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Do Fossil fuel Taxes Promote Innovation in Renewable Electricity Generation?

BY

Itziar Lazkano AND **Linh Pham**

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Do Fossil fuel Taxes Promote Innovation in Renewable Electricity Generation?*

Itziar Lazkano† Linh Pham‡

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Abstract

We evaluate the role of a fossil fuel tax and research subsidy in directing innovation from fossil fuel toward renewable energy technologies in the electricity sector. Using a global firm-level electricity patent database from 1978 to 2011, we find that the impact of fossil fuel taxes on renewable energy innovation varies with the type of fossil fuel. Specifically, a tax on coal reduces innovation in both fossil fuel and renewable energy technologies while a tax on natural gas has no statistically significant impact on renewable energy innovation. The reason is that easily dispatchable energy sources like coal-fired power plants need to complement renewable energy technologies in the grid because renewables generate electricity intermittently. Our results suggest that a tax on natural gas, combined with research subsidies for renewable energy, may effectively shift innovation in the electricity sector towards renewable energy. In contrast, coal taxation or a carbon tax that increases coal prices has unintended negative consequences for renewable energy innovation.

Key words: Electricity; Energy taxes; Renewable, coal, natural gas technologies
JEL Classification Codes: O3, Q4, L9

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†Assistant Professor, Department of Economics, University of Wisconsin-Milwaukee, PO Box 413, Bolton 840, Milwaukee, WI 53201, USA, and Visiting Associate Professor, Department of Economics, Norwegian School of Economics, Helleveien 40, 5045 Bergen, Norway. Email: lazkano@uwm.edu.

‡PhD Candidate, Department of Economics, University of Wisconsin-Milwaukee, PO Box 413, Milwaukee, WI 53201, USA. Email: linhpham@uwm.edu.

1 Introduction

The combustion of fossil fuels to generate electricity is the largest single emitter of carbon worldwide. In 2014, 70% of global electricity production came from fossil fuels such as coal, natural gas, and oil, making up 40% of global carbon emissions. In the U.S. only, electricity generation accounts for 37% of total carbon emissions and 31% of total greenhouse gas emissions (International Energy Agency, 2015b). With increasing concerns over climate change, many economists argue in favor of decarbonizing the electricity sector through higher use of less carbon-intensive technologies such as solar, wind, and other clean technologies.[1] For decades, an increasing number of private research firms have been competing for new technological breakthroughs to minimize the human carbon footprint. In addition, for at least three decades, governments throughout the world have implemented policies to promote the invention of both efficiency-improving fossil fuel technologies and technologies utilizing renewable energy.[2] In particular, there are two types of environmental policies that economists favor: subsidies to promote cleaner technologies and taxes to internalize the environmental costs of burning fossil fuels.[3,4] While these efforts have resulted in a range of technological innovations, it is unclear whether there has been a shift in innovation efforts towards cleaner technologies. In this paper, we explore the role of environmental regulations, specifically fossil fuel taxes, in shifting innovation from fossil fuel to renewable energy.

In particular, we ask the following questions. First, are fossil fuel taxes successful at promoting innovation in renewable technologies in the electricity sector? Second, how effective are research subsidies in shaping global innovation in the electricity sector? Finally, what other factors shift innovation in the electricity sector towards renewable technologies? To answer these questions, we estimate a directed technological change model using global

[1] While these technologies are commercially available, renewable energy still represents a modest share in global electricity production. According to the World Development Indicators, 21.5% of the world's total electricity generation comes from renewable sources, whereas only 5.4% comes from non-hydro renewable sources (see Table 1).

[2] According to the International Energy Agency (IEA), global subsidies for renewable energy totaled \$112 billion in 2014 while fossil fuel subsidies totaled \$493 billion (International Energy Agency, 2015e).

[3] See for example Acemoglu et al. (2012); Bovenberg and Smulders (1995, 1996); Goulder and Schneider (1999) for a rigorous characterization of the role of these policies in decarbonizing the economy.

[4] In addition to these two policies, there are other policies like feed-in tariffs and cap and trade that promote innovation. Since only some countries have implemented these policies and for a relatively short period of time, we do not quantify their effect in this study. However, we do control for these policies in our empirical analysis.

firm-level electricity patent data from 1978 to 2011. Past work has focused on the aggregate impact of all energy prices in fossil fuel and renewable technologies. In contrast, we take a different approach and distinguish fuels used in power generation (e.g., coal, natural gas, and oil) and technologies used for electricity generation (e.g., coal-fired plants, gas plants, solar power plants).[5] By doing so, we identify specific taxes that encourage and discourage renewable energy innovation.

The directed technological change (DTC) framework of Acemoglu (2002); Acemoglu et al. (2012, 2016) guides our empirical analysis. These and other DTC models predict that energy prices, taxes, subsidies and past innovation activity affect technological advancements, and that these effects depend on the elasticity of substitution between fossil fuels and renewable energy. Specifically, when fossil fuel and renewable energy technologies are substitutes, higher fossil fuel prices can shift innovation towards more renewable energy technologies. However, when they are complements, a higher fossil fuel price discourages innovation in renewable technologies. Empirical studies have presented evidence for a substitute relationship between fossil fuel and renewable technologies in the electricity sector (see, for example, Papageorgiou et al., 2016). However, this and other studies employed an aggregate measure for fossil fuel technologies that summarizes all fossil fuel technologies into one composite index. We take a different approach by disaggregating fossil fuel prices and technologies between coal, natural gas, and oil in order to capture the idiosyncrasies of the electricity market.

In the electricity grid, renewable energy technologies are imperfect substitutes for fossil fuel-burning technologies because they supply electricity intermittently (see, for example, Joskow, 2011). The intermittency issue of many renewable energy sources, especially wind turbines and solar power plants, makes them an unstable energy source for base-load power plants that supply electricity continuously without any interruption.[6] This suggests that

[5]The distinction among electricity generating technologies is important because some plants are used in base-load electricity generation while others are used in peak-load electricity generation. Base-load electricity refers to electricity generated from power stations that operate continuously and are available 24 hours a day. In contrast, peak-load power plants run only when demand for electricity is high, such as during summer afternoons when air conditioning loads are high (International Energy Agency, 2015d). In 2013, coal (41.1%), hydro (16.1%), and nuclear (10.6%) generated most global base-load power. Table 1 presents electricity production by source and region in 2013.

[6]Hydropower technology is the exception. According to the International Energy Agency (2015b), 16% of the world's total electricity generation comes from hydroelectric power plants. The most common plants store water in a reservoir and release water to create energy when electricity is needed, depending on water availability. Thus, hydroelectric plants have been able to dispatch electricity since the late 19th century. Unfortunately, large hydroelectric plants are concentrated geographically and hydroelectric capacity

as long as wind and solar energy cannot be efficiently stored for later use, they cannot replace coal from base-load electricity generation and they present an imperfect substitute for fossil fuels.[7] Thus, the supply of electricity from renewable sources must be complemented with easily dispatchable fossil fuels like coal. Then, as predicted by the directed technological change models, we should expect a higher coal price to discourage innovation in renewable technologies as well as coal-burning technologies. The main goal of our paper is to empirically test this hypothesis.

To empirically evaluate the above hypothesis, we first construct a unique firm-level panel data set where we use electricity patent application data to measure innovation. To mitigate the problem that many patents have low values, our empirical analysis focuses on "triadic" patents, which are series of patents filed at all three of the world's most important patent offices: the European Patent Office (EPO), the U.S. Patent and Trademark Office (USPTO), and the Japan Patent Office (JPO). We classify these patents into the following three groups: renewable energy, base-load fossil fuel, and peak-load fossil fuel patents. By separating fossil fuel patents into base- and peak-load technologies, we can infer about the heterogeneity in the elasticity of substitution between renewable energy and different types of fossil fuels. In addition to the main patent data, we collect data on coal, natural gas, and oil prices, research subsidies, and economic indicators. Altogether, our data set includes 13,054 firms across 26 countries between 1978 and 2011, which covers 96.20% of all triadic electricity patents globally (OECD, 2009).

Our estimation results find evidence for a mixed effect of fossil fuel prices in renewable energy innovation. First, an increase in the price of coal discourages innovation in renewable energy. The reason is that renewables rely of coal-fired plants to complement their supply to the grid. Specifically, a 10% increase in the price of coal is associated with 3.4% decrease in renewable energy innovation. In contrast, we find an insignificant impact of an increase in the price of natural gas on the firm-level likelihood of innovation in renewable energy. These results imply that a tax on coal and a carbon tax that increases the price of coal may create unintended effects by discouraging the development of renewable electricity-generating technologies. In addition to energy prices, we also find that research subsidies play a significant role in shifting the direction of innovation in the electricity sector. Our

expansion is limited.

[7] Many argue in favor of electricity storage as the solution to the intermittency issue of renewable sources, but the cost of large-scale electricity storage is the biggest roadblock for its success. See Lazkano et al. (2016) for an analysis of the role of electricity storage in the transition from fossil fuels to renewable sources in electricity generation.

results show that, to effectively direct innovation in the electricity sector towards more renewable energy, a combination of renewable energy research subsidies and natural gas taxation is desired. On the other hand, excessive reliance on a coal tax may negatively affect renewable energy innovation because the need of base-load fossil fuels to complement renewable energy.

Our paper contributes to recent empirical literature that studies incentives for innovation in the energy sector (for example, Buonanno et al. (2003); Popp (2002, 2005)).[8] While the empirical evidence from this literature is extensive, previous work has mainly focused on documenting the factors that affect clean innovations rather than focusing on whether these factors can steer innovations away from fossil fuel technologies (Newell et al., 1999; Lanzi et al., 2011). In addition, many of these papers rely on country-level data as the basis for their analysis, and have therefore ignored the responses of innovations to different environmental policy regimes at the firm level (Popp, 2002, 2010).

Methodologically, our paper closely relates to Aghion et al. (2016), who focuses on the direction of technological innovation in the auto industry. The paper also relates to Noailly and Smeets (2015) who look at innovation in the electricity sector by focusing on European firms. However, our paper also differs from these previous studies in several aspects. First, Aghion et al. (2016) and Noailly and Smeets (2015) focus on capturing the aggregate impact of all energy prices using a composite fossil fuel price index; therefore, they are unable to separate the impact of different types of energy prices on innovation. We take a different approach and distinguish between the impact of coal and natural gas prices on innovation. By doing so, we identify the relationship between renewables and different types of fossil fuels that previous empirical work overlooked. Our results show that the effectiveness of fossil fuel-price regulations in fostering renewable energy innovation varies largely with the type of fossil fuel targeted by these regulations. At the current technology level, taxing coal may be harmful for renewable innovation in the electricity sector. In contrast, taxing natural gas may steer innovation in the electricity sector towards more renewable energy by lowering the firm-level incentive to innovate in fossil fuel technology. Second, our paper is the first to explore the global pattern of innovation in the electricity sector. This is important because as shown in Table 1, electricity generation by source

[8]See also Calel and Dechezleprêtre (2012); Dechezleprêtre and Glachant (2014); Gans (2012); Hassler et al. (2012). In addition, Fischer and Newell (2008); Nesta et al. (2014); Sanyal and Ghosh (2013); Klemetsen et al. (2016) focus on the effectiveness of environmental policies to promote renewable energy technologies.

varies considerably across the most innovative regions and therefore a regional account of innovation cannot be extended to offer solutions to curb emissions from global electricity generation.[9] Finally, we are able to highlight the importance of government policies in shifting the direction of innovation in the electricity sector, alongside market forces like firm-level past knowledge stocks, energy prices, and other macroeconomic factors.

