an instrument mix which has systemic characteristics in an innovation system. Rogge and Reichardt (2013) go a step further and conceptualize the policy mix across different policy fields. They suggest a policy mix for environmental technical change (focusing on RPGT) which integrates climate, environmental and innovation policy fields. In this framework, the policy mix must fulfill certain criteria, starting with the consistency of the elements, which includes not only the consistency between the instruments and their interaction, but also between the policy strategy and between instruments and strategy. Based on this, the coherence of the processes of policy making and implementing must be ensured and contradictions between the elements should not be present. Additionally, the mix should include characteristics like credibility, stability and comprehensiveness, covering the reliability of the mix, its long term certainty, and how broad its coverage is.

3 The policy mix 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. Policies 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 which 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).

In this analysis, we focus on economic instruments supporting invention and diffusion of RPGTs. These instruments are only a part of the overall policy mix, but constitute the most relevant ones for innovative activity. The whole set of instruments in the policy mix derive from the systematization in Rogge and Reichhardt (2013) and are shown in Table 1, which contains some examples of specific instruments. They are separated by their purpose concerning innovative activity and type of instrument.

Table 1: Type-purpose instrument typology.

PRIMARY TYPE	PRIMARY PURPOSE: Technology Push	Demand Pull	Systemic
Economic Instruments	RD&D grants and loans, tax incentives, state equity assistance	Subsidies, feed-in tariffs, trading systems, taxes, levies, deposit-refund-systems, public procurement, export credit guarantees	Tax and subsidy reforms, infrastructure provision, RD&D cooperative grants
Regulation	Patent law, intellectual property rights	Technology / performance standards, prohibition of products / practices, application constraints	Market design, grid access guarantee, priority feed-in, environmental liability law
Information	Professional training and qualification, entrepreneurship training, scientific workshops	Training on new technologies, rating and labelling programs, public information campaigns	Education system, thematic meetings, public debates, cooperative RD&D programs, clusters

Source: Rogge and Reichardt (2013: 12)

3.1 Demand pull instruments

Demand pull instruments do not directly affect the inventor, but shape a market environment in which the technology can be adopted and diffuse. Different demand inducing policies exist, such as public procurement, demand subsidies, fiscal incentives or soft instruments such as standards and labels or initiatives to reduce information asymmetries (Edler 2010). In general, these instruments create or increase demand for a product which allows the producing company to gain revenues, which can be reinvested in R&D activities (e.g. Nemet 2009, Hoppmann et al. 2013).

In the beginning of the development of RPGT in the 1970s, DP 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 times between municipal services and the installation owner, granted a payment per electricity unit in relation to production costs. With the Electricity Feed-in Law ("Stromeinspeisegesetz"), 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 80% 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 (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).

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 gave 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 the program 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 three times to keep up with the demand for support. Eventually, the program ended in 2003 and was integrated in the amended version of the EEG in 2004.

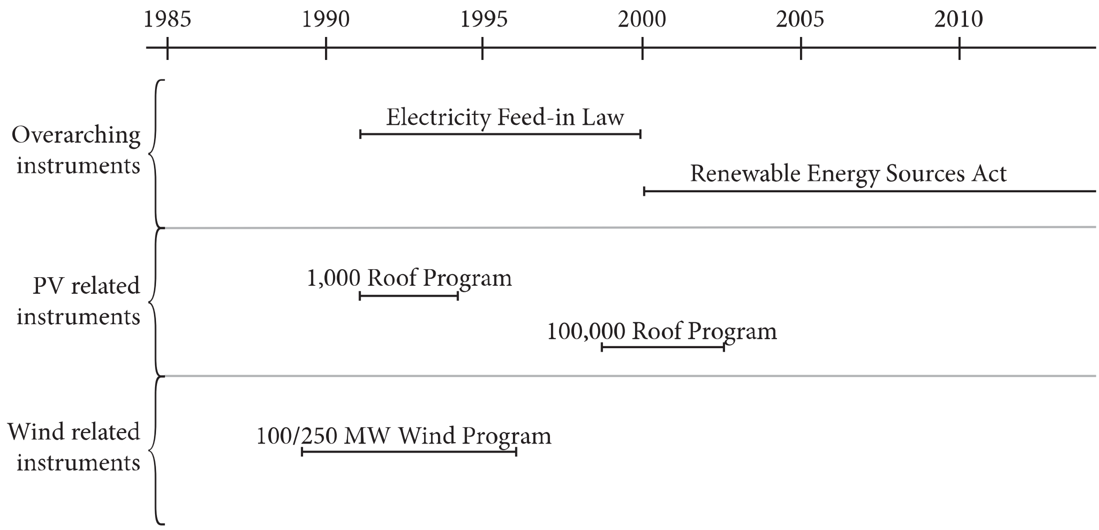

Figure 1: Main demand pull instruments in Germany.
Source: Own elaboration.

