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Environmental regulation and innovation in renewable energy technologies: Does the policy instrument matter?

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Abstract

We examine how different renewable energy support policies affect innovation in solar and wind power technologies. The analysis is conducted using policy and patent data for a large sample of 194 countries and territories. The policy data allows distinguishing two dimensions of regulation, i.e. design and intensity, and their effects on innovation. The patent data is based on the new Y02E system and covers the period 1990 to 2016 with the more recent years of both strong increases and declines in patenting activity. The results show that, first, more intense portfolios of renewable energy support policies increase patenting in solar- and wind-power-related technologies. Second, this inducement effect is the strongest for public RD&D programs, targets, and fiscal incentives. In contrast to previous studies, this paper finds a consistently positive impact of feed-in tariffs and does not detect technology-specific differences in the effectiveness of this policy instrument. Third, the positive effect on patenting activity increases significantly over time with an increase in the duration of the implemented RD&D programs and targets.

Keywords: Innovation; environmental regulation; renewable energy technologies; solar technologies; wind technologies

JEL classification: H23, O31, Q42, Q55, Q58

1 Introduction

Recent data shows a remarkable growth of renewables over the last decade. In 2013 the share of renewables in capacity additions to the global power generation was for the first time higher than the share of fossil fuels. In 2017 renewables accounted for even 70% of net additions to the global power generation capacity. This development is not limited to OECD countries. In the same year, China alone added more solar PV capacity than was installed worldwide in 2015. Among the different technologies, solar PV led the way, accounting for 55% of the newly installed capacity, followed by wind with 29% and hydro power with 11%. Overall, the global renewable energy capacity grew from 923 GW in 2004 to 2,195 GW in 2017, with the growth rates of solar and wind being considerably higher than those of hydro and other renewables.¹ Hence, renewable energy technologies developed from niche into mainstream technologies.

The strong growth of the renewable energy capacities over the last decade has been accompanied by a significant decrease in the costs of electricity production from renewable energy technologies. For example, the levelized costs of electricity (LCOE) from utility-scale photovoltaic projects declined by 73% between 2010 and 2017. By 2020 it is expected that all renewable power generation technologies, which are in commercial use, will have a comparable cost range as fossil fuel fired plants (IRENA 2018).² The decrease in costs is mainly driven by two factors. First, many governments have adopted more environmental regulations. This concerns both a more stringent regulation of carbon-based technologies, e.g. in the form of taxes or tradable emission permit systems, and massive subsidies for the development and diffusion of alternative power generation technologies, e.g. by supporting R&D or using feed-in tariffs.³ Second, innovation and knowledge spillovers, for instance from more experienced developers, have decreased the levelized costs of electricity.

Both factors, i.e. regulation and innovation, are not independent from each other. According to the conventional view on environmental policy, a stricter regulation harms the competitiveness by increasing the costs of production (Dechezleprêtre and Sato 2017). Porter (1991) challenged this view with the hypothesis that a stricter regulation increases the competitiveness. The main mechanism is innovation. A stricter and properly designed regulation induces both product and process innovations and creates innovation offsets that compensate for the additional costs of compliance (Porter and van der Linde 1995).⁴

¹ All numbers are determined from the Renewables Global Status Report of REN21 (2018).

² Contrary to that, as of 2012 only solar and onshore wind power installations in prime locations had levelized costs of electricity that allowed them to compete with energy from fossil fuels (Diederich 2016).

³ The rationale for the massive government interventions and regulation in the field of energy technologies is usually justified by multiple market failures (Rennings et al. 2000, Jaffe et al. 2005). On the one hand, energy generation by fossil fuels causes significant negative externalities and environmental damages, which are only partially internalized and put renewable energy technologies at a competitive disadvantage. On the other hand, investments into innovation and the diffusion of environmentally friendly technologies are faced with huge uncertainties and positive externalities like knowledge spillovers, which are only partially internalized by intellectual property rights. Further arguments for government interventions are based on the goal of gaining access to domestic resources as well as independence from the volatile fossil fuel markets.

⁴ The issue whether this compensation constitutes a partial or a full offset for the additional costs of compliance has resulted in an intensive academic debate and different interpretations of the Porter Hypothesis. For an overview of the interpretations and related empirical research see e.g. Ambec et al. (2013) and Cohen and Tubb (2018).

According to the Porter hypothesis, a stricter regulation creates win-win-situations. This allows both to achieve emission reductions and to increase the competitiveness, especially of the renewable energy equipment industry.⁵ An important precondition to reap the benefits from such a win-win effect is, however, that the products of the domestic renewable energy equipment industry are competitive in the world market. Innovation plays a decisive role in this context, because more advanced technologies are associated with lower levelized costs of electricity. Only those countries, which are at the forefront of the technological development in solar, wind, and other types of renewables, have a realistic chance to become major exporters in this field.

In this paper we want to analyze the relationship between environmental regulation and innovation in the renewable energy industry focusing on the regulation design, i.e. the question which policy instrument has the strongest innovation effect. Kemp and Pontoglio (2011) described three challenges for the related empirical research. The first is the difficulty to measure environmental policy, especially the design aspects of policy instruments. The second concerns methodological problems to measure innovation. The third is related to the problem that many relevant factors cannot be observed, e.g. business expectations, institutional constraints, and innovation capabilities.

According to the literature review of Popp et al. (2010), early empirical studies on the environmental policy-innovation nexus were constrained by the data availability. This concerned both the data on the innovation activity and the regulation stringency that was usually measured using survey-based pollution abatement costs. The results of these studies were mixed, i.e. both negative and positive effects on innovation were estimated (Brunnermeier and Cohen 2003; Jaffe and Palmer 1997; Lanjouw and Mody 1996). Early research also did not find clear evidence for the expectation that market-based instruments have a greater positive effect on innovation and invention than command-and-control policies (Newell et al. 1999; Popp 2003).

The research on the relationship between environmental regulation and innovation in renewable energy technologies, which only emerged during the last decade, shares some commonalities: The studies analyze either single countries or a smaller number of countries, namely mostly OECD or EU countries (Böhringer et al. 2017; Johnstone et al. 2010; Nicolli and Vona 2016); they tend to concentrate on solar and/or wind energy technologies (Braun et al. 2010; Kim et al. 2017; Schleich et al. 2017); and their data does often not include the more recent years with both a sharp rise and decline in patenting activity (Kim et al. 2017; Nesta et al. 2014; Nicolli and Vona 2016).

Johnstone et al. (2010) were among the first to explore the mechanisms of regulation-induced innovation in renewable energy technologies. They analyzed the effectiveness of five renewable energy support policies in 25 OECD countries between 1978 and 2003. Their results suggest that environmental regulation has a positive impact on innovation in general, but the effects of the policy instruments are different across technologies. For instance, feed-in tariffs increase the patenting activity for high-cost technologies like solar PV, but have a negative effect for wind power technologies. Braun et al. (2010) explored the role of three policy instruments and knowledge spillovers on solar and wind energy

⁵ According to the terminology of Jaffe and Palmer (1997), this describes the “narrowly strong” version of the Porter Hypothesis: Certain types of environmental regulation create a dynamic comparative advantage for some industries, i.e. the domestic environmental technology industry, by inducing early mover advantages.

innovations of 21 OECD member states between 1978 and 2004. They found that national spillovers foster innovation, whereas international spillovers have negligible effects.⁶

More recently, Nesta et al. (2014) investigated the effect of different environmental policies, proxied by an index, and of electricity market deregulation on innovation in seven renewables technologies for 27 OECD countries from 1976 to 2007. They found that a more competitive environment enhances the positive effects of renewable energy policies. Nicolli and Vona (2016) estimated a similar result for EU countries using alternative proxies for the policies for the period 1980 to 2007. Costantini et al. (2015) focused on biofuel technologies in 36 countries between 1990 and 2006. They found a positive impact of both demand-pull and technology-push policies, but differences in the effect of first generation and advanced generation technologies. Kim et al. (2017) added to the literature by analyzing the effects of five policies on an elaborate technological change system, which was decomposed into the three stages invention, innovation, and diffusion. Their study covered solar and wind energy policies in 16 OECD countries from 1991 to 2007. Schleich et al. (2017) focused on four policy instruments and their effects on wind energy technologies in twelve OECD countries over the period 1991 to 2011. They found that out of the four instruments only targets and public R&D fostered the patenting activity.

Cantner et al. (2016) and Böhringer et al. (2017) both used data on Germany only. While Cantner et al. (2016) analyzed the effect of different policy instruments on technology networks in solar and wind power technologies between 1980 and 2011, Böhringer et al. (2017) studied the effect of feed-in tariffs on innovation in seven different renewable energy technologies for the period 1990 to 2014. Their results support the positive innovation hypothesis, but interestingly the switch to a considerably more expensive policy after the year 2000 did not imply a significantly stronger innovation effect.

This paper builds on the existing research in order to analyze the regulation-induced innovation effects in solar and wind power technologies. We contribute to the literature in three main ways. First, our analysis extends the policy dimension. We compiled a detailed regulation database, which documents the implementation status of common renewable energy support policies. This allows us to analyze the effect of eleven different policy instruments and to enlarge the design dimension by including the duration that a policy instrument has been adopted. Hence, in the sense of Porter (1991), we can address the question whether the choice of the policy instrument matters. Second, we use the novel Y02E patent classification system to identify innovation activity related to solar and wind energy. So far, the large majority of studies relied on the international patent classification (IPC) (Johnstone et al. 2010; Nesta et al. 2014; Schleich et al. 2017), which, however, only partly allows a reliable identification of patent applications on renewable energy technologies.⁷ Thus, this paper addresses the first two challenges of empirical studies

⁶ The role of knowledge spillovers on the diffusion of innovation in energy technologies without a special reference to policy differences is analyzed in several further articles. For example, Verdolini and Galeotti (2011) focus on the role of knowledge stocks, Dekker et al. (2012) on the role of international environmental agreements, Peters et al. (2012) on R&D funding for photovoltaic modules, and Dechezleprêtre et al. (2013) on the institutional environment including intellectual property regimes and trade restrictions. While Brunel (2018) also contains the effect of regulation on trade activities, Verdolini and Bosetti (2017) use an index of policy instruments and analyze the effect on technology transfer.

⁷ A partly-related interesting recent exception are Costantini et al. (2017), who combined the Y02E patent classification with technologies in the residential sector to analyze the effect on energy efficiency innovation. They looked at 23 OECD countries between 1990 and 2010. Their model distinguished between three policy

highlighted by Kemp and Pontoglio (2011). Third, we extend the time and country dimension. Apart from Böhringer et al.'s (2017) study on Germany, no recent paper has analyzed data covering both the exponential growth in the renewables innovation activity between 2006 and 2011, and the drastic decline in patent applications thereafter. Moreover, research has usually concentrated on OECD or EU countries. We analyze patent data from 1990 until 2016 for a large set of 194 countries and territories, including countries like China, Taiwan, and India that have become increasingly important players in the field of renewable energy technologies.