The paper is organized as follows. Section 2 summarizes our theoretical hypotheses, Section 3 describes the construction of our data, and Section 4 specifies our identification strategy. Section 5 presents our empirical results and discusses their robustness and policy implications. Finally, Section 7 presents our conclusion.

2 Theoretical background: energy taxes and innovation in the electricity sector

In this section, we present theoretical predictions and testable hypotheses about the direction of innovation in the electricity sector. These predictions are based on the directed technological change framework by Acemoglu et al. (2012). Building on Acemoglu (2002); Acemoglu et al. (2012, 2016), we apply a directed technological change model to the electricity sector. Because our theoretical predictions are in line with previous work, we present our model in Appendix A and restrict this section to the discussion of the idiosyncrasies of the electricity sector, theoretical predictions, and testable hypotheses.

One distinguishing feature of electricity is that it needs to be consumed as soon as it is produced; therefore, it is important to immediately adjust electricity supply to meet changes in electricity demand to avoid blackouts or other problems. System operators resolve this issue by producing a base electricity load available 24 hours a day in order to meet the minimum demand for electricity. During times of high demand, such as during summer afternoons when air conditioning loads are high, peak electricity loads are added to meet excess demand. Thus, we can separate electricity-generating technologies in two groups: base- and peak-load technologies. There are many sources used to generate electricity with

[9]For example, Noailly and Smeets (2015) study electricity innovation among European firms, which covers only 38.07% of all electricity patents and uses fossil fuels to generate 50.6% of electricity. In contrast, the U.S. applies for most electricity generating patents and uses fossil fuels to generate 61,7% of electricity. Our data set includes firms that claim residence worldwide and covers 96.2% of all electricity patents globally (OECD, 2009). Figure B.1 shows that most firms are located in the U.S. and Japan, followed by Germany, France, and the U.K. and as shown in Table 1, electricity generation by sources differs considerably in these countries.

these technologies. Generally, coal and nuclear are used to produce base-load electricity, while hydroelectric sources are used for both base-load and peak-load electricity because it is cheap to switch them on and off. Natural gas used to meet peak electricity load but since a new supply of natural gas from shale formations is available, natural gas is used in both base and peak-load electricity. Renewable resources can potentially meet base-load electricity demand since once they are installed, the marginal cost of using them is zero. These examples show that many energy sources can be used in electricity generation but their use depends on regional electricity markets. Table 1 summarizes the sources of electricity generation by region. At the global level, fossil fuels are used to generate 66.4% of total electricity, followed by hydropower (16.1%) and nuclear (10.6%). Renewable resources excluding hydro comprise a modest share of total electricity generation. Because the expansion of hydroelectric and nuclear capacity is limited, many argue in favor of increasing the share of other renewable sources in the energy mix as a solution to curb emissions from burning fossil fuels. The expansion of renewables in the electricity grid, however, presents several technological challenges.

Table 1: Electricity production by source and region in 2013.

Region	**Production**	**Sources of electricity production (%)**					
		Fossil fuel			**Renewable**		**Nuclear**
		Coal	Natural gas	Oil	Hydropower	Other Ren.	
East Asia and Pacific	8,427.9	62.1	13.4	2.2	13.8	3.7	3.6
Europe and Central Asia	5,305.3	25.0	24.3	1.3	16.9	9.5	21.9
Latin America and Caribbean	1,546.0	6.4	25.6	10.9	47.1	5.3	2.1
Middle East and North Africa	1,323.2	3.4	64.7	21.6	3.1	0.3	0.4
North America	4,940.8	36.0	24.8	0.9	13.4	5.8	18.7
South Asia	1,372.6	63.5	9.8	5.0	13.4	4.4	2.8
Sub-Saharan Africa	454.3	53.7	7.9	3.4	20.5	0.9	3.1
World	23,354.4	41.1	21.7	3.6	16.1	5.4	10.6

Note: Electricity production is measured in kilowatt hours (billions).
Source: World Development Indicators.

One such challenge is that some electricity-generating sources such as fossil fuels are easily dispatched to the grid, while others, such as renewables, are difficult to dispatch (Joskow, 2011). For example, wind and solar technologies can only be used when the wind is blowing or the sun is shining, and in absence of large-scale electricity storage solutions, these technologies can only supply electricity to the grid intermittently. The high variability in the supply of electricity from renewable energy make them an unstable input for base-load electricity power stations that must run continuously. This implies three things. First, renewable energy technologies are imperfect substitutes for fossil fuel-burning technologies. Second, renewable energy is as of today unable to replace coal from base-load power stations. Finally, renewable electricity relies on coal-fired plants as a complement to meet the electricity demand.

While these idiosyncrasies are well understood, previous work has concentrated on studying the incentives to innovate as if renewable and fossil fuels were substitutes. Thus, this previous work has concluded that higher energy prices and taxes promote innovation in renewable technologies with the underlying assumption that renewable energy and fossil fuels are substitutes. Indeed, the empirical literature has included all fossil fuels into one composite price index and all fossil fuel technologies into one group. While the assumption of a high elasticity of substitution is appropriate for other sectors,[10] this assumption is not applicable to the electricity sector. In contrast, our goal in this paper is to analyze firm-level incentives to innovate in the electricity sector while taking into account that some electricity-generating technologies complement each other.

Our theoretical model is a general equilibrium model with two types of agents: (i) utility-maximizing consumers who consume electricity and an aggregate consumption good, and (ii) profit-maximizing firms who are either electricity generators or electricity retailers. There are two types of electricity generators: renewable and nonrenewable. Renewable generators use renewable energy to produce electricity, while nonrenewable generators use fossil fuels. At the beginning of each period, both renewable and nonrenewable generators engage in research to develop new electricity-generating technologies, which are later used to produce electricity. Each generator is eligible for a research subsidy that lowers the cost of innovation. At the end of the period, electricity retailers purchase electricity from renewable and nonrenewable generators and resell it to the end consumers. All electricity generators and retailers take prices, subsidies and initial technologies as given.

We solve the above general equilibrium model to derive the equilibrium innovation intensity for both renewable and nonrenewable technologies and we present the detailed solution of the model in Appendix A. In line with prior work, our model shows that the equilibrium innovation intensity depends on research subsidies, energy prices, and firms' research history. Moreover, the impact of energy prices on innovation depends on the elasticity of substitution between fossil fuel and renewable energy technologies. When this

[10]For example, Aghion et al. (2016) study innovation in the automobile sector under this assumption.

elasticity of substitution is sufficiently high (i.e., when fossil fuels and renewable energy are easily substitutable in electricity production), then an increase in fossil fuel prices and taxes promote innovation in renewable technologies. In contrast, when fossil fuels and renewable energy are complements, increasing fossil fuel prices and taxes discourage innovation in renewable technologies.

From these theoretical predictions, we derive the following hypotheses:

Hypothesis 1. *A higher coal price negatively affects the development of both renewable and fossil fuel based base-load technologies.*

Hypothesis 2. *A higher natural gas price negatively affects both fossil fuel based base-load and peak-load innovation.*

In addition, in line with previous work, we expect research subsidies to increase the likelihood of innovation in all technologies. Finally, the higher a firm's past innovation in a particular type of technology (knowledge stock), the more likely it is to innovate in that type of technology.

Hypothesis 3. *Research subsidies increase the likelihood of innovation in all technologies.*

Hypothesis 4. *The larger a firm's knowledge stock in a particular type of technology, the more likely it is to innovate in that type of technology.*

Next, we empirically test the above hypotheses using global firm-level panel data. We begin by describing the data set in Section 3 and turn to the empirical analysis in Sections 4 and 5.

3 Data

The estimation of the drivers of innovation requires firm-level data on research output, energy prices, taxes, research subsidies, and past innovation in addition to country-level economic data. Specifically, we measure research output and past innovation with patents, which are drawn from the OECD Patent Database (see OECD, 2009, for a description). Energy prices including taxes and research subsidies, are from the IEA, and economic data are from the Penn World Tables (International Energy Agency, 2015a,c; Feenstra et al., 2013). Altogether, our data set spans 34 years (1978-2011) across 26 countries and contains 96.2% of triadic electricity patents from all over the world. Table B.1 in

Appendix B summarizes the source of data for each variable, while Table B.2 lists countries. As follows, we describe the construction of this data set before presenting the overall descriptive statistics.

We use data on patent applications to measure innovation.[11] Each patent application contains detailed information about the inventor(s), applicant(s), and the specific type of technology, which allows us to identify specific firms, while the International Patent Classification (IPC) codes assigned to each patent make it possible to identify technologies related to electricity generation.

Individual patents differ considerably in their worth, with many patents having low values (Aghion et al., 2016). We address this issue by only considering the most valuable patents from the OECD's Triadic Patent Database.[12] A patent belongs to this database when the same applicant or inventor files the same invention at the three most important patent offices: the EPO, the USPTO, and the JPO. Triadic patents then form a highly-valued patent family, which is a collection of patents that protect the same idea across different countries. Specifically, to qualify as a triadic patent family member, a particular patent must have equivalent applications at the EPO, the JPO, and the USPTO. Because triadic patents are applied for in three separate offices, they include only the most valued patents and allow for a common worldwide measure of innovation that avoids the heterogeneity of individual patent office administrations (Aghion et al., 2016).[13]

Once we have all patent information, we select patents related to electricity generation using IPC codes. We then categorize them into two broad groups: renewable energy and fossil fuel technologies. Renewable energy technologies are identified from the World Intellectual Property Office's (WIPO) IPC Green Inventory[14], while fossil fuel technolo-

[11]Patents are a common measure of innovation in economic studies. (Popp, 2005) notes that other measures of innovation, such as R&D expenditures, are generally only available at the industry level and for limited technology types. Thus, the detailed nature of patent data proves particularly useful when examining firm-specific incentives to innovate in selected technologies.

[12]One disadvantage of triadic patent families is the lag time associated with the USPTO. Legal delays for publishing applications are 18 months after the priority date and up to 5 years between the priority date and publication date (Dernis and Khan, 2004). As a consequence, U.S. patent grants may delay the completion of data on triadic patent families. To mitigate this limitation, the OECD utilizes forecasts called "nowcasting" in order to improve the timeliness of triadic patents (Dernis and Khan, 2004). Despite this difficulty, triadic patents still provide the most inclusive measure of high-value, firm-level, innovative performance.

[13]Furthermore, the OECD utilizes "extended families," which are designed to identify any possible links between patent documents (Martinez, 2010). This is advantageous, as it provides the most comprehensive method of consolidating patents into distinct families, allowing us to include an extensive number of patented ideas.

[14]The IPC codes listed in the IPC Green Inventory have been compiled by the IPC Committee of Experts

gies are selected from the IPC codes used by Lanzi et al. (2011). Specifically, renewable energy patents are related to alternative energy production, which includes fuel cells, pyrolysis, harnessing energy from manufactured waste, wind, solar, geothermal energy, other production or use of heat, using waste heat, and devices for producing mechanical power from muscle energy. Fossil fuel technologies combine both general and efficiency-improving technologies. Specific descriptions of the IPC codes used to identify electricity-generating patents are presented in Tables B.3-B.5 in Appendix B.1. Moreover, we separate fossil fuel technologies into those used to generate base- or peak-load electricity (Tables B.6-B.7 in Appendix B.1). We build on Voigt et al. (2009) and Lanzi et al. (2012) to identify base-load technologies, while we create a list of peak-load technologies by searching for specific patents on the EPO's Espacenet patent search website.