3.2 Technology push instruments

The most prominent instruments which directly influence inventors' activity are R&D subsidies to firms, universities and public research institutes, but also loans and tax incentives for R&D expenditures are used. These instruments provide financial support to inventors who perform R&D with the aim to encourage inventive activities and to reduce the underinvestment in R&D due to positive external effects. There is empirical evidence that direct funding of R&D increases inventive output (e.g. Czarnitzki and Hussinger 2004, Alecke et al. 2012), despite the concern that a crowding out of private R&D investments takes place (see Zúñiga-Vicente et al. 2014 for a review on crowding out).

For RPGTs in Germany the main TP instrument is R&D funding by the German federal government. Federal R&D spending is documented in the German Förderkatalog (2013), 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[1]. Overall funding can be divided into funding for individual research projects at an institute or a company and collaborative research projects. In the course of the analysis we separate these two kinds of funding since they have different effects.

For the TP instrument, we select only projects which are attributed to one recipient. We collect the data from 1978 until 2011 which covers 259 research projects with a total amount of 283.4 mio. Euro in WP and 590 projects with a total of 934.9 mio. Euro in PV (in 1995 Euros). The project grants are equally distributed over the project duration to account for the length of the project. This means, if 1 mio. Euro is granted to a research project running for five years, we allocate 0.2 mio. Euro per year.

Overall funding as well as its breakdown into individual and cooperative funding is depicted in figure 2. 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.

[1] The keywords used are: “wind”, “pv”, “photovoltai*”, “solar”. Projects which are not directly relevant for inventive activity, such as energy related educational programs, and projects which do not belong to WP and PV research are removed manually from the dataset.

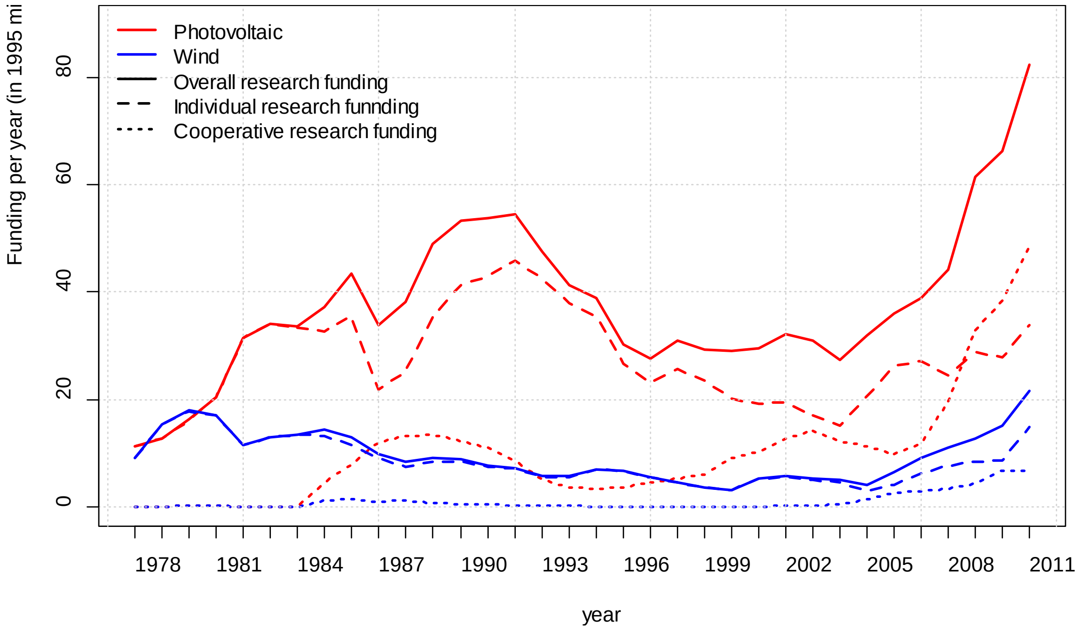

Figure 2: Federal funding of research projects in WP and PV.
Source: Own calculation based on Förderkatalog (2013).

3.3 Systemic instruments

Systemic instruments are designed to provide support at the system level of inventive activity. This includes the provision of infrastructure to facilitate learning and knowledge exchange, enhancing cooperation by cluster initiatives or fostering cooperation between inventive actors (Smits and Kuhlmann 2004). The aim of such instruments is to connect different actors, 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 have been shown to lead to higher inventive output compared to individual grants (e.g. Czarnitzki et al. 2007, Fornahl et al. 2011).