The remainder is structured as follows. Section 2 introduces the main variables, i.e. the renewable energy policy instruments and the innovation measures. In section 3 the environmental policy-innovation model is described. Section 4 presents and discusses the results. Section 5 concludes.

2 Policy and innovation measures

2.1 Environmental regulation

Detailed and reliable data on environmental regulation is one of the two main ingredients for research on regulation-induced innovation in solar and wind power technologies. Recent overviews of the measures used for environmental and climate regulation are e.g. provided in Brunel and Levinson (2016) and Althammer and Hille (2016). In this study, we measure environmental regulation along two dimensions, namely regulation design and regulation intensity.

To analyze the influence of the policy design, we collected comprehensive binary data on the implementation status of renewable energy support policies. This approach was e.g. used in Carley et al. (2017), Johnstone et al. (2010), and Nicolli and Vona (2016) for several policy instruments. Yet, compared to the prior literature in the field, we extend both the country coverage and the variety of considered policy instruments. Our database includes information on eleven types of policy instruments in 194 countries and territories from 1974 onwards. Table 1 gives an overview of the different renewable energy policies. The data was obtained from the Renewables Global Status Reports of REN21 (2005-2014b) and their Renewables Interactive Map (REN21 2015). Complementary data sources are the Joint Policies and Measures Database of the International Energy Agency (IEA) and the International Renewable Energy Agency (IRENA) (IEA and IRENA 2015) as well as the IEA Energy Technology RD&D Statistics of the OECD (2015). In order to facilitate the reasoning of the analysis, to account for the limited space, and to reduce the complexity of the robustness tests, we additionally group the eleven individual instruments into six policy clusters. This is done on the basis of similarities in the economic mechanisms of the instruments. The considered clusters are targets, RD&D support, quotas, feed-in-tariffs, fiscal incentives, and carbon trading.

The second dimension of environmental regulation is the regulation intensity. Recent research on renewable energy policies has emphasized the value of including a continuous indicator measuring the stringency of the different policy instruments (Carley and Miller 2012; Jenner et al. 2013). Such an indicator is usually constructed with the help of specific

dimensions, namely demand-pull policies (energy taxation), technology-push policy (public R&D efforts), and an indicator for soft instruments like information and voluntary approaches.

information on the implemented policy instruments, such as the tariff size, cost allocation, or contract duration. However, this requires that the policy design of a particular instrument type is sufficiently similar across jurisdictions, which is not the case for our heterogeneous set of countries. Thus, similar to other international studies in the field, we are not able to attribute regulation-induced changes in innovation to specific alterations in the regulation design, e.g. to reduced feed-in tariffs like in Germany.

Table 1: Taxonomy of policy clusters in renewable energy support

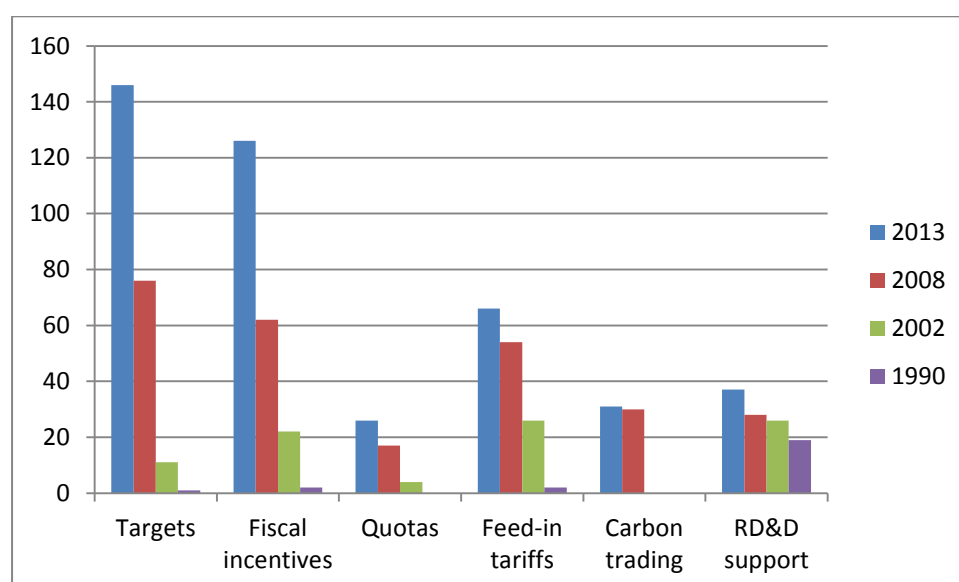
Policy cluster	Policy instrument	Basic support mechanism
Targets	Renewable energy targets or strategies	
RD&D support	Research, development and deployment programs	Technology-push
Quotas	Renewable energy quotas with certificate trading	Market-pull
	Renewable energy quotas without certificate trading	(Technology-specific)
Feed-in tariffs	Fixed-rate or premium feed-in tariffs (incl. energy production payments)	Market-pull
	Net metering	(Technology-specific)
	Public competitive bidding (Tendering)	
Fiscal incentives	Tax credits (Investment or production)	Market-pull
	Tax reduction (Carbon, energy, sales, VAT of other taxes)	(Technology-specific)
	Public spending, capital subsidies and low-cost loans	
Carbon trading	Greenhouse gas certificate trading systems	Market-pull (Technology-neutral)

Instead we capture the regulation intensity in two ways. First, we take a similar approach as in Walz et al. (2011) and include the renewable energies' share in the total electricity generation. This indicator is a very direct measure of the stringency of countries' renewable energy support policies. Compared to other common proxies of regulation intensity, such as pollution abatement and control expenditures or composite indexes (e.g. Johnstone et al. 2010), renewable energy shares have the advantage that they are available for most countries and easy to interpret and compare. In addition, they are not or only partly affected by multidimensionality and simultaneity issues, which are common in the regulation intensity measurement (Brunel and Levinson 2016).

Second, the regulation intensity is measured by the policy duration, i.e. the number of years a certain policy instrument has been implemented. On the one hand, the effect of the policy duration reflects the stability of the regulatory environment. The longer an instrument is in place, the more market participants can rely on the support policy and the stronger may be the effect on innovation. On the other hand, the effect of the policy duration also depends on the type of policy used, i.e. command-and-control policies versus market-based policies. With command-and-control policies, introducing a new instrument provides strong incentives for innovation, but when regulatory compliance is achieved, these incentives are reduced. Therefore, with no change in stringency, it is expected that the effect of policy declines over time. Only incentive based regulations, like emission taxes or permits with a "double burden" (tax payments, permit expenditures), are expected to provide long-run incentives to innovate. Through innovations the double burden may be reduced over time to reach the so-called property of dynamic efficiency.

Figure 1 shows the number of countries with implemented renewable energy support policies for each cluster in the years 1990, 2002, 2008, and 2013.⁸ A more detailed overview on the instrument level can be found in Figure B1 in Appendix B. Both figures clearly show differences in the policy adoption rates. Widespread policy instruments are renewable energy targets and strategies as well as the different types of fiscal incentives and feed-in tariffs. During the considered time period, the dissemination rates of those policy clusters are systematically higher than the ones of instruments from the carbon trading and quotas clusters. We see two reasons for the low adoption rates of the latter policies. First, instruments from these clusters are more complex and difficult to implement than, for example, fiscal incentives. Second, carbon trading and quotas support the build-up of renewable energy capacities by limiting the use of conventional energy sources or by introducing binding requirements on utility companies. Governments may be more reluctant to adopt such instruments in contrast to incentive-based measures like feed-in tariffs.

Figure 1: Number of countries with renewable energy policies by instrument cluster and year^{a, b}



^a Sources: Self prepared using IEA and IRENA (2015), OECD (2015), and REN21 (2005-2015).

^b Data on RD&D programs is almost exclusively available for OECD countries. Hence, the numbers might understate the actual dissemination of RD&D programs.

Moreover, Figures 1 and B1 indicate that the speed at which the different instruments have become adopted across countries varies considerably. In 2013 renewable energy targets and strategies were the instrument with the highest dissemination rate. Governments in 146 countries used this policy. However, the corresponding low number of countries in the years 1990 and 2002 suggest that structured support for renewable energy is a relatively recent phenomenon. With some time delay to the coordinated renewables support, the adoption rate of fiscal incentives, i.e. tax reductions as well as public spending and subsidies, and of the more advanced instruments from the feed-in tariff cluster, i.e. tendering and net

⁸ The policies are shown for these years as the results, which are presented in section 4, are based consistently on regulatory data for the period 1989 to 2013. The reasons are that the policy variables are lagged by one year and that the patent counts are calculated not only in contemporaneous terms but also as two- and three-year moving averages (See Table D2 in Appendix D).

metering, started growing exponentially. Contrary to that, the adoption rate of the more traditional policy instruments, such as RD&D programs and classical fixed rate and premium feed-in tariffs, grew rather steadily. In particular the former were already used on a wider scale during the 1990s. Hence, a large share of the RD&D programs have been implemented for relatively long time periods, which may enable inventions with a lengthy development process.⁹

2.2 Patents

Besides environmental regulation, innovation data is the second key ingredient for research on regulation-induced renewable energy innovations. We follow the literature in this field and measure countries' innovation activity by the number of patent applications for inventions that generate electricity from solar radiation or the force of wind (Böhringer et al. 2017; Johnstone et al. 2010; Nesta et al. 2014; Peters et al. 2012).

Patent data is preferred to other measures of innovation, especially R&D expenditures, as it is output-oriented, widely available, information rich, highly standardized, comprehensive, and technology-oriented (Dernis et al. 2002; Johnstone et al. 2010; Nagaoka et al. 2010). However, while patent data is a direct measure of patenting activity, it is an imperfect measure of innovation. Common drawbacks are its highly skewed value distribution (Scherer and Harhoff 2000), differences in the propensity to patent across countries and sectors (Popp et al. 2011) and over time (Dernis et al. 2002), home bias (Dernis et al. 2002), and strategic non-patenting (Arundel 2001).

Irrespective of their severity, the negative effects of these drawbacks on the estimation accuracy are largely manageable. Harhoff et al. (2003) showed that counting patent families instead of single patents corrects for the skew in the value distribution. Popp (2002) suggests to count total patents in order to control for differences in the propensity to patent across countries as well as for changes over time. Finally, a common remedy for the home bias is to use patent databases which cover multiple patent authorities (Dernis et al. 2002).

In this paper we identify relevant patent applications using the new Y02E patent classification system. The Y02E scheme is regarded as the most accurate classification system of climate change mitigation patents currently available and is increasingly becoming the respective international standard (Calel and Dechezleprêtre 2016).¹⁰ Nonetheless, the large majority of prior research relied on the IPC scheme (Johnstone et al. 2010; Nesta et al. 2014; Schleich et al. 2017). The technology classes of the IPC scheme are only partly adequate for analyses of climate change mitigation technologies in general and renewable energies in specific. For instance, while the IPC system has a distinct class for wind energy technologies, namely F03D (Wind motors), the list of relevant categories for solar energy technologies is rather long and fragmented. A number of those IPC classes cannot be

⁹ Diederich (2016) analyzed the relationship between the adoption rate of the policy instruments at hand and countries' GDP per capita, energy intensity, primary energy balance, and regional association. He observed that, in particular, higher-income and energy-importing countries from Europe and North America were the first ones to implement support policies. Later, countries with lower levels of development followed, yet their portfolios of support policies tended to be less intensive.