Next, we aggregate individual patent counts at the firm level. Using OECD's Harmonized Applicants Names (HAN) Database and REGPAT Database (OECD, 2009), we can match each patent applicant with a firm. Unfortunately, the HAN database does not contain firms' information for every patent application in our sample. Names that cannot be matched using the HAN database are synchronized using applicant information in the Triadic Patent Families Database. Although this allows us to match every patent to an applicant, it poses two difficulties. First, applicant names in the Triadic Patent Database contain a number of spelling, character, and name variations. For example, "General Electric" and "General Electric Inc" would be incorrectly treated as separate firms in the absence of name harmonization. Second, the Triadic Patent Families Database does not directly link patent applications to applicant names. Instead, applicant names are linked to family identifiers. Thus, if a given family contains more than one firm name, we are unable to determine which firm to associate with each patent. In order to minimize the complications that may result from these challenges, we harmonize the database in three steps. In the first step, we select all firms that contain full information from the HAN register. Second, we clean the firm-level information in the Triadic database. Third, we manually harmonize the Triadic and HAN databases. With these steps, we guarantee firm-level harmonization of the entire database. In addition, we account for multiple patent owners. Because some patents are owned by more than one firm, we allocate a patent to a firm weighted by the number of owners.

Following Aghion et al. (2016), we construct two variables that measure past innovation

in concordance with the United Nations Framework Convention on Climate Change (UNFCCC). For more information, see http://www.wipo.int/classifications/ipc/en/est/.

for each firm: internal and external knowledge. Internal knowledge measures past innovation by the cumulative count of all patents a firm has applied for in the past, while external knowledge measures the total number of patents other firms in the region have applied for. As listed in table B.2, we have patent data available for 73 countries and we use these to construct the regional external knowledge variables. We define five regions following the World Bank's income classification. These geographical regions are: Eastern Asia, Eastern Europe, Europe, Northern America, and Oceania. In our robustness analysis, we explore alternative definitions of spillover regions.

A distinguishing feature of innovation count data is that firms are widely heterogeneous in their success rate. While some firms make few innovations, others have a high innovation record. We create two variables to account for this permanent unobservable heterogeneity following Blundell et al. (1995). First, using patent data from 1963 to 1977, we construct a pre-sample research history variable that measures the average number of patents each firm applied for in a specific technology in the pre-sampling period. In addition, a dummy variable indicates whether a firm innovated in the pre-sample period. These variables are used to control for the size and propensity to patent of research firms.

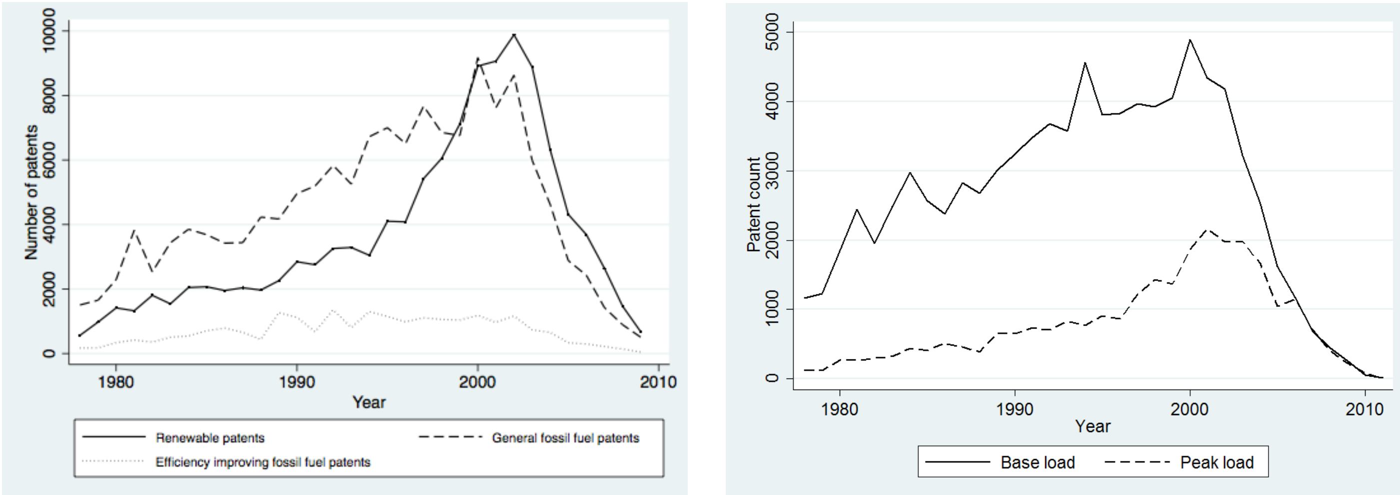
Another feature of our data set is that only some firms exist during the entire sample period. We account for this by including each firm in the data set from the first until the last year they applied for a patent. Thus, only active firms are accounted for in our panel data set.

In addition to patent data, we include data on electricity input and output prices and taxes. Our energy price and tax data are drawn from the IEA Energy Prices & Taxes database and are measured in 2005 U.S. dollars (International Energy Agency, 2015a). Specifically, we use electricity retail prices to measure output and we proxy input with the prices of thermal coal and natural gas used in the production of electricity, which are those paid by power generation companies to purchase fuels for electricity production for sale. A limitation of these data is that net prices are rarely available. To address this, we use gross (tax-inclusive) fossil fuel prices. Although this implies that we are unable to separate net prices and taxes, we are able to infer the effect of taxes in our estimates. Another issue we account for is that international companies are affected by the regulations and taxes of several countries. Because we know the locations of international firms, we address this by constructing firm-level energy prices after calculating the average energy price across all locations for each firm.

The second environmental policy we study is public research and development subsidies for the energy sector. Data are drawn from the IEA Energy Technology RD&D Statistics and span 34 years (1978-2011) and 26 countries (International Energy Agency, 2015c). This gives us the total amount of subsidies to promote the development of renewable and different fossil fuel based technologies. While our research subsidy data set contains a smaller number of countries than our patent data set, firms in the 26 countries for which research subsidy data are available account for 96.2% of global electricity triadic patents. We convert R&D data to 2005 U.S. dollars and separate them by technology type: renewable technologies, efficiency-improving fossil fuel technologies, and general fossil fuel technologies. As with energy prices, we construct a firm-level subsidy variable by calculating the average subsidies a firm is exposed to across all locations. We think of this variable as a proxy that captures a firm's exposure to research subsidies because we are unable to determine if a given research firm received any subsidies. We exclude data on other environmental policies designed to promote renewable energy, such as feed-in tariffs, due to data availability. However, we control for country-level policies using country-level fixed effects and country-by-year dummies in our identification strategy.

Finally, we use economic data to measure the size and wealth of countries from the Penn World Table (Feenstra et al., 2013). We use real GDP to measure the size of a country and real GDP per capita to measure wealth. Both GDP and GDP per capita are at constant 2005 U.S. dollars. As before, we construct a firm-level exposure variable by calculating the average across all locations.

In total, we identify 236,605 unique triadic patent applications across 13,054 firms from 1978 to 2011. Of this total, 120,059 are designated as renewable technologies, while 116,546 are classified as fossil fuel technologies. Our baseline estimates combine efficiency-improving and fossil fuel technologies into one category, but once we separate these two types of technologies, we have 99,454 and 17,092 general and efficiency-improving fossil fuel technologies, respectively. In addition, we divide fossil fuel technologies into 89,425 base-load and 27,121 peak-load technologies. Fossil fuel base load technologies include both coal and natural gas based technologies while fossil fuel peak load technologies include diesel and natural gas. Table B.8 presents the number of patents by specific technology. The table shows that solar patents account for the largest share of all renewable patents, followed by fuel cells and waste patents. On the other hand, base-load fossil fuel patents account for 76.7% of all fossil fuel patents over the period 1978 to 2011. Figures 1a and 1b illustrate the OECD's trends in patent activity from 1978 to 2011. The number of renewable and general fossil fuel patents increased considerably until the mid-2000s, while the number



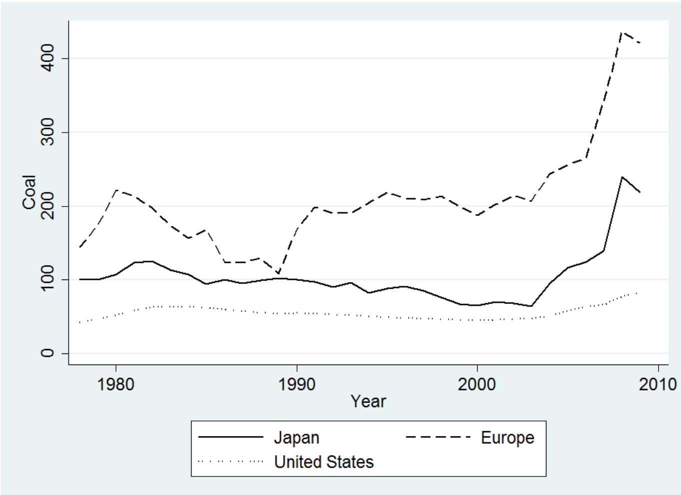
(a) Renewable, fossil fuel, and efficiency-improving patents.

(b) Base- and peak-load fossil fuel technologies.

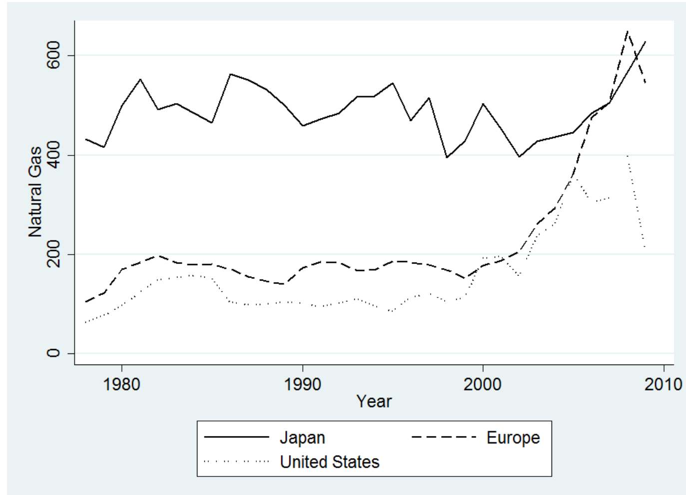
Figure 1: Annual aggregate patent count, 1978-2011.

of efficiency-improving fossil fuel patents enjoyed a modest increase. Our data also shows a downward trend in the number of patent applications between 2000 and 2009.[15] The reason for this downward trend is lag from the application date to the actual granting of the patent at the USPTO which lasts from 18 months to five years (Popp, 2005). We account for this by skipping the last 2 years of the data set to run our estimations.

[15]This trend is consistent with prior work. For example, Noailly and Smeets (2015) observe the same trend in European patents, even though they use non-triadic patent data, and Nesta et al. (2014) find a downward trend for German renewable patent families.



(a) Thermal coal for electricity generation (USD per tonne).



(b) Natural gas for electricity generation (USD per MWh).

Figure 2: The price of coal and natural gas in the most innovative regions, 1978-2009.