Examples for research infrastructures in Germany are research institutes such as the Fraunhofer Institute for Solar Energy Systems ISE, dedicated chairs at universities, or the recently founded cluster initiative SolarValley, which was successful in the leading edge cluster competition (BMBF 2012). However, cooperative research projects ("Verbundforschung") are widely used to encourage cooperation of inventive actors among each other. Cooperative research projects provide funding for teams of researchers or companies which need to build research consortia to apply for this program. Sometimes specific conditions concerning the cooperation partners are to be met, such as the requirement that only partnerships without previous joint cooperation are eligible for funding. Such incentives for cooperation have been shown to have a significant effect on inventive output, for example in the biotech sector (Fornahl et al. 2011).

For systemic instruments, we rely on the same data source as for TP funding (Förderkatalog 2013). Here, we select grants for cooperative research. To identify collaborative grants, the project needs to have the term “Verbundforschung” in the project title, which is specifically used to describe these cooperative grants. We identify 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 344.2 mio Euro for PV and 35.1 mio. Euro for WP, respectively. The amount of annual cooperative funding is displayed in figure 2. It was introduced in WP and PV in the beginning of the 1980s, and especially in PV it showed 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.

4 Inventor networks in photovoltaic and wind power technologies

4.1 Reconstructing 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 Patstat April 2014 database (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 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.

4.2 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 1 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 invented 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 which 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 dominating 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).

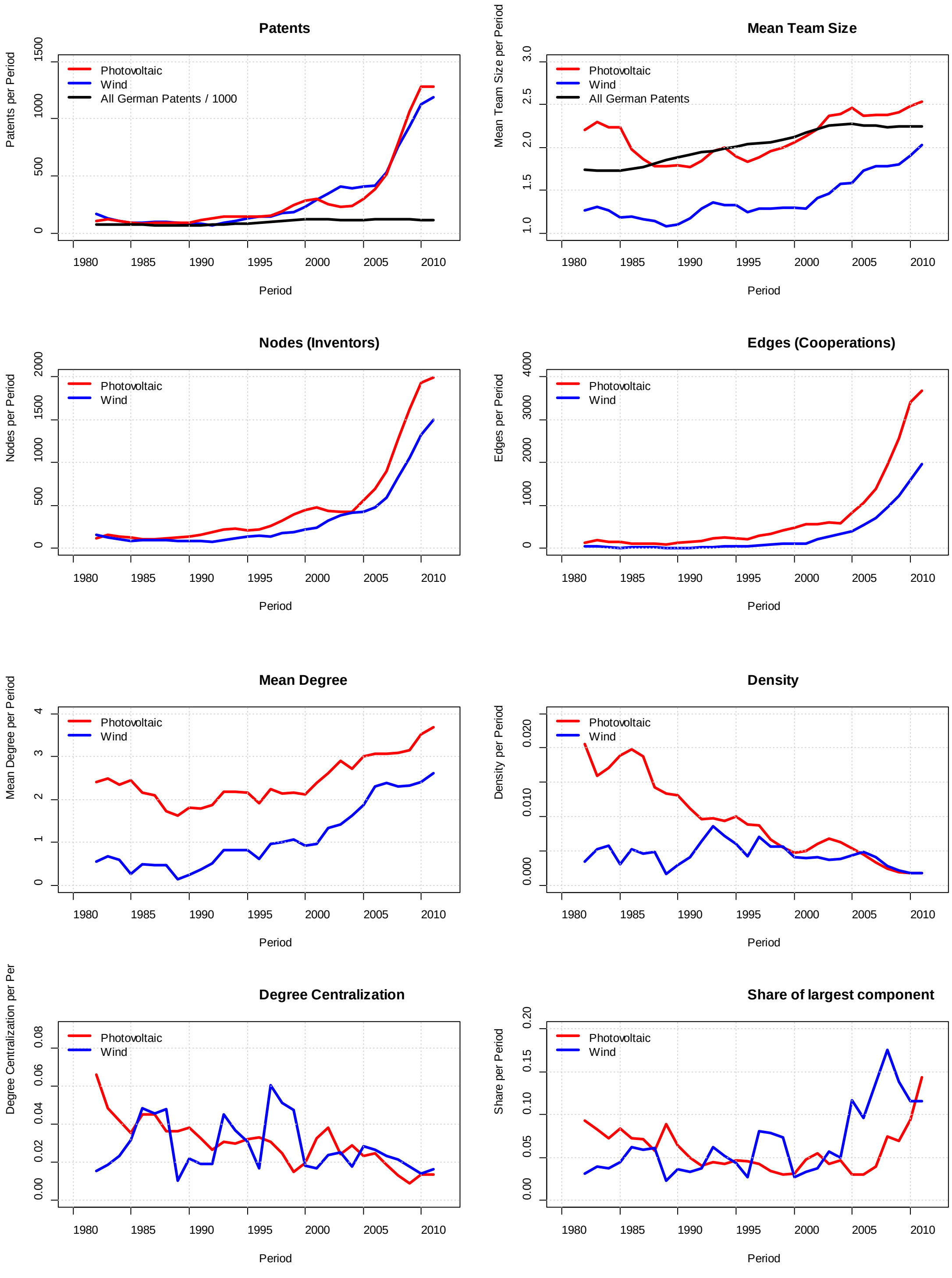

Figure 3: The structure of WP and PV networks.