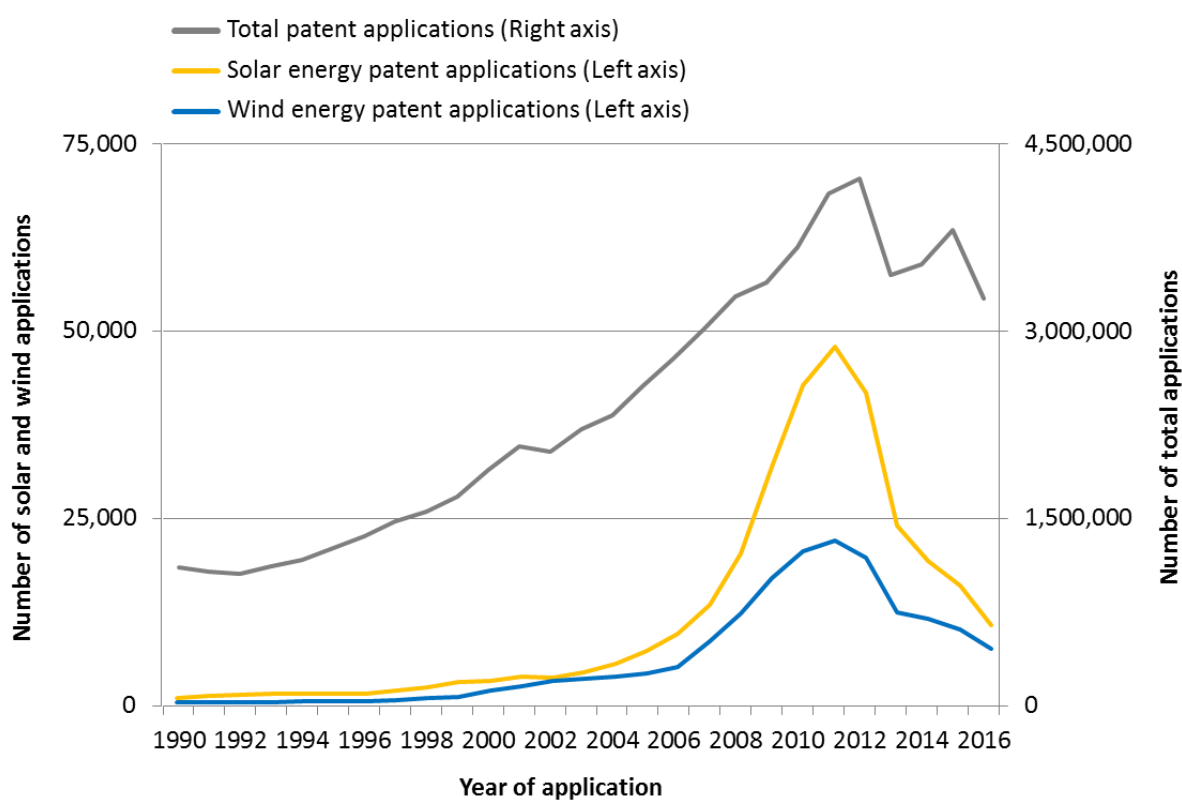
¹⁰ The Y02E classification scheme was developed by a consortium of experts from the European Patent Office (EPO), the International Center for Trade and Sustainable Development (ICTSD), and the United Nations Environment Programme (UNEP).

assigned unambiguously, because they relate to both solar cells and other types of semiconductors (Diederich 2016). Thus, for solar energy and also other climate change mitigation technologies there is a considerable risk of committing type I and II errors, i.e. to falsely or incompletely select patent applications. As the Y02E system was developed specifically for the reliable identification of patents on “technologies which control, reduce, or prevent greenhouse gas emissions of anthropogenic origin, as set forth by the Kyoto Protocol” (Veefkind et al. 2012), the risk of type I and II errors is reduced to a minimum (Hurtado-Albir et al. 2013; Isaka 2013; Veefkind et al. 2012). The specific technology classes that are relevant for our analysis are Y02E 10/5 for solar energy and Y02E 10/7 for wind energy.

Diederich (2016) determined the number of patent applications for solar and wind energy technologies for the period 1980 to 2011 using the IPC codes applied in previous studies and compared the numbers to the ones using the Y02E classes. He showed that the estimates are fairly similar for wind energy patents. However, the corresponding estimates for solar energy patents vary between 104 thousand and 3.4 million for alternative sets of IPC classes, reflecting the significant level of ambiguity in the patent identification.

Our data on patent applications is obtained from the European Patent Office’s worldwide patent statistical database PATSTAT (EPO 2018). PATSTAT is regarded as the largest open access patent database (Nagaoka et al. 2010). The spring 2018 version includes roughly 80 million patent applications from well over 200 countries and territories (EPO 2018). This wide geographical coverage helps to assure that home bias is not an issue in our analysis.

Figure 2: Development of patenting activity between 1990 and 2016^{a, b}



^a Source: Self prepared using EPO(2018).

^b Only patent applications for which applicant information are available are displayed.

The development of total patent applications as well as renewable energy patent applications using the Y02E scheme is shown in Figure 2 for the period 1990 to 2016. Apart from minor slowdowns in the patenting activity during the recessions in the early 1990s, 2000s, and 2008/09, the number of total annual patent applications grew steadily until 2012. From the 2012 peak until 2015 total patenting fell by 9.7%. Contrary to that, the annual patent applications in solar and wind energy tended to grow exponentially. In particular after the years 2005 and 2006 the speed of technological change increased considerably. Given that the implementation rates of renewable energy policies strongly increased during the same period, this may provide a first indication that environmental regulation has been a main driver of innovation in solar and wind energy technologies. However, from the 2011 peak until 2015, the patent applications on renewable energy technologies declined much stronger than total patenting, namely by 66.6% for solar energy and 54.0% for wind energy. While the adoption rate of renewable energy policies continued to rise during the period, these policies were predominantly implemented in late adopter countries with a low patenting activity. In only few cases the policy mixes of countries with a high patenting activity, which are listed in Table 2, were supplemented with additional policy instruments.

Moreover, for every year Figure 2 displays higher patent counts for solar energy than for wind energy. This is in line with the estimates in Diederich (2016). Yet, we would be cautious in interpreting the different number of patent applications as an indication for a higher innovativeness in the solar energy industry. Both the complexity of patenting eligibility and the propensity to patent may vary between the industries.

Table 2 shows the distribution of renewable energy patent applications across countries. As can be seen, the patenting activity has been highly concentrated. The four countries with the highest aggregate number of innovations in solar and wind energy, i.e. the United States, Japan, Germany, and South Korea, account for roughly 50% of the total patent applications between 1980 and 2016. These countries are not only the ones with the highest patenting activity in solar and wind energy, but tend to be innovative in many technological fields. Hence, they are also the four countries with the highest patenting activity in general. Technology-wise, the United States and Japan are by far the two countries with the highest aggregate number of patent applications in solar energy. Similarly, Germany and the United States are the dominant innovators in wind energy technologies. South Korea and Denmark come in third place for solar and wind energy respectively. The decline in the number of renewables patent applications after 2011 has been mainly driven by the innovation activity in these five leading countries. This indicates that solar and wind energy technologies have become more mature and that developing products, which generate electricity with significantly lower costs, has been increasingly more difficult.

If the patenting activity in renewables is analyzed in relative terms, i.e. set relative to the country's overall number of patent applications, the picture is somewhat different. For solar energy technologies South Korea, Japan, and Taiwan are the countries that are most innovative relative to their overall patenting output. Specifically, 10.7 out of 1,000 patent applications of South Korean residents are related to solar energy. For Japan and Taiwan the corresponding ratios are 8.6 and 7.5. For wind energy technologies the values are even higher for Denmark, the forerunner in the field, and Spain. For every 1,000 patent applications 49.9 and 16.2 are wind energy patents in Denmark and Spain respectively. Germany, the dominant country in wind energy patenting in absolute terms, comes in third

place with a ratio of 5.4. An interesting similarity is that these countries with the highest share of patent applications in solar and wind energy are also among the nations, which already adopted renewables support policies in the early 1990s.

Despite the high concentration of patent applications in few countries, our data shows that renewable energy patents have been filed in a growing number of countries and also increasingly in multiple countries. This highlights the importance of analyzing an extended set of countries. The growing internationalization process started for the wind energy technologies, where patents were already filed in 51 different countries in 1987. Solar energy picked up with a delay and reached 53 countries only in the year 1999. The milestone of 100 countries was passed in 2008 for wind energy and 2010 for solar energy. A reason for the higher values for wind energy may be the consistently lower levelized costs of electricity that have allowed a more independent growth from renewable energy support policies.

Table 2: Renewable energy patent applications between 1980 and 2016 by country^a

Country	Number of renewable energy patents				Number of renewable energy patents per 1,000 patents		
	Solar	Wind	Total		Solar	Wind	Total
United States	67,642	22,948	90,590	(17.5%)	5.3	1.8	7.1
Japan	53,109	10,515	63,624	(12.3%)	8.6	1.7	10.3
Germany	27,422	27,942	55,364	(10.7%)	5.3	5.4	10.7
Korea, South	37,796	11,076	48,872	(9.4%)	10.7	3.1	13.8
China	6,174	6,426	12,600	(2.4%)	2.2	2.3	4.5
Denmark	264	11,898	12,162	(2.3%)	1.1	49.8	50.9
Taiwan	9,937	2,008	11,945	(2.3%)	7.5	1.5	9.1
France	7,785	3,365	11,150	(2.2%)	4.0	1.7	5.8
United Kingdom	4,565	4,690	9,255	(1.8%)	3.6	3.7	7.2
Spain	1,573	5,264	6,837	(1.3%)	4.8	16.2	21.1
Netherlands	2,802	2,010	4,812	(0.9%)	3.7	2.7	6.4
Switzerland	3,414	1,019	4,433	(0.9%)	4.1	1.2	5.4
Canada	2,223	1,952	4,175	(0.8%)	3.3	2.9	6.1
Italy	2,320	1,762	4,082	(0.8%)	2.8	2.2	5.0
Israel	1,916	593	2,509	(0.5%)	7.0	2.2	9.2
Sweden	714	1,689	2,403	(0.5%)	1.1	2.6	3.7
Australia	1,792	606	2,398	(0.5%)	6.5	2.2	8.7
Russia	528	1,761	2,289	(0.4%)	1.1	3.7	4.8
Belgium	1,336	767	2,103	(0.4%)	5.5	3.1	8.6
Austria	1,200	901	2,101	(0.4%)	4.1	3.1	7.2
Other	5,305	11,216	16,521	(3.2%)	1.5	3.1	4.6
Unknown	97,113	50,416	147,529	(28.5%)	3.3	1.7	5.1
Total	336,930	180,824	517,754	(100.0%)	4.6	2.5	7.0

^a Source: Self prepared using EPO (2018); Notes: Only patent applications for which applicant information are available are displayed. Patent applications that were filed by applicants from several countries are equally considered for the patent counts of the respective countries.