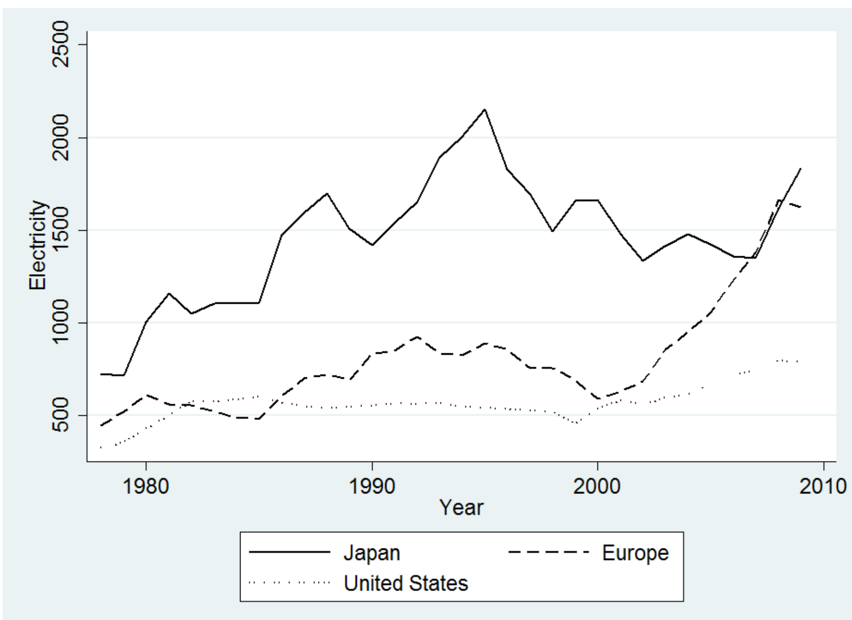


Figure 3: Electricity retail price (USD per MWh) in the most innovative regions, 1978-2009.

Figures 2 and 3 illustrate the evolution of coal, natural gas and electricity prices in the most innovative countries: U.S., Japan, and OECD-Europe.[16] Coal price is measured in USD per tonne while natural gas and electricity prices are measured in USD per MWh. All inputs used in the production of electricity followed a similar trend. Coal was the cheapest input and most heavily used for electricity production in many countries. The price of coal stayed low and stable in the U.S., while it rose considerably in Japan and Europe after 2000, peaking in 2008. Because coal is heavily used for base-load electricity production in the U.S., it is no surprise that the price of electricity also hit its lowest price in 2000 and its highest price in 2008. In Japan, however, the price of electricity followed the price of natural gas, which presents a higher variation than in other regions. Finally, the average European price showed a rapid rise after 2000. Figures 4, 5, 6 show a scatter plot of energy prices and the total number of patents in each type of technology for the U.S., Japan, and OECD-Europe. The figures show a negative correlation between coal prices and innovation in both renewable and fossil fuel technologies. On the other hand, natural gas prices show a weaker correlation with innovation in all types of technologies.

[16]Prices in Europe are represented by the average prices of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the U.K..

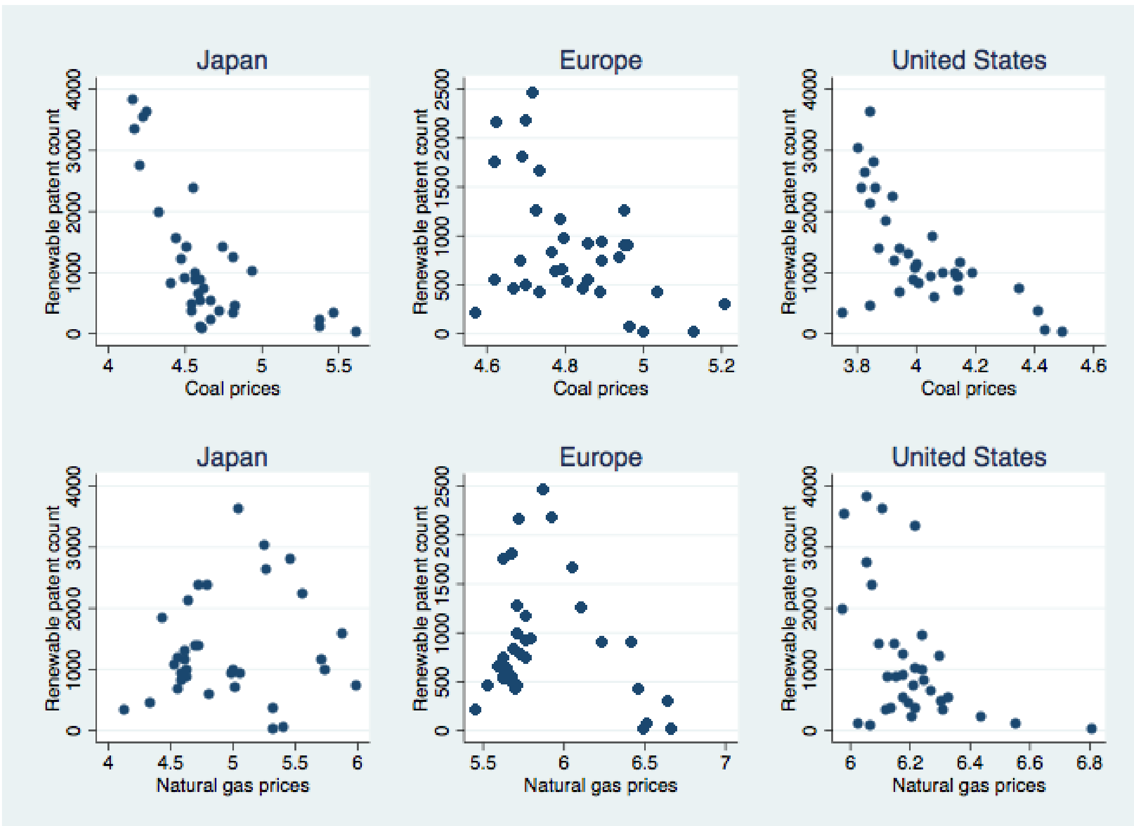


Figure 4: Renewable innovation and energy prices.

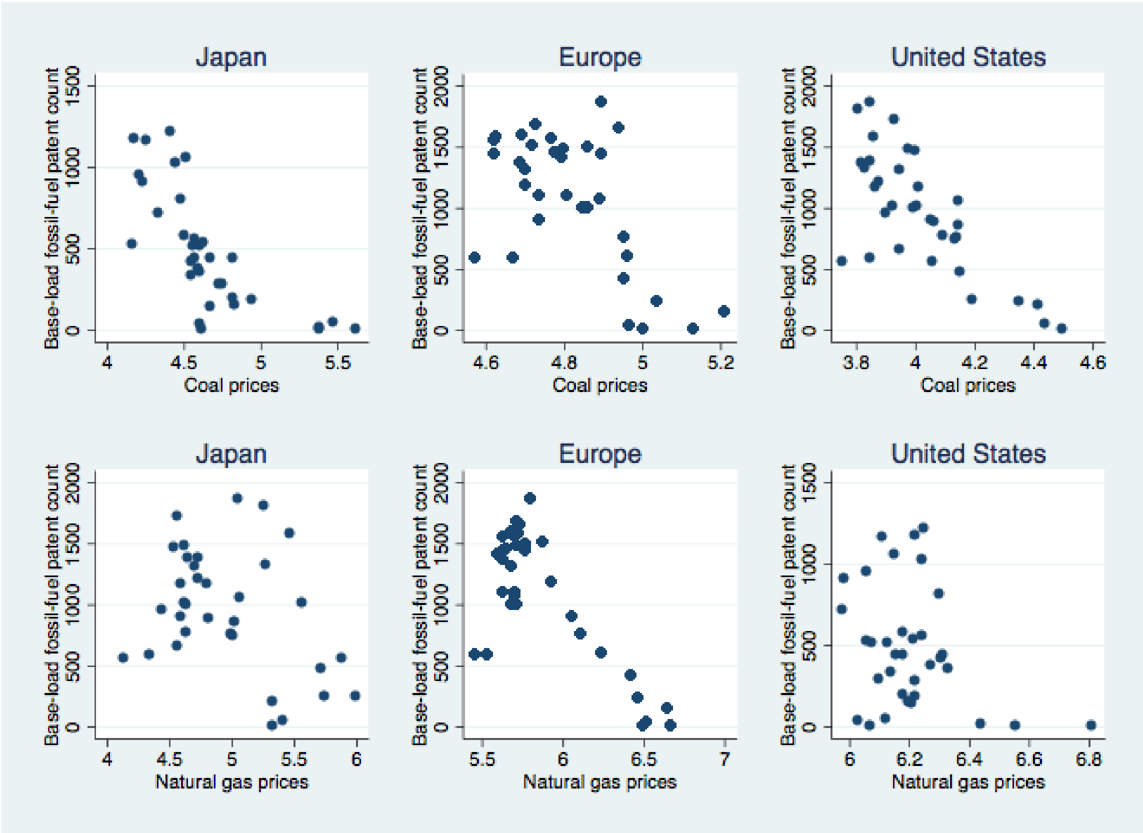


Figure 5: Base-load fossil fuel innovation and energy prices.

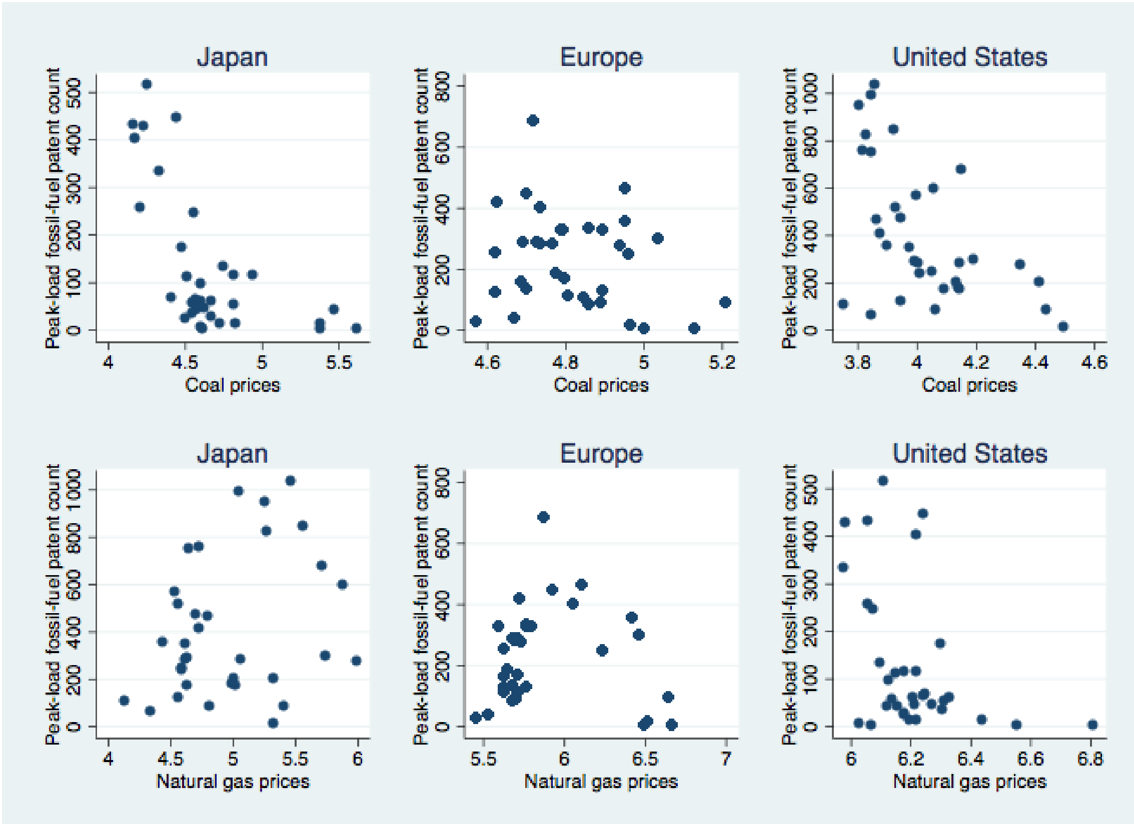


Figure 6: Peak-load fossil fuel innovation and energy prices.