5 Hypotheses

Since we have elaborated the different policy instruments in place supporting PV and WP and described the evolution and dynamics in the inventor networks, it is important to analyze how the different policies influence the size and the structure of the network.

Network size

Several studies look at the development of patent data, which is a measure for the size of the network, and how different policies influence patenting activity. Johnston et al (2010) evaluate for 25 countries how several RPGTs patents are affected by different kinds of instruments. They show that specific R&D expenditures foster inventive activity especially for WP and PV. FITs have only a significant effect for PV. Wangler (2013) focusses his analysis only on inventive activity in Germany. He estimates that public R&D expenditures and an increase in market size have a positive effect on inventive activity. In a similar attempt Böhringer et al. (2014) find mixed results. They estimate a positive effect on invention for public R&D expenditures and installed capacity for RPGTs in general for a longer timeframe. However, concerning single technologies, they only find a significant impact for WP capacity and not for PV. In a shorter timeframe, covering only the period where the EEG is in place, they find no significant effect on inventive activity. According to these findings we assume that technology push instruments foster inventive activity and increase the size of the networks by enhancing inventive activities.

H1a: The technology push instrument increases the size of the network

Concerning the effect of systemic instruments on network size, there is no empirical evidence known to us. However, since they are mainly financial instruments as well, they may also increase inventive activity. Furthermore, their systemic component to form cooperation with previously unknown cooperation partner could increase the size of the network as well, since new actors become involved in these technologies. Especially the German program is designed to attract new actors, or facilitate cooperation between former unknown actors, which may include previously not inventing actors.

H1b: The systemic instrument increases the size of the network

As stated above, the evidence for the effect of demand pull instruments on invention is inconclusive. We argue that it may have an indirect effect on network size. First and foremost, demand pull instruments establish markets and/or increase market size. This creates strong incentives for firms to expand production capacity to serve demand whereby they appropriate economies of scale and learning effects that allow developing more efficient production processes or new machinery (Arrow 1962, Peters et al. 2012, Lindman and Söderholm 2012). Furthermore, with a larger market for renewable energy technologies, 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.

H1c: The demand pull instrument increases the size of the network

Network structure

To our knowledge, there is no empirical evidence concerning the effect of different policies on the structural dynamics of inventor networks, at least for RPGT. Looking at technology push instruments, they are not designed to influence the connectivity structure inside the network, since such individual R&D grants do not encourage cooperation. Furthermore, the inventors, especially working for private companies, may be concerned about secrecy and could prefer not to cooperate to keep their knowledge.

H2a: The technology push instrument has no effect on cooperation inside the 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 at the same time integrate them in the structure by linking them to each other. Moreover, in view of the complexity of new technologies and the requirement of various knowledge and technological components to be brought together, cooperation in creating new ideas should increase to exchange knowledge and competences. On the network level that should show up in a higher degree of interaction.

H2b: The systemic instrument increases cooperation inside the network

Demand pull instruments may have no effect on the connectivity inside the network. They increase the size, but provide no incentive to engage in cooperation between different actors.

H2c: The demand pull instrument has no effect on cooperation in the network

Policy Mix

In addition to the individual policy types we also look at their common effects. The three kinds of instruments are in place at the same time and influence the change in size and structure of the networks. Together, they form a policy mix which may enhance the effect of each single instrument. Buen (2006) shows for WP in Denmark that a mix of demand and supply side instruments fosters technological development and diffusion, compared to Norway, where such a mix was not present. Guerzoni and Raiteri (2014) show that in the presence of public procurement and direct subsidies the innovative output is higher than the sum of both instruments, emphasizing the importance of interacting policy and the presence of a market for the technologies.

In the case of RPGTs it can be argued that a certain market demand must be present to encourage inventors to engage in R&D activity. Here, we can assume that market demand interacts with TP 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 pursue R&D activities.

H3a: Demand pull and technology push instruments are complementary in increasing the size of the network

A similar line of arguments may hold for the structure of the network. Here may also be the demand for the technology a requirement for actors to engage in R&D activity. The usage of systemic instruments can in combination persuade actors which are not inventing in RPGT to team up with actors already in the marked to cooperate on R&D activity. This would increase the connectivity inside the network.