2.3 Knowledge stock

A further aspect of innovation data are knowledge stocks. It is uncommon to develop new inventions entirely from scratch. Instead developers rather build on the existing knowledge and advance it further. Thus, access to a larger knowledge stock tends to facilitate the invention of new technologies. The strong growth of renewables patenting activity shown in

Figure 2 until 2011, which increased with the growing aggregate number of innovations, seems to confirm this notion.

Popp (2002, 2005) and Popp et al. (2011) developed the standard approach to construct knowledge stocks in environmental models. Following their approach we calculate the knowledge stock $KSTOCK_{count_Y}$ at time t for technology $_Y$ by aggregating annual patent applications $count_Y$ and adjusting the values by the rate of decay α_1 and the rate of diffusion α_2 .¹¹

$$KSTOCK_{count_Y_t} = \sum_{s=0}^t e^{-\alpha_1(s)} (1 - e^{-\alpha_2(s+1)}) count_Y_{t-s} \quad (1)$$

As introduced before, patent data is characterized by a skewed value distribution with many low- and few high-value patents. In order to measure the value of individual patents, several researchers have suggested using data on the patent family size, i.e. the number of countries in which a patent has been filed (Harhoff et al. 2003; Lanjouw and Schankerman 2004; van Zeebroeck 2011). Popp et al. (2011) developed this idea further and proposed two filters, namely to include only patent applications filed in several countries (family size > 1) and to weight patent counts by the family size. The four resulting alternative patent counts are: first, the simple count (SC), where every patent family is counted once; second, the family count (FC), where only patent families for which patents are filed in several countries are counted; third, the size-weighted simple count (SCw), where every patent family is weighted by its family size; and fourth, the size-weighted family count (FCw), where patent families for which patents are filed in several countries are weighted by their family size. While Popp et al. (2011) considered each of the patent count approaches to calculate knowledge stocks, they favored the size-weighted family count as it fitted their sample best. We will also select the preferred patent count approach on the basis of the statistical fit with our data and provide robustness checks in section 4.2.

3 Research model

In order to analyze how different renewable energy support policies affect innovation in wind and solar power technologies, several specifications are estimated. The different models can be summarized in equations (2) and (3). In equation (2) we regress patents on the policy clusters:

$$SC_Y_{i,t} = \alpha_i + \alpha_t + \beta_0 + \sum \beta_c C_E_{c,i,t-1} + \sum \beta_{cT} (C_E_{c,i,t-1} * LENGTH_{C_E_{c,i,t-1}}) \\ + \beta_1 KSTOCK_{SC_Y_{i,t-1}} + \beta_2 TOTPAT_{i,t-1} + \beta_3 GLOBCAP_{t-1} \\ + \beta_4 DOMSHARE_Y_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

In equation (3) we regress patents on the individual policy instruments:

$$SC_Y_{i,t} = \alpha_i + \alpha_t + \beta_0 + \sum \beta_p I_E_{p,i,t-1} + \sum \beta_{pT} (I_E_{p,i,t-1} * LENGTH_{I_E_{p,i,t-1}}) \\ + \beta_1 KSTOCK_{SC_Y_{i,t-1}} + \beta_2 TOTPAT_{i,t-1} + \beta_3 GLOBCAP_{t-1} \\ + \beta_4 DOMSHARE_Y_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

¹¹ The rate of decay captures the speed at which older patents become obsolete and the rate of diffusion captures time delays until knowledge becomes available to other inventors. In line with prior studies, we use a rate of decay of 0.10 and a rate of diffusion of 0.25 (Lovely and Popp 2011; Popp 2003; Popp et al. 2011). The rates imply a lag structure peaking after four years, which lies between the three and five years regularly suggested in the R&D literature (Griliches 1995).

The indices i and t represent the respective country and year. The indices c and p reflect the numbering of the policy clusters and instruments. In both equations the simple count of patent applications SC_Y for technology $_Y$ filed by domestic residents with a national or international patent office is the regressand.¹² Following Johnstone et al. (2010), we estimate the regulation-innovation nexus for each renewable energy technology individually and in aggregation. Accordingly, SC_Y represents either patent applications in solar (SC_S), wind (SC_W), or both technologies (SC_SW).

The main group of explanatory variables are the measures of environmental regulation design and intensity. To measure the regulation design we use two approaches. On the one hand, we use the clustered instruments, where ΣC_E reflects a set of binary variables denoting whether or not an instrument of a policy cluster has been implemented in a certain country and year. The six policy clusters are targets ($C_TARGETS$), RD&D support (C_RDD), quotas (C_QUOTAS), feed-in tariffs (C_FIT), fiscal incentives (C_FISCAL), and carbon trading ($C_TRADING$). On the other hand, we use the individual regulation instruments, where ΣI_E reflects a set of binary variables indicating whether or not a specific instrument has been implemented in a respective country and year. The eleven instrument types are renewable energy strategies and targets (I_TARG), research, development, and deployment programs (I_RDD), renewable energy quotas with certificate trading (I_QUOTWT) and without certificate trading ($I_QUOTWOT$), fixed rate or premium feed-in tariffs (I_FIT), net metering (I_NETMET), public competitive bidding (I_TEND), investment and production tax credits (I_TAXC), tax reductions (I_TAXR), public spending, capital subsidies, and low-cost loans (I_PUB), and greenhouse gas certificate trading (I_TRAD).

The effect of the regulation intensity is captured in two ways. In the first set of estimations, intensity is only measured by the share of solar and wind in the domestic electricity generation $DOMSHARE_Y$, where $_Y$ stands for the technology-specific shares of solar power ($_S$), wind power ($_W$), or both ($_SW$). In a second set of estimations, the regulation intensity is also measured by the duration a certain policy has been implemented ($LENGTH_{C_E}$ and $LENGTH_{I_E}$).

As introduced in section 2.1, the incentives of command-and-control policies and market-based policies are expected to differ with regards to both their initial effects on innovation in the year of implementation and their changes in the effects over time. Therefore, in equations (2) and (3) both effects are separated for the different policy clusters and instruments. On the one hand, the direct terms of the policy design covariates (C_E and I_E) can be interpreted as intercept dummies. In other words, their coefficients β_c and β_p provide information on the base effects. On the other hand, the policy duration variables are interacted with the corresponding policy design binaries ($C_E*LENGTH_{C_E}$ and $I_E*LENGTH_{I_E}$) and the interaction terms can be interpreted as slope dummies. Hence, the coefficients β_{cT} and β_{pT} help analyzing how the policy effects evolve over time.

¹² We have selected the patent count approach based on the statistical fit with our sample. Examples of results using different patent counts are shown in columns (1), (1c), (1d), and (1e) in Table D1 in Appendix D. As can be seen, the Chi² statistics of the unweighted count models (SC and FC) are generally larger than the ones of the weighted count models (SCw and FCw). While the same holds true for the Chi² statistics of the family counts (FC and FCw) compared to those of the simple counts (SC and SCw), the family count models partly experience convergence problems in the maximum likelihood estimation when more detailed specifications are estimated. Despite of this, our findings generally remain unchanged if alternative patent counts are used.

In order to control for the effects of other innovation drivers than environmental regulation, we include three control variables proposed in the literature. The first control is the domestic knowledge stock calculated using simple counts $KSTOCK_{SC_Y}$, where $_Y$ is again a placeholder for solar ($_S$), wind ($_W$), or both ($_SW$). Popp (2005) shows that the access to existing knowledge has a positive effect on research activities and the success of future inventions. Thus, we expect that patenting in solar and wind power technologies increases with the size of the respective knowledge stock.

As a second non-regulatory innovation driver the general propensity to patent needs to be controlled for. Earlier research showed that the rate at which newly developed innovations are patented varies across countries, sectors, and over time (Cohen et al. 2002; Dernis et al. 2002; Levin et al. 1987). Fortunately, when analyzing two closely related renewable energy industries or a single technology, sector-specific differences in the propensity to patent are less of a concern. In order to account for the country- and time-specific differences, we apply the reasoning of Popp (2002) and include the total number of patent applications by domestic applicants $TOTPAT$.

A third control variable is the year-by-year change in the global electricity generation capacity $GLOBCAP$ from all energy technologies. The change in the installed capacity controls for the incentives of the solar and wind power industry to innovate because of general market opportunities for power plants manufacturers (Peters et al. 2012).

Tables C1 and C2 in Appendix C provide an overview of all variables, the respective data sources, and the regular descriptive statistics. In general, the dataset is strongly balanced. The few missing values, which are deleted listwise, are mostly the result of the breakup of Yugoslavia and changes in the national states in the Eastern Bloc in the early 1990s.

To account for the discrete nature of the patent data, the models are estimated using a fixed effect negative binomial model for panel data with robust standard errors (Hausman et al. 1984). Count data models, like the negative binomial model and Poisson model, have been commonly applied in the field (Böhringer et al. 2017; Johnstone et al. 2010; Nicolli and Vona 2016; Schleich et al. 2017). A necessary condition for using the Poisson model is that the dependent variables follow a Poisson distribution that requires equidispersion. This is not the case for our patent counts. Instead the descriptive statistics in Table C2 in Appendix C indicate that the dependent variables are overdispersed, i.e. their variances are larger than the means. In such cases, the use of the negative binomial model is preferred (Wooldridge 2002). Moreover, the negative binomial model is generally more efficient (Blundell et al. 1995; Lawless 1987).

Endogeneity due to both reverse causality and omitted variables can be a major issue in the estimation of the policy-induced effects on innovation (Nesta et al. 2014). As our main interest is to analyze the heterogeneous effect of different policies, preferred methods like propensity score matching, which was e.g. implemented in Caeli and Dechezleprêtre (2016), and an instrumental variable approach with out-of-sample instruments are not feasible given the high number of potentially endogenous policies (Nicolli and Vona 2016). Instead, endogeneity concerns are often addressed in this research field by lagging the explanatory variables and/or using fixed effects (Böhringer et al. 2017; Costantini et al. 2015; Schleich et al. 2017). We follow an analogous approach by lagging all explanatory variables by one period and including country and time fixed effects, i.e. α_i and α_t respectively. The covariates are also lagged as the effects of the environmental policy and control variables

are not contemporaneous. Moreover, the fixed effects control for unobserved heterogeneity across countries and over time. Nonetheless, parts of the endogeneity related to the environmental regulation variables may still be persistent, e.g. if an omitted variable varies on the country-time dimension.

4 Results and discussion

4.1 Effects of policy design and duration

While Table 3 shows the regression results for equation (2) when clustered policy instruments are analyzed, Table 4 presents the output for equation (3) when the individual policy instruments are used. For each of the approaches and the different technologies, two specifications are estimated. In the base specification the policy design covariates are included but not yet their policy duration. In the extended specification the interaction effects of the policy duration with the respective policy design variables are added in order to analyze if the policy effects change over time.