Figure 7 illustrates global aggregate research subsidies. Most subsidies were directed towards general fossil fuel technologies until the early 1990s, when subsidies towards efficiency-improving fossil fuel technologies took off. Moreover, general fossil fuel subsidies decreased from 1980 to 2000, and after reaching their lowest point in 2000, they started increasing again. On the other hand, subsidies for renewable technologies peaked around the 1980s, and after a decade of relatively smaller subsidies, they started increasing again in the late 1990s.

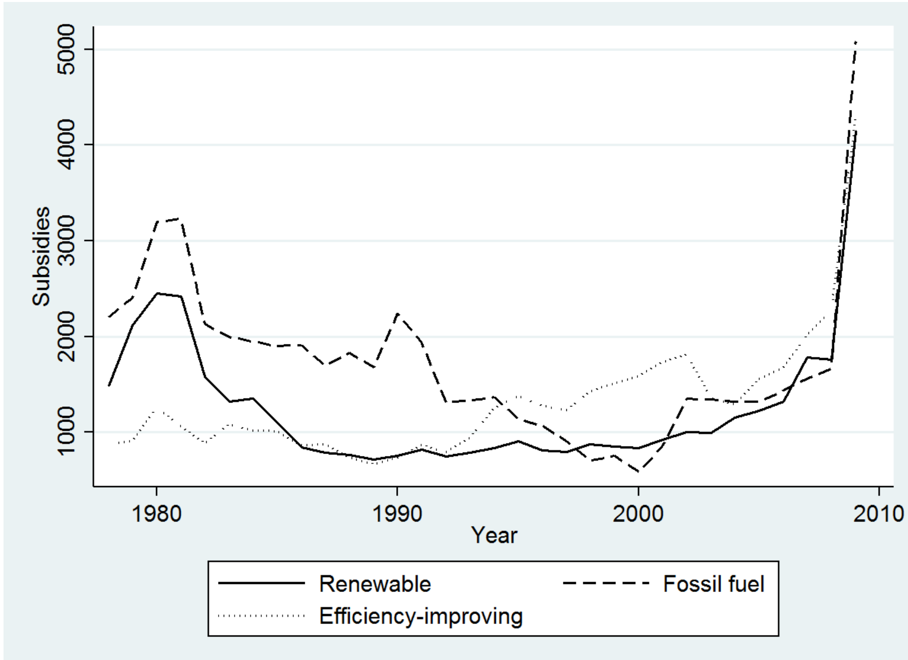


Figure 7: Global RD&D subsidies in million USD in renewable, general fossil fuel and efficiency-improving technologies, 1978-2009.

4 Identification strategy

This section describes the econometric approach we adopt to identify the firm-level determinants of innovation in the electricity sector. We estimate a dynamic innovation model with fixed effects. This model accounts for current patent applications $y_{j,it}$ that depend on past patent applications $y_{j,it-1}$ for firm i's innovation in technology j in year t and it captures the feedback effects that result from innovations in different technologies affecting each other (Cameron and Trivedi, 2013). In particular, our baseline specification with one lag is:

$$\mathbb{E}[y_{j,it}|\mathbf{X_{j,it}}, \mathbf{Y_{j,it-1}}, \alpha_{j,i}] = \alpha_{j,i}\lambda_{j,i}, \tag{1}$$

where $\mathbf{X_{j,it}} = (\mathbf{x_{j,it}}, \mathbf{x_{j,it-1}}, \ldots, \mathbf{x_{j,i1}})$ are observable variables, $\mathbf{Y_{j,it-1}} = (y_{j,it-1}, \ldots, y_{j,i1})$ is a vector of past innovations, $\alpha_{j,i}$ captures individual technology-specific fixed effects, and $\lambda_{j,i}$ is the specified function of $y_{j,it-k}$, $\mathbf{x_{j,it}}$, and $\boldsymbol{\beta}$. We consider a linear feedback model to explain how $y_{j,it-1}$ enters $\lambda_{j,i}$ following Blundell et al. (2002). Specifically:

$$\mathbb{E}[y_{j,it}|\mathbf{X_{j,it}}, \mathbf{Y_{j,it-k}}, \alpha_{j,i}] = \rho y_{j,it-1} + \exp(\mathbf{x}'_{\mathbf{j,it}}\boldsymbol{\beta})\alpha_{j,i}, \tag{2}$$

where the lagged of past innovations enters linearly. The observable variables $\mathbf{x_{j,it}}$ are the determinants of innovation discussed in section 2. Thus, we estimate:

$$\begin{aligned} y_{j,it} =& \mathbf{A_{it-1}} + \exp(\ln \mathbf{P_{it-1}}\beta_{\mathbf{j,p}} + \ln \mathbf{S_{j,it-1}}\beta_{\mathbf{j,s}} + \ln \mathbf{EI_{it-1}}\beta_{\mathbf{j,e}} \\ &+ \gamma_1 \ln X_{j,it} + \gamma_2 ID_{it} + D_{nt})\alpha_{j,i} + \mu_{j,it}, \end{aligned} \tag{3}$$

where j denotes the type of technology, while i, n and t represent firm, country and year. In the baseline specification, technology type j is renewable (r) or fossil fuel (f). In addition, we consider efficiency-improving (e), base-load (b) and peak-load (p) fossil fuel technologies. $y_{j,it}$ is the number of patents in technology j that firm i applied for in year t.

One of the main determinants of current innovation is past innovation. $\mathbf{A_{it}}$ indicates the firm's existing stock of knowledge, which depends both on the firm's internal cumulative stock of past renewable and fossil fuel innovation, as well as aggregate knowledge spillovers from other firms. More specifically, following Aghion et al. (2016), a firm's total knowledge stock is given by internal and external knowledge stocks following $\mathbf{A_{it}} = \mathbf{K_{j,it}}\beta_{\mathbf{j,k}} + \mathbf{SPILL_{j,it}}\beta_{\mathbf{j,spill}}$. The internal knowledge stock $\mathbf{K_{j,it}}$ is a vector of firm i's patent stock of the designated technology type j in year t. The external knowledge stock $\mathbf{SPILL_{j,it}}$ is a vector of knowledge spillover from other firms for technology type j, calculated as the aggregate patent stocks of all other firms located in the same region as firm i. The baseline specification considers a 1-year lag in past innovations, but we consider other lag structures in the robustness section 6.

Another main determinant of innovation is given by energy prices and taxes. $\mathbf{P_{it}}$ is a vector that denotes a firm's exposure to energy prices including taxes in year t. We take the prices of both inputs and outputs in the electricity sector into account. Specifically, we use coal and natural gas prices as a proxy for input prices in electricity generation and electricity prices to proxy for output prices. We use alternative measures in our robustness analysis. Recall that we characterize governments' support for innovation, $\mathbf{S_{it}}$, using R&D subsidies in the energy sector. We use R&D subsidies in renewable energy as a measure of government's support for innovation in renewable technologies, while we use subsidies in efficiency-improving and pure fossil fuel technologies as a measure of government's support for innovation in fossil fuel technologies. We control for other country-level environmental policies, such as feed-in tariffs, with country-level fixed effects.

Our empirical model also accounts for other macroeconomic factors that may impact innovation, such as the economic environment of countries in which the firm is located. Specifically, $\mathbf{EI_{it}}$ is a vector that captures the firm-specific exposure to the economic environment, which we characterize by its size (proxied by GDP) and wealth (proxied by GDP per capita). Note that we calculate $\mathbf{EI_{it}}$ for each firm by taking the average of all the economic indicators across the countries in which the firm is located. This allows us to account for the fact that a multinational firm is exposed to the macroeconomic and policy conditions of all countries in which the firm operates, not just its home country. We consider other controls in the robustness section.

A challenge to estimate a linear feedback model with fixed effects is to get consistent estimates. We account for this by controlling for firm-level unobserved heterogeneity using patenting in the pre-sampling period following (Blundell et al., 1995, 1999). Specifically, we use information on firms' pre-sample history of successful innovation. Taking advantage of our extended patent data set, we include the average pre-sample patent count ($X_{j,it}$) for each firm and technology type. In addition, we use a dummy variable (ID_{it}) that equals 1 if the firm innovated in the pre-sample period (1963-1977).

We control for time-varying, firm- and country-specific differences using fixed effects. Specifically, we use a set of dummy variables (D_{nt}), which include year, country and country–year dummies to control for time-varying country-specific differences. Because all country-level variables, such as energy prices and research subsidies have been converted into firm-level variables, country and time dummies can be used to control for other unobserved variations in electricity markets and relevant policies such as feed-in tariffs across countries over time. Finally, $\alpha_{j,i}$ denotes a firm-level fixed effect, which captures other time-invariant unobservable firm-specific characteristics, such as differences in firm size, industry focus, and others.[17]

Finally, $\mu_{j,it}$ denotes the error term by technology type. We cluster standard errors at the firm level for each technology since our data are structured at the firm level. Since some of our firms are international and we calculate their average energy prices, subsidies

[17]The large number of fixed effects often presents another challenge to obtain consistent estimates of dynamic innovation models because of a potential incidental parameter problem. As Blundell et al. (1999) and Lancaster (2002) show, a linear Poisson maximum likelihood model has no incidental problem in parameters and therefore the maximum likelihood estimation of our model obtains consistent estimates.

and macroeconomic indicators taking into account all their locations, there are additional correlations in the data. Following Thompson (2011), we deal with this by using fixed effects in one dimension and clustering in the other dimension given that our data are not nested. Thus, dummies control for country fixed effects and the standard errors are clustered at the firm level.

We estimate the linear dynamic count data model in equation (3) using a fixed-effect Poisson estimator while controlling for pre-sample history (Blundell et al., 1995, 1999). The equation for each technology is estimated separately. We analyze alternative estimators in the robustness analysis in Section 6.

This identification strategy shows that energy prices, research subsidies, and past innovation cause any differences in a firm's probability to apply for a patent in each technology type after controlling for pre-sample, macroeconomic, country and time-varying heterogeneity.

5 Estimation results

In this section, we present our main estimation results followed by multiple robustness tests to validate our results. Our main objectives are to identify whether increasing fossil fuels prices promotes innovation in renewable technologies and to quantify how research subsidies shape the direction of technological change in the electricity sector. To do this, we estimate the innovation equation given by equation (3) and we present our main results in Tables 2-5.

We use coal prices as a proxy for input prices in the electricity sector for our baseline estimation Table 2. To validate our results, we present multiple robustness checks in Section 6. Standard errors in all estimations are clustered at the firm level for each technology. Overall, our estimation results show that energy prices, R&D subsidies, and past innovation significantly influence innovation in the electricity sector. Therefore, policies targeting these factors can potentially direct innovation towards renewable energy. Let us first discuss how each of these factors determines the pattern of innovation in the electricity sector.