H3b: Demand pull and the systemic instrument are complementary in increasing collaboration within the network

6 Policy impact on network size and structure

6.1 Data and variables

Dependent variables

For the analysis we use two dependent variables (see table 2 for an overview of all variables). The size of the network is given by the number of nodes, i.e. the number of distinct inventors, and is supposed to indicate the intensity of inventive activity in the respective fields. As pointed out in section 4.2, these show an exponential trend. To account for this, we use the first difference of network size, Δ *Nodes*. *Mean Degree*, which is the average number of collaboration partners of the nodes, is a simple measure to account for network structure (see figure 3).

Independent variables

To operationalize *DP*, we use the logarithm of new installations 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 DP instrument (Peters et al. 2012, Wangler 2013, Dechezleprêtre and Glachant 2014 and others use this proxy for PV and WP as well). 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 (2013) for both technologies (see figure 4). This approach, however, does not differentiate between different possible causes for an increase in installed capacity.

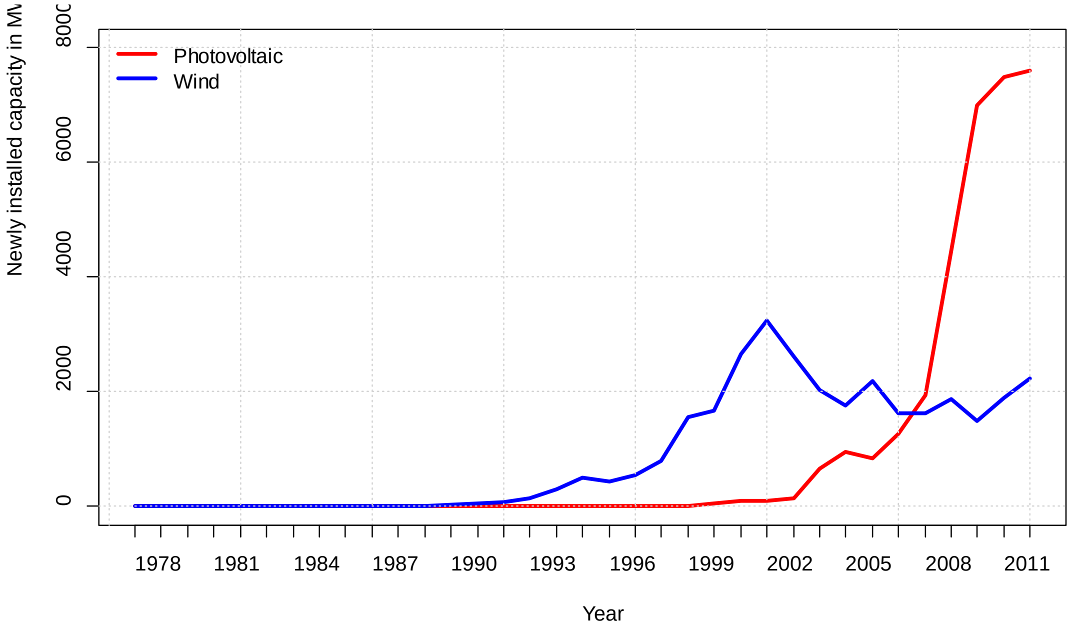

Figure 4: Yearly installed capacity per technology.
Data sources: Bergek and Jacobsson (2003), Jacobsson et al. (2004) and BMWi (2013)

The operationalization of *TP* and *SYS* is straightforward since they are provided as monetary values. 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.

Controls

We control for other factors than policy measures which 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. However, as documented in tables 7 and 8, the correlation between *Team Size* and *DP* is rather high and we can only control in some regressions for the increasing trend. 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). 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.

Table 2: Variables and descriptive statistics

Variable	Description	RPGT	Min.	Median	Mean	Max.	SD	Observations (Period)
Δ *Nodes*	Differences in the size of 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	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	Differences of technology push 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	Differences of the systemic instrument 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*	Differences in oil price		-42.64	-0.79	1.60	27.84	14.74	31
								(1981 until 2011)
Δ *Patents*	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)

6.2 Results

To estimate the effect of the different policy instruments on the size and structure of the network we use simple OLS time series regressions. Since the exact time structure of relationships between the variables and their influence on the dependent variables is unclear, we follow an explorative approach. First, we identify reasonable lag structures and then estimate the effect of the different instruments on the size and structure of the network to test our hypotheses.

Lag structures

Analyzing the influence of a specific policy instrument on inventive activity and on the network structure requires a time lag between the introduction or application of the instrument and the realization of an inventive output. Usually it takes some years from the implementation of a policy instrument until its results, especially in the case of inventive output, are observable. There are different lag structures discussed in the literature (see Hall et al. 1986 for a general discussion) which can be applied to account for the time it takes between policy implementation to a patented invention. If this would not be the case, the policy instrument would rather influence the propensity to patent already existing inventions, instead of incentivizing inventive activity (Scherer 1983). Different lag structures have been proposed in the context of on 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, however 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 the 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.