Starting with the base specification of the clustered policy instruments in Table 3 in columns (1) to (3), it can be seen that the coefficient estimates of all but one of the policy design variables are positive and significant. In other words, all renewable energy support policies seem to foster the patenting activity, hence, meriting the implementation of more intensive portfolios of renewable energy support policies.

Even though the importance of the different policy clusters partly varies across technologies, RD&D programs (*C_RDD*) are estimated to have the strongest positive effect on innovation in both solar and wind power. On average, the presence of RD&D programs increases patent applications by 87% (*SC_SW*), 145% (*SC_S*), and 67% (*SC_W*).¹³ Fiscal incentives (*C_FISCAL*) are also identified as an important driver of patenting activity, especially of inventions related to solar power. An explanation for the strong, positive effect may be that instruments from this cluster tend to reduce the business risk of the inventors as their mechanisms are very tangible. For instance, government purchase programs, capital subsidies, and subsidized loans entail a relatively certain and immediate benefit for their recipients. The third important policy cluster are targets (*C_TARGETS*). This rather strong effect comes as a surprise, because announcing targets is often not combined with concrete supply-side or demand-side policies. The effect could reflect a forward-looking response of firms to new regulations, expecting that concrete policies will follow the announcement of the target (Albirizio et al. 2017; Hille and Möbius 2018). Furthermore, the coefficient may capture remaining policy effects that are not explained by the other policy clusters.

In columns (4) to (6) the policy duration interaction effects with the policy design variables are included. The estimations show that the strongest effect of the policy duration can be found for targets (*C_TARGETS_LENIGHT*) as well as RD&D programs (*C_RDD_LENIGHT*). The longer these measures are used, the stronger is the effect on innovation in solar and wind power. The duration effect of the other policy clusters is either positive or negative, but not significant. Overall, the effects seem to be comparatively small. For example, while the sheer presence of RD&D programs (*C_RDD*) is estimated to increase average patent applications for solar and wind energy by 49% in column (4), an additional year that the

¹³ As the fixed effect negative binomial model is an exponential model, the expected percentage effect on patent application can be obtained by calculating $(e^{\beta}-1)*100$.

programs have been implemented (*C_RDD_LENGTH*) increases the corresponding patent applications by 4.9%. Only after 9 years the duration effect outweighs the base effect. However, given that RD&D programs are expected to take time until they reach full efficiency and that in many countries renewables support policies have only been implemented on a wider scale during the last years of our sample, the low average values appear reasonable.

Table 3: The effect of regulation on innovation using policy clusters

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Variable	<i>SC_SW_t</i>	<i>SC_S_t</i>	<i>SC_W_t</i>	<i>SC_SW_t</i>	<i>SC_S_t</i>	<i>SC_W_t</i>
<i>C_TARGETS</i>	0.406*** (0.085)	0.332*** (0.096)	0.483*** (0.102)	0.251** (0.111)	0.116 (0.108)	0.396*** (0.136)
<i>C_RDD</i>	0.626*** (0.118)	0.898*** (0.166)	0.513*** (0.134)	0.397*** (0.136)	0.621*** (0.211)	0.263* (0.157)
<i>C_QUOTAS</i>	0.234** (0.110)	0.284** (0.121)	0.150 (0.110)	0.201* (0.113)	0.248** (0.125)	0,073 (0.150)
<i>C_FIT</i>	0.291*** (0.097)	0.198* (0.111)	0.320*** (0.096)	0.252** (0.103)	0.172 (0.135)	0.245** (0.108)
<i>C_FISCAL</i>	0.398*** (0.131)	0.575*** (0.129)	0.317** (0.123)	0.320** (0.124)	0.448** (0.184)	0.229** (0.106)
<i>C_TRADING</i>	0.396*** (0.118)	0.433*** (0.145)	0.325** (0.138)	0.218 (0.165)	0.174 (0.180)	0.220 (0.138)
<i>C_TARGETS_LENGTH</i>				0.047** (0.018)	0.068** (0.034)	0.046** (0.022)
<i>C_RDD_LENGTH</i>				0.048*** (0.014)	0.050*** (0.017)	0.047*** (0.011)
<i>C_QUOTAS_LENGTH</i>				-0,033 (0,027)	-0,047 (0,049)	-0,031 (0,025)
<i>C_FIT_LENGTH</i>				0,002 (0,024)	-0,011 (0,030)	0,019 (0,024)
<i>C_FISCAL_LENGTH</i>				-0,013 (0,026)	0,004 (0,041)	-0,030 (0,025)
<i>C_TRADING_LENGTH</i>				0,015 (0,026)	0,024 (0,047)	-0,007 (0,031)
<i>KSTOCK_{SC_Y}^a</i>	0,001 (0,006)	-0,001 (0,010)	0,011 (0,007)	-0,002 (0,006)	-0,007 (0,007)	-0,001 (0,019)
<i>TOTPAT</i>	0.004* (0,002)	0.005** (0,002)	0.004** (0,002)	0,004 (0,008)	0,004 (0,006)	0,004 (0,003)
<i>GLOBCAP</i>	0.178*** (0,028)	0.176*** (0,036)	0.162*** (0,033)	0.180*** (0,026)	0.179*** (0,037)	0.157*** (0,034)
<i>DOMSHARE_Y^a</i>	0,007 (0,011)	0,057 (0,078)	0,008 (0,012)	-0,015 (0,013)	-0,083 (0,071)	-0,005 (0,018)
Constant	-1.785*** (0.163)	-2.358*** (0.162)	-1.776*** (0.151)	-1.772*** (0.159)	-2.347*** (0.157)	-1.751*** (0.143)
Observations	4,693	4,693	4,693	4,693	4,693	4,693
Wald Chi ²	824.6***	608.0***	837.3***	688.0***	861.6***	848.0***

Notes: *** p<0.01, ** p<0.05, * p<0.10; robust standard errors in parentheses

^a The Y in the variables *KSTOCK_{SC_Y}* and *DOMSHARE_Y* is a placeholder for the data of SW (Solar and wind energy), S (Solar energy), and W (Wind energy), which is used in the respective columns.

Table 4: The effect of regulation on innovation using policy instruments

Dependent variable	(7)	(8)	(9)	(10)	(11)	(12)	
Variable	SC_SW_t	SC_S_t	SC_W_t	SC_SW_t	SC_S_t	SC_W_t	
$I_TARGETS$	0.406*** (0.105)	0.387*** (0.129)	0.494*** (0.102)	0.136 (0.172)	0.064 (0.161)	0.282* (0.171)	C_TARGETS
I_RDD	0.640*** (0.140)	0.916*** (0.173)	0.527*** (0.142)	0.382*** (0.148)	0.620*** (0.156)	0.244* (0.127)	C_RDD
I_QUOTWT	0.198 (0.192)	0.252 (0.265)	0.085 (0.218)	0.151 (0.216)	-0.089 (0.419)	-0.023 (0.272)	C_QUOTAS
$I_QUOTWOT$	0.220* (0.127)	0.313** (0.132)	0.152 (0.133)	0.224 (0.174)	0.298* (0.160)	0.122 (0.185)	
I_FIT	0.231*** (0,081)	0.177* (0,099)	0.253*** (0,077)	0.223*** (0,086)	0.172 (0,124)	0.223** (0,093)	C_FIT
I_NETMET	0,013 (0,148)	-0,023 (0,226)	-0,039 (0,139)	-0,079 (0,184)	-0,096 (0,258)	-0.200 (0,171)	
$I_TENDERING$	0.131 (0,163)	0,049 (0,178)	0.177 (0,164)	0,064 (0,192)	0,042 (0,202)	0.102 (0,211)	
I_TAXC	0.175 (0,113)	0.116 (0,160)	0.168 (0,106)	0.346* (0,206)	0.347 (0,232)	0.318 (0,196)	C_FISCAL
I_TAXR	0,006 (0,113)	0.126 (0,140)	-0,060 (0,128)	-0,018 (0,100)	0,000 (0,142)	-0,037 (0,105)	
I_PUB	0.380*** (0,123)	0.422*** (0,132)	0.314** (0,124)	0.217* (0,115)	0.270* (0,143)	0.157 (0,106)	
$I_TRADING$	0.313*** (0,105)	0.335** (0,139)	0.260 (0,160)	0.110 (0,145)	-0,007 (0,177)	0.124 (0,159)	C_TRADING
$I_TARGETS_LENGTH$				0.059** (0,030)	0.077*** (0,029)	0.068** (0,029)	
I_RDD_LENGTH				0.054*** (0,017)	0.052*** (0,019)	0.053*** (0,013)	
I_QUOTWT_LENGTH				0,072 (0,110)	0,077 (0,118)	0,081 (0,080)	
$I_QUOTWOT_LENGTH$				-0.082** (0,036)	-0.093** (0,045)	-0.065* (0,039)	
I_FIT_LENGTH				-0,006 (0,020)	-0,016 (0,025)	0,003 (0,025)	
I_NETMET_LENGTH				0,034 (0,047)	0,013 (0,073)	0,005 (0,041)	
$I_TENDERING_LENGTH$				0,007 (0,044)	0,003 (0,056)	0,002 (0,049)	
I_TAXC_LENGTH				-0,020 (0,066)	-0,026 (0,066)	-0,016 (0,059)	
I_TAXR_LENGTH				-0,032 (0,036)	-0,013 (0,041)	-0,044 (0,027)	
I_PUB_LENGTH				0,026 (0,030)	0,041 (0,035)	0,008 (0,028)	
$I_TRADING_LENGTH$				0,051 (0,043)	0,064 (0,060)	0,015 (0,050)	
$KSTOCK_{SC_Y}^a$	0,000 (0,003)	-0,003 (0,010)	0,007 (0,019)	-0,004 (0,004)	-0,008 (0,007)	-0,006 (0,024)	
$TOTPAT$	0.004*** (0,002)	0.004** (0,002)	0.004* (0,002)	0,004 (0,005)	0,004 (0,003)	0,003 (0,003)	

Table 4 continued:

Dependent variable	(7)	(8)	(9)	(10)	(11)	(12)
Variable	SC_SW_t	SC_S_t	SC_W_t	SC_SW_t	SC_S_t	SC_W_t
<i>GLOBCAP</i>	0.189*** (0,032)	0.185*** (0,038)	0.175*** (0,035)	0.182*** (0,032)	0.176*** (0,036)	0.162*** (0,035)
<i>DOMSHARE_Y</i> ^a	0,010 (0,012)	0,054 (0,051)	0,011 (0,019)	-0,031 (0,023)	-0,138 (0,096)	-0,005 (0,025)
Constant	-1.793*** (0.148)	-2.361*** (0.149)	-1.788*** (0.171)	-1.741*** (0.158)	-2.294*** (0.156)	-1.737*** (0.140)
Observations	4,693	4,693	4,693	4,693	4,693	4,693
Wald Chi ²	1,395***	1,539***	699.3***	713.5***	1,892***	1,300***

Notes: *** p<0.01, ** p<0.05, * p<0.10; robust standard errors in parentheses

^a The Y in the variables $KSTOCK_{SC_Y}$ and $DOMSHARE_Y$ is a placeholder for the data of SW (Solar and wind energy), S (Solar energy), and W (Wind energy), which is used in the respective columns.