5.1 Are energy taxes successful at promoting innovation in renewable technologies?

The main estimation results in columns (1) and (2) of Table 2 suggest that energy prices and taxes have a significant impact on firm-level innovation. Specifically, a 10% increase in coal prices leads to a 3.8% decrease in the probability of applying for a renewable patent. This finding is in line with the theoretical directed technological change literature that shows a negative effect of fossil fuels on renewables when renewable and fossil fuel technologies are complements. However, our finding is in contrast to previous empirical work that concludes that fossil fuel prices promote innovation in renewable technologies. One explanation is that in the electricity sector, intermittent renewable sources are unable to supply electricity constantly and they rely on easily dispatchable technologies like coal-fired plants to meet the electricity demand. Cheap fossil fuels such as coal are typically used to generate base-load electricity that is easily dispatchable and available at all times. On the other hand, more expensive fossil fuels such as natural gas have been typically used in the generation of peak-load electricity that complements base-load electricity during peak hours (when the demand for electricity is high). While it may sound counterintuitive, it is thus reasonable to find that the number of renewable and base-load fossil fuel patents respond similarly to changes in coal prices. Columns (3)-(5) of Table 2 further explore this relationship by separating fossil fuel patents into base- and peak-load patents. We find that higher coal prices have a negative and statistically significant effect on innovations in renewable and base-load fossil fuel technologies, but no significant impact on peak-load fossil fuel innovations.

These results imply that making coal more expensive, for example, by increasing coal taxes or setting a carbon tax, is an ineffective tool to encourage innovation in renewable technologies. In absence of large-scale storage solutions, intermittent renewable sources such as wind and solar cannot fully replace coal in electricity generation; therefore, a tax on coal produces unintended negative effects on the development of renewable technologies.

Tables 3 and 4 further explore the relationship between coal and natural gas prices and innovation in renewable, base- and peak-load fossil fuel patents. Specifically, we analyze: (i) Coal and electricity prices, (ii) Coal prices only, (iii) Natural gas prices and electricity prices, and (iv) Coal and natural gas prices.[18] In the robustness analysis, we also consider

[18]We omit electricity prices in specifications (ii) and (iv) to address a potential endogeneity issue as electricity output prices are affected by the prices of inputs such as coal or natural gas. Tables 3 and 4

the square term of coal prices, oil prices and the gap between electricity and coal prices. Overall, we find evidence for a negative relationship between coal prices and innovation in renewable and base-load fossil fuel patents, thereby confirming the complementary relationship between renewable and base-load fossil fuel technologies in electricity generation. In contrast, increasing natural gas prices is only associated with a decrease in base-load fossil fuel innovation; it has no statistically significant impact on innovation in renewable energy. In addition, our estimates show that energy prices do not significantly affect the development of peak-load fossil fuel technologies (columns (5) in Table 2, columns (9)-(12) in Table 4). We explore additional specifications in the robustness section (6).

In addition to coal prices, firm-level innovation also depends on electricity prices; however, we only find a significant impact of electricity prices on fossil fuel innovation. Column (2) of Table 2 suggests that a 10% increase in electricity prices increases the probability of applying for a patent in fossil fuel by 4%. Moreover, the relationship between electricity prices and fossil fuel innovation is primarily driven by base-load innovations. As columns (4) and (5) of Table 2 show, increasing electricity prices has a positive and statistically significant impact on base-load innovations, where a 10% increase in electricity prices leads to a 3.7% increase in the number of base-load patents. On the other hand, the effect of electricity prices on peak-load innovations is much smaller and statistically nonsignificant. These effects are not surprising because coal, which is used in base-load electricity generation, contributes to 41.1% of global electricity generation (International Energy Agency, 2015b).

In addition to separating fossil fuel patents into base- and peak-load technologies, we also classify fossil fuel patents into general fossil fuel patents and efficiency-improving technologies.[19] Columns (3)-(5) of Table 5 report the estimation results for renewable, general fossil fuel, and efficiency-improving fossil fuel technologies. The coefficients on coal prices are negative and significant in all columns. Specifically, a 10% increase in coal prices decreases the number of patents in renewable, pure fossil fuel, and efficiency improving technologies by 3.5%, 3.3%, and 6.6% respectively.

To summarize, we find evidence that increasing coal prices discourages innovation not only in base-load electricity generation technologies, but also in renewable technologies. In

show that the impact of energy prices on innovation is robust to alternative specifications of energy prices.

[19]Tables B.4 and B.5 in Appendix B.1 detail the IPC codes for efficiency-improving and pure fossil fuel technologies. Ideally, we would like to further separate efficiency-improving and fossil fuel technologies into base- and peak-load technologies; however, the number of observations for each sub-group is too small to produce any significant result.

addition, we find evidence of a negative impact of coal prices on efficiency-improving fossil fuel technologies. Therefore, our results suggest that policymakers looking for solutions to reduce the use of coal in electricity generation should be careful when taxing coal as it may have unintended consequences for innovation in renewables as well as efficiency-improving fossil fuel technologies. Taxing natural gas, however, does not significantly affect innovation in renewable and peak-load technologies, but it does discourage innovation in base-load technologies.

5.2 How effective are research subsidies in shaping global innovation in the electricity sector?

In addition to energy prices and taxes, government research subsidies play an important role in determining innovation in the electricity sector. The results from Table 2 show that innovation in renewable energy technologies is significantly increased by an increase of those technologies' research subsidies. In particular, a 10% increase in renewable research subsidies increases the number of patents in renewable energy by 1.4% (columns (1) and (3)). Our results also suggest that research subsidies play a role in the development of fossil fuel technologies. While subsidies for general fossil fuel technologies promote innovation in base-load technologies, efficiency-improving subsidies increase the probability of successfully innovating in peak-load technologies. Specifically, increasing subsidies for general fossil fuel technologies by 10% increases the number of base-load fossil fuel patents by 1.4%, while a 10% increase in subsidies for efficiency-improving fossil fuel technologies increases the number of peak-load fossil fuel patents by 3.3%. The results are robust to alternative specifications of energy prices (Tables 3 and 4).

In Table 5, we classify fossil fuel technologies into general fossil fuel and efficiency-improving technologies. After we separate these technologies, we find that general fossil fuel technologies promote the development of efficiency-improving technologies. Specifically, a 10% increase in general fossil fuel technologies increases the number of efficiency improving patents by 1.2%. Note, however, that we do not find any evidence that research subsidies improve the success rate of general fossil fuel research (column (2) in Table 2). One explanation for this small impact of research subsidies on fossil fuel innovation is that market forces have created strong incentives to develop fossil fuel technologies because the market share of fossil fuels in electricity generation has long been and remains very large (International Energy Agency, 2015b). We turn to studying these market forces in the next subsection.

In summary, the analysis in Sections 5.1 and 5.2 proves that environmental policies such as energy prices, taxes, and research subsidies are effective at shifting the direction of innovation in the electricity sector. Not surprisingly, our results in Tables 2 through 5 show that research subsidies play a role in promoting the development of all types of technologies in electricity generation. Note, however, that as seen in Figure 7, the amount of subsidies directed at fossil fuels is larger than that directed towards renewables. This implies that allocating more research subsidies to renewable innovators and cutting back on research subsidies to fossil fuel innovators can potentially shift innovation in the electricity sector towards more renewable energy. However, our results also suggest that, at the current technology level, renewable and fossil fuel technologies are complements in electricity production; therefore, energy price taxes may not have the expected effect on changing the direction of electricity-related innovations towards cleaner technologies. Our results are consistent with Acemoglu et al. (2012)'s theoretical conclusions that the optimal policy to promote clean innovation involves both taxes and research subsidies, and that excessive reliance on tax policies may have some negative impacts on innovation.

5.3 What other factors shift innovation in the electricity sector toward renewable technologies?

In addition to environmental policies, a firm's innovation is determined by its past innovation and macroeconomic indicators. Past innovation is a combination of the firm's internal cumulative stock of past innovation and the aggregate knowledge spillovers from other firms within the same region. Columns (1) and (2) of Table 2 indicate that a firm is more likely to innovate in fossil fuel technologies if it has a larger knowledge stock in fossil fuels. In addition, accumulated knowledge about peak-load technologies and/or general fossil fuel technologies plays a significant role in fostering fossil fuel innovation in the current period, as shown in columns (3)-(5) of Tables 2 and 5. On the other hand, firms that invested in more renewable innovations in the past are less likely to be involved in inventing renewable technologies in the current period. One possible explanation is that unlike fossil fuels, storable forms of renewable energy are not readily available to generate electricity at all times; therefore, the use of renewable energy in electricity production is intermittent. Unfortunately, many of the storage technologies are in their early development stages, and thus the lack of cheap and large-scale storage solutions may hinder further innovation in renewable technologies.

Moreover, we find that a firm's probability of successfully innovating in renewable research is affected by spillovers from other firms' innovation activities within the same region.[20] Specifically, a firm located in a region with a larger stock of fossil fuel innovations by other firms is less likely to apply for a renewable patent (Table 2). In addition, Table 4 shows that a firm located in a region with an extensive knowledge stock of peak-load technologies is also less likely to innovate in renewable technologies. Finally, a firm located in a country with extensive renewable research is less likely to innovate in base-load fossil fuel technologies. Note that most coefficients on the spillover variables are not statistically significant in most cases, and even when they are, the coefficients are close to zero. One explanation for this phenomenon could be that regional innovation spillovers may have two opposite effects on firm-level decisions to conduct research. First, a firm is more willing to engage in research if it is located in a research-intense region because the firm can benefit from the existing knowledge created by other firms (i.e., standing on the shoulders of giants). At the same time, more intensive regional innovation activity also means tougher competition, which makes it more difficult to devise new patents. These two effects offset each other, leading to a small overall regional knowledge spillover effect on innovation.

In short, our estimation results suggest that a firm's past innovation is a strong determinant of future successful innovations. Specifically, firm-level innovation activity in renewables is negatively impacted by firms' internal knowledge stock, while fossil fuel innovation is positively affected by past innovation. On the other hand, it is not necessarily true that a firm is more likely to conduct research or to successfully create new innovations if it is exposed to a larger level of knowledge spillover from other firms within the same region. Our results are robust to alternative price measures, lag structures, pre-sample conditions, and to separating general fossil fuel technologies from efficiency-improving technologies.[21]

Finally, we consider other determinants of innovations such as country size (proxied by GDP) and wealth (proxied by GDP per capita). In our baseline estimates, we find that country size negatively affects innovation in all technology types, while wealth promotes innovation in base-load technologies in the electricity sector. When we classify fossil fuel technologies into general fossil fuel patents and efficiency-improving technologies (Table

[20] In our baseline results, we calculate regional knowledge spillovers using the World Bank income classification of countries. We define regional spillover variables instead of country-level spillover variables because we are interested in employing country-level fixed effects in our estimations.

[21] We find similar results when we exclude energy prices from our estimation.

5), our results show that a 1% increase in GDP decreases a firm's incentive to conduct efficiency-improving research by 1.449%.

Table 2: Baseline: Fixed-effect Poisson estimates of the determinants of firm-level innovation in renewable and fossil fuel technologies using global data from 1978 to 2009.