Since the appropriate lag structure is not clear, we empirically explore an appropriate lag structure. We estimate the effect of the different kinds of policy instruments on the network size and structure for a range from lag of five years until a foresight of five years for each variable. Based on the estimation, we select the lag structure based on significant variables and the highest explanatory power (adj. R^2). This results in a lag of one year for *TP* and *SYS*, which is in line with the literature. For *DP*, we receive a good fit for a lag of four years, as well as for a foresight of one year, which is in line with the model in Wangler (2013). Both lag types seem reasonable. A long term effect of a DP instrument, such as a FIT, would generate profits, which are invested in inventive activity that shows success only some years later. Therefore, we interpret significant results for the four year lag as an indication for a *resource effect*. However, all DP instruments which are subject to this analysis were intensively discussed in the public before introduction, so that the actors could anticipate policies well before their introduction and change their inventive behavior (*anticipation effect*). In implementing these 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 3-year moving windows.

Models

We estimate 10 different models to test the effect of the policy instruments on two dependent variables in two technologies. The first three models are included to test if funding in general affects inventive activity. Here we aggregate *TP* and *SYS* to replicate the setup of previous studies. In model 1, we use only the change in this aggregate to estimate the sole effect of monetary subsidies. In the second and third model we include *DP* with a foresight and a lag of four years. The fourth model uses *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.

We explicitly model the policy mix in the two final regressions, in which an interaction term between single instruments is included. The interaction term is supposed to grasp the consistency of the policy mix by checking if the respective instruments work in the same direction. Model 9 introduces an interaction between *TP* and *DP* with a four year lag.[2] The last model employs an interaction between *DP* and *SYS*.

6.2.1 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.[3] All models show no critical variance inflation factors, except for the interaction term in model 10.

In the first three models for WP (table 3), we observe that an increase in overall funding (the sum of *TP* and *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 policy mix on innovation in different technologies becomes clear by comparing the results for WP with those for PV (table 4). 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*.

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

[3] The results for changes in the number of patents, which is highly correlated with network size (appendix 2), are very similar and are documented in tables 9 and 10 in appendix 3.

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 H1b 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 H1c 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. However, due to problems of multicollinearity, we cannot include *DP* and *export market* in the same model. 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, the respective results call for a deeper discussion. 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*) seems to be decisive. Since Germany was a forerunner with its DP policies, these results show how firms could generate profits on the domestic market that provided resources to invest in inventive activities, while expectations regarding the size of export markets are also important drivers of firms' R&D strategies.

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 policy 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 H3a. 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. However, as noted above, we are skeptical with respect to models 10 in both technologies because of multicollinearity.

Table 3: Regression results for Δ Nodes Wind 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 $Patents_{t-1}$	-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

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

Table 4: Regression results for Δ Nodes Photovoltaic 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 $Patents_{t-1}$	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

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

6.2.2 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. Critical variance inflation factors are only present for the interaction term in model 10.

The first three models show in the case of WP (table 5) and PV (table 6) 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 H2a 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. Another difference between the two technologies appears with respect to the role of demand. In WP, the *resource effect* is driven by national demand (*DP*), while the *anticipation effect* is stronger for international demand. In PV, the *resource effect* is always stronger than the *anticipation effect* and *DP* seems more important than the size of the *export market*. Overall, demand plays an important role in both technologies, especially in providing the resources for stronger interaction in R&D. These findings are contrary to our expectations in H2c, 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 H3b, 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* reduces the incentive to engage in R&D collaboration.

Table 5: Regression results for Mean Degree Wind 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

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

Table 6: Regression results for Mean Degree Photovoltaic 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

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

7 Conclusions

This study attempts to shed light on the influence of the German policy mix and its constituting instruments on the size and the structure of inventor networks in wind power (WP) and photovoltaics (PV) in Germany. Based on time series regressions for each technology, we find different effects of the instruments on each technological system. 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 within a policy mix.

In particular, we find that the network size, i.e. the number of actors in the innovation system, is positively affected by technology push (TP) and systemic instruments (SYS) in WP, whereas in PV it is not clear-cut how these two instruments affect network size. However, demand pull instruments (DP), such as the EEG, have a strong positive effect in PV in creating resources for inventive activity, 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, the *anticipation effect* seems to be relatively more important. Considering the international context export market dynamics are closely correlated with domestic demand in Germany, which is most likely driven by foreign policies towards RPGTs. These export market dynamics play an important role in WP where actors anticipate market opportunities and increase their inventive activities. In the case of PV, domestic factors, such as the EEG, are more prominent than export opportunities. Since Germany was a forerunner with its DP policies, our results show how PV firms could generate profits on the domestic market that provided resources to invest in inventive activities. Concerning the policy mix, the size of the networks benefits from the complementarity of TP and DP, this forms a consistent policy mix.