Concerning the other covariates, only the coefficients of the change in the global generation capacity (*GLOBCAP*) are highly significant in all columns. The positive coefficient estimates are similar for the different technologies, indicating that changes in the general market opportunities for power plant manufacturers influence the innovation activities in the solar and wind power industry to a similar extent. Moreover, the effect of the total domestic patents (*TOTPAT*) is significantly positive in columns (1) to (3) and again there are no substantial technology-specific differences. The two covariates $KSTOCK_{SC_Y}$ and $DOMSHARE_Y$ are insignificant, but robust across all specifications.

The regression results for equation (3) in Table 4 allow analyzing the innovation effects of the individual policy instruments. In general, the coefficient estimates of instruments that are equivalent to a cluster, i.e. *I_TARGETS*, *I_RDD*, and *I_TRADING*, support the robustness of the cluster estimates. More interesting are clusters that encompass more than one instrument. Our analysis of columns (7) to (9) shows that within these clusters, the positive and significant cluster effect found in the corresponding columns (1) to (3) in Table 3 is driven by only one instrument.

Within the quota cluster, this instrument is quotas without trading (*I_QUOTWOT*). The lack of significance of the other policy instrument (*I_QUOTWT*) indicates that such measures do not encourage innovation in solar and wind power. We see at least two explanations for the insignificant effect. First, tradable renewable certificates (TRCs or RECs) tend to favor the rather mature and, thus, price competitive technologies like hydro, geothermal, and biomass. Second, technology-specific quotas give limited incentives to innovate.

Within the feed-in tariff cluster, patenting applications are driven by classical fixed rate and premium tariffs (*I_FIT*). The more advanced instruments, i.e. net metering (*I_NETMET*) and public competitive bidding (*I_TEND*), are estimated to have no significant effect on innovation. From a theoretical view this is surprising as a major goal of these advanced instruments is to decrease the levelized costs of electricity by imposing competitive pressures on energy equipment manufacturers. One possible explanation is that the more advanced instruments have predominantly been implemented fairly late, namely during or after the years of peak innovative activity. Contrary to that, fixed rate and premium tariffs had often already been in place before the years 2005 and 2006, when the speed of technological development in the solar and wind industry started growing exponentially.

Within the fiscal incentives cluster, the main drivers of innovation are public spending, capital subsidies, and low-cost loans (*I_PUB*). These immediate government interventions support the innovation activities of renewable energy equipment manufactures through very concrete mechanisms, allowing them to get a relatively reliable estimate of the business implications. Once granted, the measures entail immediate payments by the government or at least a certain market success. Contrary to that, tax reductions (*I_TAXR*) and tax credits (*I_TAXC*) are rather indirect and less projectable, as they depend on the firm's actual market penetration.

When comparing the magnitude of the corresponding policy design coefficients for solar and wind power in Tables 3 and 4, one further characteristic becomes evident. While the coefficients of both technologies point in the same direction, the ones in the solar-specific regressions tend to be larger. In other words, the policy clusters and instruments show stronger innovation effects for solar power. Two exceptions are targets (*C_TARGETS* and *I_TARGETS*) and feed-in tariffs (*C_FIT* and *I_FIT*), where the coefficients for wind power are larger. Such a difference cannot be observed for the control variables. However, one should be cautious to directly interpret this characteristic as an indication for technology-specific differences in the effectiveness of policy measures. The difference may as well be a mere consequence of the overall higher number of patent applications for solar power, which we found in the descriptive section 2.2, or of differences in the propensity to patent across technologies.

Last, the policy duration effects of the individual instruments in columns (10) to (12) in Table 4 show similar pattern as those of the clustered instruments in Table 3. The strongest positive effects are found for targets (*I_TARGETS_LENGTH*) and RD&D programs (*I_RDD_LENGTH*). Their positive influence on the patenting activity is estimated to increase with every additional year that the instrument is implemented. While the duration effects are still relatively small, the size of the coefficients of both instruments slightly increased in comparison to the respective coefficients using policy clusters. The coefficients of the other instruments are predominantly not significant and in the case of quotas without certificate trading (*I_QUOTWOT_LENGTH*) significantly negative. The latter result may be explained by our prior expectation that the incentives to innovate of policy instruments without a double burden decrease over time. In that regard, the negative coefficient can also be interpreted as evidence for the narrow Porter hypothesis, according to which only suitably designed policies can sustainably foster innovation. Renewable energy quotas without trading do not seem to provide these long-run incentives.

4.2 Robustness tests

To ensure the robustness of our results, we conduct several tests. First, we estimate the models for alternative sets of countries. As can be seen in columns (1a) and (1b) in Table D1 in Appendix D, the estimates are relatively consistent if G20 countries or OECD members, which are analyzed in many previous studies, are considered instead of the whole set of countries in column (1). Yet, there are some differences mainly in the magnitude of the coefficients. For instance, for G20 countries the global electricity generation capacity seems to be of higher importance than for OECD countries. Following the argumentation in Diederich (2016), we suggest that this may be explained by the different types of innovation that residents of these countries tend to patent. Technologically advanced firms in OECD countries may concentrate on the development of inventions at the technological forefront,

which often requires access to a large knowledge stock. On the contrary, G20 member states, which comprise a number of developing countries, may, on average, be more concerned about the development of application-related innovation that depends on the applied know-how of a large installed base.

Second, we analyze the issue of alternative patent count approaches. While simple patent counts are used in our main estimations, family counts are often regarded as the preferred measure, because they have a tendency to be less biased. Therefore, we rerun the regressions with alternative patent counts as the regressand and as the input for the respective knowledge stocks. As can be observed in the examples of results for the aggregated solar and wind technologies in columns (1c) to (1e) in Table D1 in Appendix D, our estimates are fairly robust to changes in the patent count approach. Hence, using size-weighted simple counts, family counts, and size-weighted family counts instead of simple counts does not change the findings.

Third, instead of analyzing contemporaneous patents as the dependent variable, we use two-year moving averages and three-year moving-averages. This allows us to account for potentially longer time periods needed to initiate R&D activities, discover new technologies, and file the patent application. The estimations further reduce the risk of reverse causality without changing our findings drastically. Examples of results are shown in Table D2 in Appendix D. Two differences are particularly interesting. On the one hand, the effect of quotas (*C_QUOTAS*) becomes insignificant once the moving averages are considered. In the light of the negative policy duration effects estimated for quotas without certificate trading in Table 4, the change in the estimates can again be understood as evidence for the decreasing incentives to innovate over time of policy instruments without a double burden. On the other hand, a similar change in the significance levels can be observed for the policy duration coefficient of targets (*C_TARGETS_LENGTH*). This can be an indication that targets are expected to be only the first step to structure the renewable energy support efforts. For a lasting effect, concrete supply- or demand-side policies need to be implemented.

4.3 Comparison to previous literature

This study complements and, in parts, revises the findings of the previous literature. Yet, when comparing our results to the ones of prior studies, it needs to be kept in mind that we rely on a different database. Specifically, we use a new patent identification classification for wind and solar energy technologies and our sample has an extended geographic and temporal scope. Moreover, despite the fact that many other studies also use binary data to measure the policy design, the analyzed policy instruments and clusters may be defined differently.

Our research agrees with the majority of studies that environmental regulation spurs the patenting activity in renewable energy technologies (Böhringer et al. 2017; Johnstone et al. 2010; Kim et al. 2017). In particular, the usual finding that research, development, and deployment programs have a strong positive effect on innovation is confirmed (Braun et al. 2010; Nicolli and Vona 2016; Peters et al. 2012). Our results are also in line with Schleich et al. (2017), who identified the presence of targets as one of the most favorable drivers of the patenting activity. Similarly, our estimates confirm the hypothesis of IRENA (2018) and Peters et al. (2012) that the change in the global capacity of renewables creates learning

and knowledge effects, which are likely to foster further innovation and decrease the costs of these technologies.

However, there is also one area of dissent. Many studies that compared the relative effects of different environmental policies found significant technology-specific differences (Costantini et al. 2015; Johnstone et al. 2010; Kim et al. 2017). For example, feed-in tariffs usually had a negative or insignificant effect on innovation in wind technologies, whereas the corresponding effect on solar energy technologies was positive (Johnstone et al. 2010; Nicolli and Vona 2016). The usual interpretation of this differential effect is that price-based policies are favorable during early phases of the technological development, whereas quantity-based policies like renewable energy certificates are more adequate for mature technologies. We find significant positive effects for both technologies and the results are fairly robust for both the policy cluster and the instrument estimations.

5 Conclusion

The aim of this study was to gain new insights on the relationship between policy design and innovation in the field of renewable energy technologies. We focused on solar and wind energy, which are the technologies with the highest growth rates of the installed capacity over the last decade. Our study advances the prior research by extending the policy, country, and time dimension and by applying the novel Y02 patent classification system.

We find that, first, more intensive portfolios of renewable energy support policies foster innovation related to solar and wind energy. Second, while the importance of the policy instruments partly varies across technologies, the direction of their effects on innovation are quite similar. On the cluster level the strongest policy effects can be found for RD&D programs, renewable energy targets, and fiscal incentives. Within clusters that encompass more than one policy instrument, the cluster effect is usually driven by one instrument only. Third, there is a tendency towards larger policy effects in the solar-specific regressions, whereas targets and feed-in tariffs constitute exceptions. Yet, given that the patenting activity in the solar industry has been generally higher, we would be careful to directly interpret this as a technology-specific difference in the effectiveness of policy instruments. Hence, our estimates rather do not support this finding of Johnstone et al. (2010) and others. Fourth, a longer policy duration is found to significantly increase the patenting activity in the case of RD&D programs and targets.

Our results show that renewable support policies have been a major driver of patenting activity in solar and wind power technologies. The regulation-induced innovations have helped to remarkably decrease the levelized costs of electricity, and as IRENA (2018) expects, by 2020 all technologies that are now in commercial use will be competitive with fossil fuels. However, to meet the advanced goals of the Paris Climate Agreement and the aspirations of the Sustainable Development Goals, this will not be enough. Power generation only accounts for 20% of global total final energy demand, whereas heating and cooling and the transport sector account for 80% (REN21 2018). In these areas alternative technologies lag behind. Therefore, the challenge in the near future will be to adapt the policy instruments to these intended uses.