	Dependent variable: firm-level number of patents				
	Renewable	Fossil fuel	Renewable	Fossil fuel base load	Fossil fuel peak load
	(1)	(2)	(3)	(4)	(5)
Energy prices including taxes					
L1.Coal price	-.3864**	-.2919	-.4139**	-.4051**	-.5788
	(.1801)	(.2197)	(.1666)	(.1695)	(.3614)
L1.Electricity price	.1745	.2533	.2475	.3674	-.02734
	(.222)	(.2845)	(.1925)	(.2372)	(.37)
Research subsidies					
L1.Renewable	.1589**	.04735	.1275*	-.02836	.1749
	(.07334)	(.1122)	(.07382)	(.08402)	(.2144)
L1.Fossil fuel	.00146	.0569	.02102	.06796	.06561
	(.03799)	(.05768)	(.04018)	(.0585)	(.08176)
L1.Efficiency-improving	.01012	.06886	.0401	-.00051	.3624***
	(.04104)	(.0728)	(.04048)	(.05797)	(.1072)
Past innovation knowledge					
L1.Renewable	-.00055***	-.00046	-.00045***	5.3e-05	-.00077
	(.00013)	(.00043)	(.00016)	(.00052)	(.00062)
L1.Fossil fuel	4.9e-05	.00025***			
	(.00017)	(4.9e-05)			
L1.Baseload			-.001***	-.00076***	.00036
			(.00027)	(.00023)	(.00049)
L1.Peakload			.00098***	.00082***	.00017
			(.0002)	(.00017)	(.00031)
Past innovation spillovers					
L1.Renewable	-2.3e-05	-3.0e-05	-5.8e-06	-1.4e-05	-5.2e-05
	(2.0e-05)	(2.7e-05)	(1.8e-05)	(2.1e-05)	(5.1e-05)
L1.Fossil fuel	-3.7e-05***	-5.7e-06			
	(1.4e-05)	(1.6e-05)			
L1.Baseload			2.2e-05	2.3e-05	5.5e-05
			(1.9e-05)	(2.3e-05)	(3.5e-05)
L1.Peakload			-.00013***	-9.9e-05*	-2.7e-05
			(4.8e-05)	(5.5e-05)	(9.4e-05)
Macroeconomic indicators					
L1.GDP	-.1463	-.1171	-.1941**	-.1632*	-.4785**
	(.08928)	(.1004)	(.09409)	(.09283)	(.1935)
L1.GDP per capita	-.362	.591	.2939	1.267**	.6879
	(.815)	(.8263)	(.8069)	(.644)	(1.629)
Pre-sample history	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39293	27233	39317	25194	9782

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table 3: Fixed-effect Poisson estimates of fossil fuel price effect in renewable and fossil fuel technologies.

	Dependent variable: firm-level number of patents							
	Renewable				Fossil fuel			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Energy prices including taxes								
L1.Coal price	-.3864**	-.3381*		-.3385*	-.2919	-.2275		-.2416
	(.1801)	(.2105)		(.201)	(.2197)	(.183)		(.1902)
L1.Natural gas price			-.1464	.00125			-.03939	.04175
			(.1206)	(.1275)			(.1146)	(.1248)
L1.Electricity price	.1745		.1184		.2533		.1633	
	(.222)		(.2632)		(.2845)		(.2433)	
Research subsidies								
L1.Renewable	.1589**	.1505**	.1175	.1507**	.04735	.04613	.03395	.05016
	(.07334)	(.07605)	(.07551)	(.07337)	(.1122)	(.1125)	(.1117)	(.1121)
L1.Fossil fuel	.00146	-.01132	-.02565	-.01126	.0569	.04474	.04178	.04705
	(.03799)	(.03848)	(.04143)	(.03969)	(.05768)	(.05448)	(.06002)	(.0564)
L1.Efficiency-improving	.01012	.02349	.03183	.02339	.06887	.08057	.08037	.07852
	(.04104)	(.04398)	(.0407)	(.04351)	(.0728)	(.07036)	(.06754)	(.06932)
Past innovation knowledge								
L1.Renewable	-.00055***	-.00056***	-.00055***	-.00056***	-.00046	-.00049	-.00042	-.00049
	(.00013)	(.00013)	(.00013)	(.00013)	(.00043)	(.00042)	(.00045)	(.00042)
L1.Fossil fuel	4.9e-05	5.0e-05	6.3e-05	5.0e-05	.00025***	.00025***	.00025***	.00025***
	(.00017)	(.00017)	(.00017)	(.00017)	(4.9e-05)	(4.7e-05)	(4.8e-05)	(4.7e-05)
Past innovation spillovers								
L1.Renewable	-2.3e-05	-2.7e-05	-3.1e-05	-2.7e-05	-3.0e-05	-3.4e-05	-3.3e-05	-3.3e-05
	(2.0e-05)	(1.8e-05)	(2.1e-05)	(1.9e-05)	(2.7e-05)	(2.6e-05)	(2.6e-05)	(2.6e-05)
L1.Fossil fuel	-3.7e-05***	-3.6e-05***	-3.1e-05**	-3.6e-05**	-5.7e-06	-4.6e-06	-4.6e-06	-6.1e-06
	(1.4e-05)	(1.3e-05)	(1.3e-05)	(1.4e-05)	(1.6e-05)	(1.5e-05)	(1.5e-05)	(1.6e-05)
Macroeconomic indicators								
L1.GDP	-.1463	-.1571*	-.09257	-.157*	-.1171	-.1473	-.07268	-.1499
	(.08928)	(.0882)	(.09196)	(.08751)	(.1004)	(.1003)	(.1013)	(.1015)
L1.GDP per capita	-.362	-.1069	.1375	-.1098	.5909	.8459	.7526	.8235
	(.815)	(.9062)	(.7839)	(.7866)	(.8263)	(.8207)	(.828)	(.8104)
Pre-sample patents	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample activity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39293	39293	39293	39293	27233	27233	27233	27233

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table 4: Fixed-effect Poisson estimates of fossil fuel price effect in renewable, base- and peak-load technologies.

	Dependent variable: firm-level number of patents											
	Renewable				Base load				Peak load			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Energy prices including taxes												
L1.Coal price	-.4144**	-.3437*		-.3522*	-.4051**	-.2934**		-.2999**	-.5788	-.5825		-.5652
	(.1666)	(.1838)		(.1862)	(.1695)	(.1492)		(.1466)	(.3614)	(.3366)		(.3329)
L1.Natural gas price			-.1594	.0267			-.1061	.02338			-.1955	-.06678
			(.1274)	(.124)			(.1158)	(.135)			(.2452)	(.2031)
L1.Electricity price	.2498		.1497		.3674		.2335		-.02734		-.05545	
	(.1925)		(.2376)		(.2372)		(.2114)		(.37)		(.3948)	
Research subsidies												
L1.Renewable	.1273*	.1285*	.1017	.1302*	-.02835	-.02006	-.03171	-.02055	.1749	.1747	.1394	.1732
	(.0738)	(.07463)	(.07427)	(.07368)	(.08402)	(.0842)	(.08214)	(.08432)	(.2144)	(.2137)	(.2059)	(.2126)
L1.Fossil fuel	.02175	-.00256	-.01638	-.00101	.06796	.04559	.04525	.04696	.06561	.06759	.02104	.06334
	(.04014)	(.04278)	(.04187)	(.04555)	(.0585)	(.05426)	(.05941)	(.05406)	(.08176)	(.08105)	(.08605)	(.08102)
L1.Efficiency-improving	.03971	.05236	.05897	.05143	-.00051	.01431	.01779	.0136	.3624***	.3622***	.3746***	.3634***
	(.04047)	(.0409)	(.04037)	(.04201)	(.05797)	(.05757)	(.05633)	(.05767)	(.1072)	(.1071)	(.1036)	(.1057)
Past innovation knowledge												
L1.Renewable	-.00045***	-.00046***	-.00045***	-.00046***	5.3e-05	2.4e-05	8.6e-05	2.2e-05	-.00077	-.00076	-.00063	-.00077
	(.00016)	(.00016)	(.00016)	(.00016)	(.00052)	(.00051)	(.00054)	(.00051)	(.00062)	(.00062)	(.00061)	(.00062)
L1.Baseload	-.001***	-.00102***	-.00097***	-.00102***	-.00076***	-.00078***	-.00074***	-.00078***	.00036	.00036	.00037	.00036
	(.00027)	(.00027)	(.00027)	(.00027)	(.00023)	(.00023)	(.00024)	(.00023)	(.00049)	(.00049)	(.00047)	(.00049)
L1.Peakload	.00098***	.00102***	.00101***	.00101***	.00082***	.00086***	.00084***	.00085***	.00017	.00016	.00019	.00018
	(.0002)	(.0002)	(.00021)	(.0002)	(.00017)	(.00018)	(.00019)	(.00018)	(.00031)	(.0003)	(.00029)	(.00029)
Past innovation spillovers												
L1.Renewable	-5.7e-06	-1.7e-05	-2.4e-05	-1.5e-05	-1.4e-05	-2.2e-05	-2.5e-05	-2.1e-05	-5.2e-05	-5.1e-05	-6.3e-05	-5.5e-05
	(1.8e-05)	(1.8e-05)	(1.9e-05)	(1.8e-05)	(2.1e-05)	(2.1e-05)	(2.0e-05)	(2.0e-05)	(5.1e-05)	(4.8e-05)	(4.6e-05)	(4.5e-05)
L1.Baseload	2.2e-05	1.4e-05	1.5e-05	1.4e-05	2.3e-05	1.8e-05	1.9e-05	1.9e-05	5.5e-05	5.6e-05	4.8e-05	5.3e-05
	(1.9e-05)	(2.2e-05)	(1.8e-05)	(2.2e-05)	(2.3e-05)	(2.3e-05)	(2.3e-05)	(2.3e-05)	(3.5e-05)	(3.9e-05)	(3.9e-05)	(3.9e-05)
L1.Peakload	-.00013***	-.0001**	-8.6e-05*	-.00011**	-9.9e-05*	-8.6e-05	-7.6e-05	-9.1e-05	-2.7e-05	-2.9e-05	2.2e-05	-1.4e-05
	(4.8e-05)	(5.1e-05)	(4.7e-05)	(5.3e-05)	(5.5e-05)	(5.4e-05)	(6.1e-05)	(6.1e-05)	(9.4e-05)	(9.7e-05)	(.00011)	(9.4e-05)
Macroeconomic indicators												
L1.GDP	-.1944**	-.2132**	-.1444	-.2111**	-.1632*	-.2097**	-.1189	-.209**	-.4785**	-.4749**	-.3556*	-.477**
	(.09409)	(.09119)	(.09491)	(.09064)	(.09283)	(.09458)	(.09471)	(.09462)	(.1935)	(.1869)	(.189)	(.1865)
L1.GDP per capita	.287	.4706	.6094	.4498	1.267**	1.511**	1.409**	1.52**	.6879	.6785	.78	.6797
	(.8069)	(.8171)	(.8016)	(.7814)	(.644)	(.6394)	(.6565)	(.6585)	(1.629)	(1.65)	(1.575)	(1.64)
Pre-sample history	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39317	39317	39317	39317	25194	25194	25194	25194	9782	9782	9782	9782

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table 5: Fixed-effect Poisson estimates of innovation in general and efficiency-improving nonrenewable technologies using global data from 1978 to 2009.