The structure of the network is driven in WP as expected by SYS, but in PV it is again not that clear-cut. However, the structure is influenced by DP in both technologies, especially by providing resources for R&D collaboration. On the policy mix level, we find that SYS and DP complement each other to enhance cooperation. This favors the use of systemic instruments to support functions concerning knowledge exchange in the innovation system. However, the effect between TP and DP is negative for PV, which might question the relevance of TP to enhance cooperation. But this might be plausible, since the instrument does not aim to foster cooperation and should provide enough resources to conduct R&D without cooperation. Here, the policy maker's strategy needs to be considered.

In general we can conclude that the German policy mix is consistent in enhancing the size and the interaction in the technologies' inventor networks. Especially the simultaneous presence of

DP and TP or SYS seems effective for infant industries that compete with incumbent technologies to foster inventions and cooperation. Also the systemic part of funding drives cooperation and seems to be an adequate instrument to support interaction and knowledge exchange. We also find that DP has two different effects; it can create resources for the inventive actors which they can reinvest in inventive activity, and it also reduces uncertainty about future market opportunities which enhances inventive activity. This should be considered in the policy maker's strategy.

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 may lead to further insights into the effect of the different policy instruments. Unfortunately, data that allows to differentiate funding between TP and SYS is not readily available for other countries. Also the role of potential export markets could be modeled in more detail by accounting for country specific RPGT policies or trade relationships between countries. The scope of the covered technologies could also be extended; however, WP and PV are the most prominent ones in Germany in terms of inventive activity and installed capacity.

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Appendix 1: Patent selection

The selection of the relevant patents was done by combining IPC classes and keywords, which required are to appear in the abstract or title of the patent document. 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 (2015):

	IPC Class	Keyword combination
Wind Power	F03D%	
	H02K 7/18 B63B 35/00 E04H 12/00	(%wind% + (%turbine% | %power% | %mill% | %energ%))
Photovoltaic	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 7: Correlations Wind Power

	Δ Nodes	Mean Degree	TP	SYS	DP	Export Market	Δ Oilprice	Δ Patents	Team Size
Δ Nodes	---	0.820 ***	0.737 ***	0.781 ***	0.537 ***	-0.285	0.266	0.808 ***	0.646 ***
Mean Degree	0.000	---	0.630 ***	0.824 ***	0.700 ***	-0.244	0.384 **	0.947 ***	0.843 ***
TP	0.000	0.000	---	0.602 ***	0.523 ***	-0.284	0.250	0.707 ***	0.591 ***
SYS	0.000	0.000	0.001	---	0.310	-0.448 **	0.276	0.765 ***	0.501 ***
DP	0.003	0.000	0.004	0.101	---	0.251	0.432 **	0.783 ***	0.957 ***
Export Market	0.134	0.202	0.135	0.015	0.189	---	0.057	-0.158	0.025
Δ Oilprice	0.163	0.040	0.191	0.147	0.019	0.769	---	0.405 **	0.443 **
Δ Patents	0.000	0.000	0.000	0.000	0.000	0.412	0.029	---	0.902 ***
Team Size	0.000	0.000	0.001	0.006	0.000	0.897	0.016	0.000	---

Upper triangle: Pearson correlation coefficient, lower triangle: p-values

Table 8: Correlations Photovoltaic

	Δ Nodes	Mean Degree	TP	SYS	DP	Export Market	Δ Oilprice	Δ Patents	Team Size
Δ Nodes	---	0.633 ***	0.185	0.451 **	0.711 ***	-0.056	0.216	0.740 ***	0.539 ***
Mean Degree	0.000	---	0.183	0.556 ***	0.891 ***	-0.441 **	0.360 *	0.876 ***	0.691 ***
TP	0.335	0.341	---	-0.029	0.065	-0.467 **	0.084	0.071	-0.135
SYS	0.014	0.002	0.882	---	0.535 ***	-0.520 ***	0.081	0.609 ***	0.254
DP	0.000	0.000	0.736	0.003	---	-0.274	0.420 **	0.969 ***	0.899 ***
Export Market	0.772	0.017	0.011	0.004	0.150	---	0.057	-0.254	0.025
Δ Oilprice	0.260	0.055	0.665	0.677	0.023	0.769	---	0.447 **	0.443 **
Δ Patents	0.000	0.000	0.716	0.000	0.000	0.183	0.015	---	0.866 ***
Team Size	0.003	0.000	0.485	0.183	0.000	0.897	0.016	0.000	---