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Appendix A:

Table A1: List of countries and territories

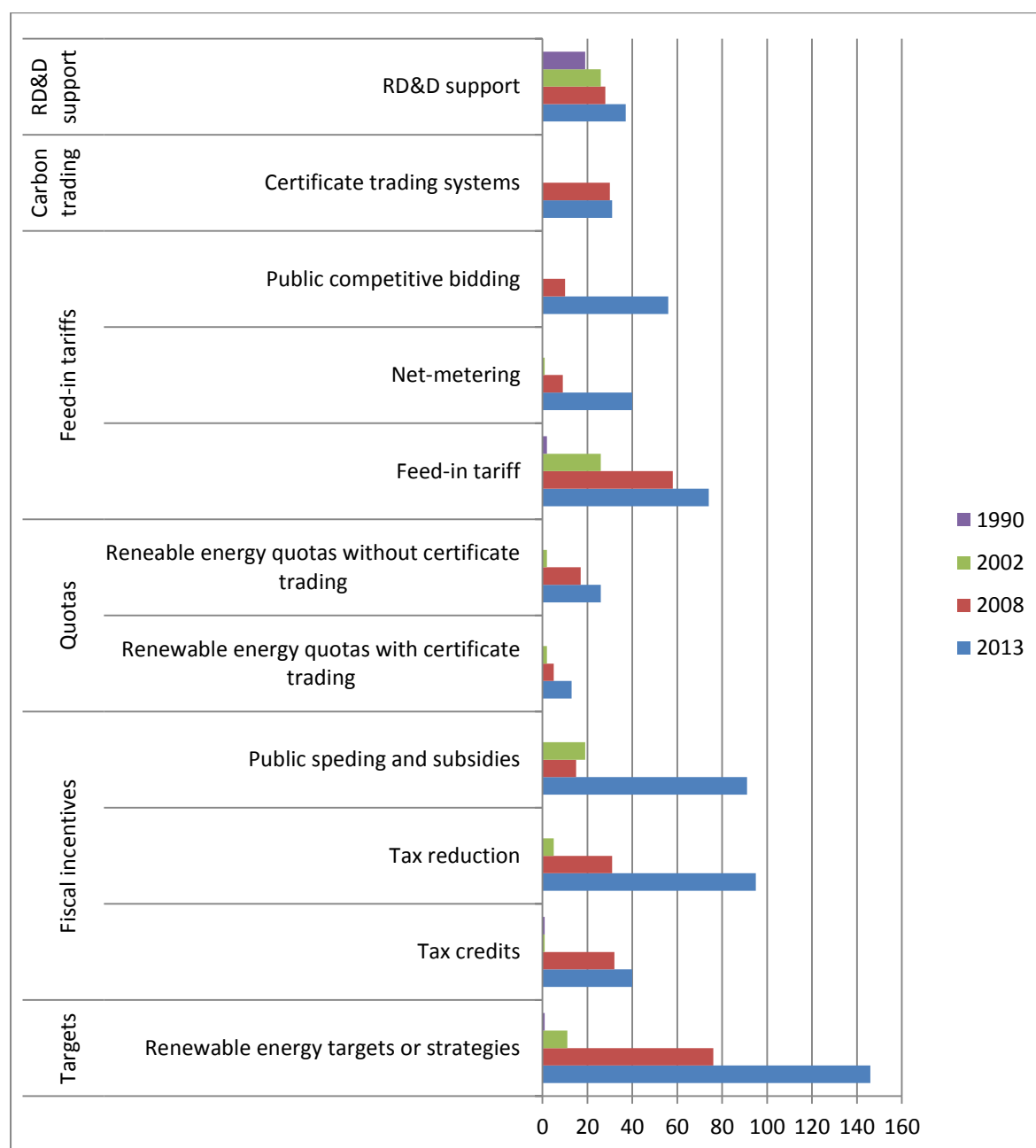
Afghanistan	Djibouti	Laos
Albania	Dominica	Latvia
Algeria	Dominican Republic	Lebanon
Angola	Ecuador	Lesotho
Antigua and Barbuda	Egypt	Liberia
Argentina	El Salvador	Libya
Armenia	Equatorial Guinea	Lithuania
Aruba	Eritrea	Luxembourg
Australia	Estonia	Macedonia
Austria	Ethiopia	Madagascar
Azerbaijan	Faroe Islands	Malawi
Bahamas, The	Fiji	Malaysia
Bahrain	Finland	Maldives
Bangladesh	Former Serbia & Montenegro	Mali
Barbados	France	Malta
Belarus	Gabon	Mauritania
Belgium	Gambia, The	Mauritius
Belize	Georgia	Mexico
Benin	Germany	Moldova
Bhutan	Ghana	Mongolia
Bolivia	Greece	Montenegro
Bosnia and Herzegovina	Greenland	Morocco
Botswana	Grenada	Mozambique
Brazil	Guatemala	Namibia
Brunei	Guinea	Nauru
Bulgaria	Guinea-Bissau	Nepal
Burkina Faso	Guyana	Netherlands
Burma (Myanmar)	Haiti	Netherlands Antilles
Burundi	Honduras	New Zealand
Cambodia	Hungary	Nicaragua
Cameroon	Iceland	Niger
Canada	India	Nigeria
Cape Verde	Indonesia	Niue
Central African Republic	Iran	Norway
Chad	Iraq	Oman
Chile	Ireland	Pakistan
China	Israel	Palestinian Territories
Colombia	Italy	Panama
Comoros	Jamaica	Papua New Guinea
Congo (Brazzaville)	Japan	Paraguay
Congo (Kinshasa)	Jordan	Peru
Cook Islands	Kazakhstan	Philippines
Costa Rica	Kenya	Poland
Cote d'Ivoire (Ivory Coast)	Kiribati	Portugal
Croatia	Korea, North	Qatar
Cuba	Korea, South	Romania
Cyprus	Kosovo	Russia
Czech Republic	Kuwait	Rwanda
Denmark	Kyrgyzstan	Saint Kitts and Nevis

Table A1 continued:

Saint Lucia	Sri Lanka	Turkey
Saint Vincent/Grenadines	Sudan and South Sudan	Turkmenistan
Samoa	Suriname	Uganda
Sao Tome and Principe	Swaziland	Ukraine
Saudi Arabia	Sweden	United Arab Emirates
Senegal	Switzerland	United Kingdom
Serbia	Syria	United States
Seychelles	Taiwan	Uruguay
Sierra Leone	Tajikistan	Uzbekistan
Singapore	Tanzania	Vanuatu
Slovakia	Thailand	Venezuela
Slovenia	Timor-Leste (East Timor)	Vietnam
Solomon Islands	Togo	Yemen
Somalia	Tonga	Zambia
South Africa	Trinidad and Tobago	Zimbabwe
Spain	Tunisia	

Appendix B:

Figure B1: Number of countries with renewable energy policies by instrument and year^{a, b}



^a Sources: Self prepared following Diederich (2016) and using IEA and IRENA (2015), OECD (2015), and REN21 (2005-2015).

^b Data on RD&D programs is almost exclusively available for OECD countries. Hence, the numbers might understate the actual dissemination of RD&D programs.

Appendix C

Table C1: Definition of variables

Variable	Description	Unit	Source
(a) Innovation measures			
<i>count_S^a</i>	Count of patent applications on solar power (Y02E 10/5) by domestic applicants	Patent applications	EPO (2018)
<i>count_W^a</i>	Count of patent applications on wind power (Y02E 10/7) by domestic applicants	Patent applications	EPO (2018)
<i>count_SW^a</i>	Count of patent applications on solar (Y02E 10/5) or wind power (Y02E 10/7) by domestic applicants	Patent applications	EPO (2018)
(b) Knowledge stocks			
<i>KSTOCK_{count_S}^a</i>	Stock of domestic patent applications on solar power (Y02E 10/5)	1,000 patent applications	Calculated using EPO (2018)
<i>KSTOCK_{count_W}^a</i>	Stock of domestic patent applications on wind power (Y02E 10/7)	1,000 patent applications	Calculated using EPO (2018)
<i>KSTOCK_{count_SW}^a</i>	Stock of domestic patent applications on solar (Y02E 10/5) or wind power (Y02E 10/7)	1,000 patent applications	Calculated using EPO (2018)
(c) Changes in generation capacities			
<i>GLOBCAP</i>	Year-by-year change in total global electricity generation capacity (all conventional and renewable energy technologies)	%-points	EIA (2018)
(d) Total patents			
<i>TOTPAT</i>	Simple count of total patent applications by domestic applicants on any technology	1,000 patent applications	EPO (2018)
(e) Regulation design indicators (Dummy variables: 1 = cluster (<i>C_</i>) or policy (<i>I_</i>) exist)			
<i>C_TARGETS</i>	Existence of at least one policy from the targets cluster	[0, 1]	IEA and IRENA, OECD, REN21
<i>C_RDD</i>	Existence of at least one policy from the research, development, and deployment programs cluster	[0, 1]	IEA and IRENA, OECD, REN21
<i>C_QUOTAS</i>	Existence of at least one policy from the quotas cluster	[0, 1]	IEA and IRENA, OECD, REN21
<i>C_FIT</i>	Existence of at least one policy from the feed-in tariffs cluster	[0, 1]	IEA and IRENA, OECD, REN21
<i>C_FISCAL</i>	Existence of at least one policy from the fiscal incentives cluster	[0, 1]	IEA and IRENA, OECD, REN21
<i>C_TRADING</i>	Existence of at least one policy from the greenhouse gas trading systems cluster	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_TARG</i>	Existence of renewable energy targets or strategies	[0, 1]	IEA and IRENA, OECD, REN21

Table C1 continued:

Variable	Description	Unit	Source
(e) Regulation design indicators (Dummy variables: 1 = cluster (<i>C_</i>) or policy (<i>I_</i>) exist)			
<i>I_RDD</i>	Existence of research, development, and deployment programs	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_QUOTWOT</i>	Existence of renewable energy quotas	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_QUOTWT</i>	Existence of renewable energy quotas with certificate trading systems	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_FIT</i>	Existence of fixed rate or premium feed.in tariffs (incl. energy production payments)	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_NETMET</i>	Existence of net metering	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_TEND</i>	Existence of public competitive bidding (tendering)	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_TAXC</i>	Existence of investment of production tax credits	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_TAXR</i>	Existence of tax reductions for carbon, energy, sales, VAT or other taxes	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_PUB</i>	Existence of public spending, capital subsidies, or low-cost loans	[0, 1]	IEA and IRENA, OECD, REN21
<i>I_TRAD</i>	Existence of greenhouse gas certificate trading systems	[0, 1]	IEA and IRENA, OECD, REN21
(f) Regulation intensity measures – Duration of the policy design indicators listed in category (e)			
<i>LENGHT_{C_E}^b</i>	Consecutive years since at least one policy from the respective policy cluster has been implemented	Years	IEA and IRENA, OECD, REN21
<i>LENGHT_{I_E}^b</i>	Consecutive years that a policy instrument has been implemented	Years	IEA and IRENA, OECD, REN21
(g) Regulation intensity measures – Renewable energy shares			
<i>DOMSHARE_S</i>	Share of solar in total electricity generation	%-points	EIA (2018)
<i>DOMSHARE_W</i>	Share of wind in total electricity generation	%-points	EIA (2018)
<i>DOMSHARE_SW</i>	Aggregated share of solar and wind in total electricity generation	%-points	EIA (2018)

^a The term *count* included in the variable names in categories (a) and (b) is a placeholder for the four different approaches to count patent applications.

^b The *_E* in the variable names in category (f) is a placeholder for the 11 instruments and 6 clusters listed in category (e).

Table C2: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
(a) Innovation measures					
<i>SC_S_t</i>	4,850	45.490	437.660	0	10,761
<i>SC_W_t</i>	4,850	24.418	171.176	0	3,852
<i>SC_SW_t</i>	4,850	69.908	585.751	0	13,872
<i>SC_SW_{MovAv2}</i>	4,850	71.341	579.899	0	13,707
<i>SC_SW_{MovAv3}</i>	4,850	72.287	570.138	0	12,822
<i>FC_SW_t</i>	4,850	56.088	488.217	0	11,589
<i>SCw_SW_t</i>	4,850	336.143	2,803.597	0	66,249
<i>FCw_SW_t</i>	4,850	332.112	2,812.604	0	66,941
(b) Knowledge stocks					
<i>KSTOCK_{SC_S}</i>	4,850	0.086	0.848	0	24.263
<i>KSTOCK_{SC_W}</i>	4,850	0.051	0.371	0	9.158
<i>KSTOCK_{SC_SW}</i>	4,850	0.137	1.168	0	32.188
<i>KSTOCK_{FC_SW}</i>	4,850	0.108	0.990	0	27.391
<i>KSTOCK_{SCw_SW}</i>	4,850	0.730	6.385	0	164.881
<i>KSTOCK_{FCw_SW}</i>	4,850	0.715	6.369	0	167.116
(c) Changes in generation capacities					
<i>GLOBCAP</i>	4,850	3.219	1.139	1.471	5.722
(d) Total patents					
<i>TOTPAT</i>	4,850	7.483	44.094	0	892.022
(e) Regulation design indicators					
<i>C_TARGETS</i>	4,850	0.204	0.403	0	1
<i>C_RDD</i>	4,850	0.127	0.333	0	1
<i>C_QUOTAS</i>	4,850	0.055	0.228	0	1
<i>C_FIT</i>	4,850	0.174	0.379	0	1
<i>C_FISCAL</i>	4,850	0.189	0.391	0	1
<i>C_TRADING</i>	4,850	0.054	0.225	0	1
<i>I_TARG</i>	4,850	0.204	0.403	0	1
<i>I_RDD</i>	4,850	0.127	0.333	0	1
<i>I_QUOTWOT</i>	4,850	0.014	0.117	0	1
<i>I_QUOTWT</i>	4,850	0.041	0.199	0	1
<i>I_FIT</i>	4,850	0.151	0.358	0	1
<i>I_NETMET</i>	4,850	0.034	0.181	0	1
<i>I_TEND</i>	4,850	0.049	0.216	0	1
<i>I_TAXC</i>	4,850	0.072	0.258	0	1
<i>I_TAXR</i>	4,850	0.113	0.316	0	1
<i>I_PUB</i>	4,850	0.152	0.359	0	1
<i>I_TRAD</i>	4,850	0.054	0.225	0	1
(f) Regulation intensity measures – Duration of the policy design indicators					
<i>C_TARGETS_LENGTH</i>	4,850	1.104	2.844	0	27
<i>C_RDD_LENGTH</i>	4,850	1.551	4.884	0	40
<i>C_QUOTAS_LENGTH</i>	4,850	0.284	1.376	0	15
<i>C_FIT_LENGTH</i>	4,850	1.217	3.436	0	26
<i>C_FISCAL_LENGTH</i>	4,850	1.182	3.341	0	36
<i>C_TRADING_LENGTH</i>	4,850	0.260	1.243	0	9
<i>I_TARG_LENGTH</i>	4,850	1.104	2.844	0	27
<i>I_RDD_LENGTH</i>	4,850	1.551	4.884	0	40
<i>I_QUOTWOT_LENGTH</i>	4,850	0.072	0.488	0	7
<i>I_QUOTWT_LENGTH</i>	4,850	0.212	1.165	0	12

Table C2 continued:

Variable	Obs.	Mean	Std. Dev.	Min	Max
(f) Regulation intensity measures – Duration of the policy design indicators					
<i>I_FIT_LENGTH</i>	4,850	1.128	3.365	0	26
<i>I_NETMET_LENGTH</i>	4,850	0.138	0.913	0	16
<i>I_TEND_LENGTH</i>	4,850	0.175	0.918	0	11
<i>I_TAXC_LENGTH</i>	4,850	0.465	2.233	0	36
<i>I_TAXR_LENGTH</i>	4,850	0.527	1.869	0	18
<i>I_PUB_LENGTH</i>	4,850	0.919	2.744	0	25
<i>I_TRAD_LENGTH</i>	4,850	0.260	1.243	0	9
(g) Regulation intensity measures – Renewable energy share					
<i>DOMSHARE_S</i>	4,693	0.041	0.308	0	7.725
<i>DOMSHARE_W</i>	4,693	0.434	2.030	0	34.471
<i>DOMSHARE_SW</i>	4,693	0.474	2.141	0	34.820

Appendix D

Table D1: Robustness tests using alternative samples of countries and patent counts

Dependent variable	<i>SC_SW_t</i>	<i>SC_SW_t</i>	<i>SC_SW_t</i>	<i>SCw_SW_t</i>	<i>FC_SW_t</i>	<i>FCw_SW_t</i>
Country scope	All	OECD	G20	All	All	All
Variable	(1)	(1a)	(1b)	(1c)	(1d)	(1e)
<i>C_TARGETS</i>	0.406*** (0.085)	0.378*** (0.125)	0.394** (0.183)	0.453*** (0.111)	0.402*** (0.133)	0.409*** (0.140)
<i>C_RDD</i>	0.626*** (0.118)	0.498*** (0.143)	0.503* (0.260)	1.083*** (0.167)	1.035*** (0.150)	1.486*** (0.192)
<i>C_QUOTAS</i>	0.234** (0.110)	0.254* (0.152)	0.319* (0.193)	0.221** (0.111)	0.249** (0.114)	0.229* (0.132)
<i>C_FIT</i>	0.291*** (0.097)	0.242** (0.103)	0.154 (0.103)	0.279*** (0.094)	0.263*** (0.089)	0.282*** (0.108)
<i>C_FISCAL</i>	0.398*** (0.131)	0.465*** (0.112)	0.591*** (0.189)	0.281** (0.133)	0.388*** (0.137)	0.327** (0.163)
<i>C_TRADING</i>	0.396*** (0.118)	0.600*** (0.141)	0.431** (0.194)	0.371** (0.149)	0.441*** (0.136)	0.375* (0.196)
<i>KSTOCK_{Y_SW}</i> ^a	0.001 (0.006)	0.001 (0.002)	0.000 (0.008)	-0.003 (0.003)	0.000 (0.015)	-0.004 (0.003)
<i>TOTPAT</i>	0.004* (0.002)	0.004*** (0.002)	0.004*** (0.001)	0.005*** (0.002)	0.004** (0.002)	0.005** (0.002)
<i>GLOBCAP</i>	0.178*** (0.028)	0.081** (0.033)	0.171*** (0.029)	0.153*** (0.031)	0.183*** (0.032)	0.163*** (0.030)
<i>DOMSHARE_SW</i>	0.007 (0.011)	0.006 (0.012)	0.036 (0.037)	0.008 (0.012)	0.010 (0.013)	0.013 (0.013)
Constant	-1.785*** (0.163)	-1.351*** (0.210)	-1.454*** (0.194)	-2.574*** (0.172)	-2.493*** (0.153)	-3.238*** (0.153)
Observations	4,693	850	500	4,693	4,693	4,693
Wald Chi ²	824.6***	654.8***	479.1***	510.1***	1,444***	1,008***

Notes: *** p<0.01, ** p<0.05, * p<0.10; robust standard errors in parentheses; ^a The Y in the variable *KSTOCK_{Y_SW}* is a placeholder for SC (Simple count), SCw (Size-weighted simple count), FC (Family count), and FCw (Size-weighted family county).

Table D2: Robustness tests comparing contemporaneous with moving average patent counts

Dependent variable	(1)	(1f)	(1g)	(4)	(4f)	(4g)
Variable	SC_SW_t	SC_SW_{MovAv2}	SC_SW_{MovAv3}	SC_SW_t	SC_SW_{MovAv2}	SC_SW_{MovAv3}
<i>C_TARGETS</i>	0.406*** (0.085)	0.429*** (0.101)	0.439*** (0.122)	0.251** (0.111)	0.331** (0.140)	0.405*** (0.105)
<i>C_RDD</i>	0.626*** (0.118)	0.380*** (0.102)	0.316*** (0.118)	0.397*** (0.136)	0.201 (0.157)	0.174 (0.133)
<i>C_QUOTAS</i>	0.234** (0.110)	0.138 (0.111)	0,044 (0.105)	0.201* (0.113)	0.137 (0.114)	0,072 (0.096)
<i>C_FIT</i>	0.291*** (0.097)	0.319*** (0,066)	0.282*** (0,086)	0.252** (0.103)	0.290*** (0,096)	0.267*** (0,099)
<i>C_FISCAL</i>	0.398*** (0.131)	0.378*** (0,110)	0.351*** (0,118)	0.320** (0.124)	0.305*** (0,106)	0.299** (0,129)
<i>C_TRADING</i>	0.396*** (0.118)	0.401*** (0,101)	0.399*** (0,119)	0.218 (0.165)	0.331** (0,168)	0.447*** (0,136)
<i>C_TARGETS_LENGTH</i>				0.047** (0.018)	0,032 (0,023)	0,015 (0,018)
<i>C_RDD_LENGTH</i>				0.048*** (0.014)	0.041*** (0,011)	0.040*** (0,010)
<i>C_QUOTAS_LENGTH</i>				-0,033 (0,027)	-0,037 (0,024)	-0,037 (0,026)
<i>C_FIT_LENGTH</i>				0,002 (0,024)	0,000 (0,022)	-0,002 (0,020)
<i>C_FISCAL_LENGTH</i>				-0,013 (0,026)	-0,005 (0,030)	-0,004 (0,023)
<i>C_TRADING_LENGTH</i>				0,015 (0,026)	-0,002 (0,039)	-0,022 (0,031)
<i>KSTOCK_{SC_SW}</i>	0,001 (0,006)	-0,001 (0,002)	-0,005 (0,003)	-0,002 (0,006)	-0,004 (0,006)	-0,006 (0,007)
<i>TOTPAT</i>	0.004* (0,002)	0.004** (0,002)	0.004*** (0,001)	0,004 (0,008)	0,004 (0,004)	0.004* (0,002)
<i>GLOBCAP</i>	0.178*** (0,028)	0.206*** (0,026)	0.237*** (0,031)	0.180*** (0,026)	0.193*** (0,028)	0.203*** (0,030)
<i>DOMSHARE_SW</i>	0,007 (0,011)	0,005 (0,008)	-0,001 (0,008)	-0,015 (0,013)	-0,009 (0,014)	-0,005 (0,010)
Constant	-1.785*** (0.163)	-1.291*** (0.123)	-1.065*** (0.149)	-1.772*** (0.159)	-1.256*** (0.149)	-0.986*** (0.148)
Observations	4,693	4,693	4,693	4,693	4,693	4,693
Wald Chi ²	824.6***	891.6***	1,398***	688.0***	851.2***	1,122***

Notes: *** p<0.01, ** p<0.05, * p<0.10; robust standard errors in parentheses