Upper triangle: Pearson correlation coefficient, lower triangle: p-values

Appendix 3: Patent Regressions

Table 9: Regression results for Δ Patents 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	38,103***	0,060	8,562	19,703*	-17,507	-84,214*	-2,461	-22,283	-26,581*	2,925
	(11,577)	(21,745)	(14,996)	(10,647)	(20,464)	(44,775)	(15,364)	(26,100)	(14,273)	(14,442)
$(TP + SYS)_{t-1}$	14,305***	10,874*	9,797*							
	(4,806)	(5,493)	(5,275)							
TP_{t-1}				9,031**	5,711	4,962	5,945	6,596	-4,126	6,462
				(3,767)	(4,582)	(3,448)	(4,435)	(3,977)	(2,866)	(4,382)
SYS_{t-1}				35,983**	32,399**	22,536	29,655*	27,820*	29,773**	-5,401
				(13,399)	(14,185)	(15,467)	(15,763)	(15,177)	(14,390)	(12,516)
DP_{t+1}		7,242*			7,118*					
		(3,989)			(3,546)					
DP_{t-4}			7,120				5,876		8,037**	3,247
			(4,199)				(4,116)		(3,204)	(4,514)
$DP_{t-4} \times TP_{t-1}$									2,449**	
									(0,952)	
$DP_{t-4} \times SYS_{t-1}$										6,201*
										(3,053)
Δ $Oilprice_{t-1}$	-0,039	-0,340	-0,465	-0,257	-0,551	-0,826	-0,583	-0,379	-0,339	-1,033
	(0,693)	(0,584)	(0,583)	(0,854)	(0,764)	(0,670)	(0,751)	(0,789)	(0,649)	(0,707)
Δ $Patents_{t-1}$	0,217	-0,049	0,023	0,477	0,213	0,328	0,285	0,375	0,573	0,381
	(0,303)	(0,377)	(0,347)	(0,285)	(0,330)	(0,286)	(0,335)	(0,277)	(0,449)	(0,318)
Export Market $_{t+1}$						14,487*				
						(7,053)				
Export Market $_{t-4}$								7,391		
								(4,347)		
Adj. R^2	0,449	0,479	0,494	0,519	0,551	0,588	0,544	0,544	0,611	0,590
Obs.	29	29	29	29	29	29	29	29	29	29

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

Table 10: Regression results for Δ Patents Photovoltaic as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	15,316	-53,380**	-43,626**	7,516	-51,426*	-161,236***	-39,297**	-148,025***	-23,023**	-59,405***
	(16,135)	(24,398)	(19,571)	(21,737)	(26,121)	(48,827)	(16,488)	(51,531)	(9,362)	(17,073)
$(TP + SYS)_{t-1}$	3,523	3,511**	2,533***							
	(2,481)	(1,401)	(0,897)							
TP_{t-1}				3,294	3,754**	3,199**	2,731**	3,895*	1,071	3,848***
				(2,230)	(1,808)	(1,475)	(1,035)	(1,961)	(0,662)	(1,104)
SYS_{t-1}				5,234***	1,681	-0,202	0,235	1,110	1,310	6,301**
				(1,344)	(2,066)	(2,326)	(2,073)	(2,061)	(1,857)	(2,947)
DP_{t+1}		18,047***			19,724***					
		(5,491)			(7,062)					
DP_{t-4}			28,195***				30,926***		20,055***	36,420***
			(5,360)				(7,145)		(4,242)	(6,697)
$DP_{t-4} \times TP_{t-1}$									1,966***	
									(0,356)	
$DP_{t-4} \times SYS_{t-1}$										-1,107***
										(0,389)
Δ Oilprice $_{t-1}$	0,499	-0,949**	-1,121**	0,593	-1,183*	-1,410**	-1,399*	-1,025	-0,836	-1,243*
	(0,942)	(0,437)	(0,412)	(0,871)	(0,595)	(0,537)	(0,701)	(0,690)	(0,842)	(0,630)
Δ Patents $_{t-1}$	0,813	1,278**	1,310**	1,027**	1,092*	0,841*	1,082***	0,863*	0,974***	1,504***
	(0,549)	(0,609)	(0,476)	(0,434)	(0,591)	(0,439)	(0,321)	(0,488)	(0,185)	(0,437)
Export Market $_{t+1}$						33,255***				
						(8,999)				
Export Market $_{t-4}$								38,669***		
								(12,998)		
Adj. R^2	0,030	0,505	0,645	0,013	0,507	0,600	0,664	0,441	0,775	0,741
Obs.	29	29	29	29	29	29	29	29	29	29

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

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