	Dependent variable: firm-level number of patents				
	Renewable	Fossil fuel	Renewable	Fossil fuel general	Fossil fuel Eff.- improv.
	(1)	(2)	(3)	(4)	(5)
Energy prices including taxes					
L1.Coal price	-.3864**	-.2919	-.2829*	-.2756	-.4781**
	(.1801)	(.2197)	(.1734)	(.2306)	(.2044)
L1.Electricity price	.1745	.2533	.104	.2184	-.1111
	(.222)	(.2845)	(.2284)	(.2966)	(.3321)
Research subsidies					
L1.Renewable	.1589**	.04735	.1633**	.06486	-.05534
	(.07334)	(.1122)	(.07353)	(.1074)	(.1177)
L1.Fossil fuel	.00146	.0569	-.01499	.07245	.1021
	(.03799)	(.05768)	(.03968)	(.05756)	(.07579)
L1.Efficiency-improving	.01012	.06886	.0225	.07435	.1242
	(.04104)	(.0728)	(.0416)	(.07893)	(.1022)
Past innovation knowledge					
L1.Renewable	-.00055***	-.00046	-.00055***	-.00054	-.00016
	(.00013)	(.00043)	(.00014)	(.00045)	(.00043)
L1.Fossil fuel	4.9e-05	.00025***			
	(.00017)	(4.9e-05)			
L1.Pure fossil fuel			.00013	.00033***	.00033***
			(.00034)	(6.5e-05)	(8.9e-05)
L1.Efficiency-improving			-.00072	-.00064	-.00188***
			(.00266)	(.00044)	(.00053)
Past innovation spillovers					
L1.Renewable	-2.3e-05	-3.0e-05	-2.9e-05	-3.8e-05	-2.6e-05
	(2.0e-05)	(2.7e-05)	(2.3e-05)	(2.7e-05)	(3.0e-05)
L1.Fossil fuel	-3.7e-05***	-5.7e-06			
	(1.4e-05)	(1.6e-05)			
L1.Pure fossil fuel			-5.0e-05**	-5.8e-06	-2.7e-05
			(2.0e-05)	(2.1e-05)	(2.9e-05)
L1.Efficiency-improving			7.9e-05	4.6e-05	9.3e-05
			(5.9e-05)	(8.9e-05)	(.00013)
Macroeconomic indicators					
L1.GDP	-.1463	-.1171	-.1616	-.07996	-.1449*
	(.08928)	(.1004)	(.1012)	(.09475)	(.08561)
L1.GDP per capita	-.362	.5909	-.1454	.6122	.6944
	(.815)	(.8263)	(.8161)	(.7438)	(.5516)
Pre-sample history	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39293	27233	39292	26221	10768

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

6 Robustness analysis

To complete our empirical analysis, we discuss potential caveats associated with our analysis. Specifically, we investigate common estimation issues of dynamic count data models, alternative energy tax specifications, the selection of the most innovative countries and firms, alternative definitions of spillovers, adequate lag structures and other macroeconomic controls.

We start by considering the choice of estimator. One distinguishing feature of patent data is that in each period, the number of patents that a firm applies for depends on two factors. First, it depends on whether they decide to engage in research on a given technology. Second, it depends on whether the firm's R&D activity is successful (i.e., results in a patent application). In other words, a firm can have a zero patent count in a given period either because its R&D activity was not successful or simply because it chose not to enter the research market. This explains why we typically observe a large number of zeros in patent data. To account for this over-dispersion in the data, we employ a zero-inflated Poisson estimator, where we first use a logit model to determine whether a firm engaged in research in a given period, i.e., the extensive margin. Then we use a Poisson estimator to determine whether the firm is successful at innovating, conditional on a positive R&D decision, i.e., the intensive margin.

Table C.1 presents zero-inflated Poisson estimation results for the baseline specification in equation (3). We lag the explanatory variables by one period to account for the delayed responses of firms and to reduce contemporaneous feedback effects. Columns (1) and (2) present Poisson estimates of firm-level patent counts; i.e. the intensive margin which explains whether a firm's research activity successfully leads to the application of a new patent. On the other hand, columns (3) and (4) present our logit estimates of the extensive margin which explains a firm-level likelihood to engage in research in a given period.[22] These results confirm our main findings.

Another issue to consider when working with count panel data is the degree of over-dispersion, a situation where the variance exceeds the mean. The negative binomial distribution is more appropriate than a fixed-effects Poisson specification when data exhibits a high degree of over-dispersion. Our data do not represent a high over-dispersion problem as we control for entry and exit of firms in the market; therefore, our baseline estimates use

[22]Because the logit estimates explain the probability of observing excess zero patent counts, a negative impact on the likelihood of excess zero patents is interpreted as a positive probability of engaging in research.

a Poisson fixed effects estimator. However, one might argue that firms in our unbalanced panel appear to be more productive than in reality because we only include them in the sample after they apply for their first patent. To address this, we consider fully balanced panel data where all firms are active from 1978 to 2009. The fully balanced panel data exhibits an over-dispersion problem because the variance is 88 times larger than the mean; therefore, we use a negative binomial specification. Poisson estimates are used as a starting point for the negative binomial estimation. Table C.2 shows that our main results are robust to a negative binomial specification.

Another potential issue to consider with a Poisson regression specification is unobserved heterogeneity. Our baseline estimates include technology-specific average patenting activity prior to our sampling period of 1978-2009 (Blundell et al., 1995). These controls are not statistically significant for any technology type, which suggests that pre-sampling patenting activity is not a strong determinant of the likelihood of innovation during the sampling period.[23] However, controlling for pre-sampling activity allows us to take the wide heterogeneity in firms' innovation success rate into consideration. In addition, we estimate our baseline specification with alternative definitions of patenting activity in the sampling period. In particular, we consider the average number of total patents prior to 1978 and the technology-specific average patenting activity only in the years a firm was active in the pre-sampling period. Because our main results and the estimated values are unchanged, we do not report a table with these estimates; however, they are available upon request.

In addition to considering alternative estimators, we also choose alternative variables to represent the effect of fossil fuels, past innovations, and macroeconomic indicators. Regarding the effect of fossil fuel prices in innovation, Table C.3 presents additional fossil fuel prices. In particular, we consider the square term of coal prices and the gaps between electricity, coal, and oil prices. These estimates suggest that a higher gap between electricity and coal prices promotes innovation in renewable technologies, which implies a complementary relationship between renewable energy innovation and base-load fossil fuel innovation. We do not find evidence for a statistically significant effect of oil prices on innovation. We do not find this surprising because at the global level, the use of oil in electricity generation is modest (see Table 1).

In addition to energy prices, we analyze past innovation in more detail. One might

[23]In Table C.13, we exclude pre-sample activity from our sample and find results consistent with our main estimation results.

argue that it takes several years before past innovation affects current innovation levels. To address this, we include past firm-level and spillover innovations lagged by 2 and 3 years in Tables C.4 and C.5. Our main conclusions about the impact of past innovation are still valid with these alternative lag structures.

Another issue related to past innovations relates to the definition of spillovers. Our baseline estimates, which include 11 regions, show that spillovers are not strong determinants of innovation. One reason for this low significance is that we are using triadic patents, which by construction, have a global nature. We do, however, consider alternative definitions of regions. In particular, we consider one global innovation spillover as well as five geographical regions: Africa, Asia and the Pacific, Europe, Latin America and the Caribbean, and North America. Overall, Table C.6 shows that these coefficients are similar to our earlier estimates in Table 2; therefore, our main results are robust to different definitions of regional spillovers.

Finally, we consider alternative macroeconomic characteristics in addition to controlling for the size of the economy and its wealth. Following Carlino et al. (2007), who present evidence for a positive effect of employment density on the innovation rate, we also control for population density. Table C.7 shows that population density is not statistically significant and that our main results are robust. One might also argue that energy consumption could be a determinant of innovation. Because the correlation between GDP and energy consumption is 85%, we exclude country-level energy consumption from our estimates. We include a country fixed effect in all our specifications to control for other macroeconomic indicators.

In addition to considering different specifications of our main equation, we categorize our data into sub-groups to identify whether groups of firms behave differently systematically. First, we analyze the choice of countries. While our data set contains 26 countries, the majority of patent applications are concentrated in a small number of countries. In Table C.8, we conduct a firm-level fixed-effect Poisson estimation using data from France, Germany, Japan, U.K. and U.S., which are the five countries with the largest number of patents in the sample. Compared to our full sample estimates, we find a stronger negative impact of coal prices on renewable innovation in these five countries, which reassures our prediction about the complementarity between renewable energy and base-load fossil fuel in electricity generation.

Our second group categorization involves firms. Our data contain a diverse set of 13,054 firms. We separate these firms into large and small research firms in Table C.9. We consider a firm large if they applied for more than 15 patents in total during the sampling period. These firms represent the top 15% of innovators in our sample. We consider alternative definitions of large firms, including 20 (top 11,7%) and 10 (top 21,7%) patents per firm, but these results are consistent with those in Table C.9, and we exclude them from the Appendix. Finally, we categorize firms as specialized or mixed firms in Table C.10. We consider a firm specialized if they only apply for patents in either renewable, base-, or peak-load technologies while mixed firms are those that applied for a patent in more than one technology. Specialized firms represent 53% of our sample. Table C.10 shows that firms that specialized in renewable technologies are more likely to be negatively affected by an increase in the price of coal than other types of firms. Moreover, compared with mixed firms, specialized firms also respond more strongly to changes in research subsidies and past innovation.

A final issue we address is the definition of renewable technologies. While most patent applications in renewable technologies involve solar and wind technologies (see Table B.8), a small number of patents include technologies that can be used for base-load electricity generation. To address this, we exclude patent applications from hydro, geothermal, and biomass technologies from renewable technologies in Table C.11. These results show that our main results are robust. In addition, we found that increasing coal prices produces a more negative impact on the innovation of these peak-load renewable energies, which is in line with the complementary relationship between base- and peak-load electricity. Finally, in Table C.12, we categorize all patent applications into technologies used for base- and peak-load electricity generation, instead of renewable and fossil fuel technologies. We found that increasing the coal price negatively affects innovation in both base- and peak-load technologies. As explained earlier, this is due to the fact that base- and peak-load power plants complement each other in electricity generation.

Overall, these alternative specifications show that our main results presented in Section 5 are robust to different assumptions and econometric specifications. This suggests idiosyncrasies in the responses of innovation to changes in energy prices in the electricity sector. Specifically, because renewable energies like the sun or wind complement base-load fossil fuels such as coal in electricity generation, discouraging fossil fuel innovation through coal or carbon taxes may produce unintended negative consequences on renewable innovation. On the other hand, taxing peak-load fossil fuels such as natural gas may steer the direction of innovation in the electricity sector towards more renewable energy by lowering fossil fuel innovation. Finally, our results also suggest that to effectively promote innovation in renewable energy, a combination of tax and research subsidy policies is desirable.

7 Policy recommendations and concluding remarks

As scientists and policymakers seek options to reconcile concerns about climate change with economic growth targets, increasing the use of renewable technologies seems crucial, particularly for carbon-intensive sectors such as electricity generation. The idiosyncrasies in the substitution relationship between renewable technologies and various types of fossil fuel technologies imply that an all-inclusive tax policy that raises the price of all fossil fuels may have unintended consequences in the development of renewable technologies. In the present paper, we explore this issue by analyzing the specific roles of various fossil fuel taxes on renewable innovation in the global electricity market.

Our study supports the idea that policymakers interested in using energy price signals to induce renewable innovation in the electricity sector must carefully structure energy regulations and taxes. In contrast to previous work, we are able to infer about the relationship between energy prices and innovation in base- and peak-load fossil fuel technologies. While many expect energy taxes to reduce the innovation gap by promoting the invention of renewable technologies, we find that coal prices have a negative impact on the invention of renewable technologies. This implies that until we are able to replace the use of coal from base-load electricity generation, renewable energy sources and coal are complements in electricity generation. Thus, taxing coal and a carbon tax that raises coal prices have negative effects not only on the development of base-load technologies, but also on the development of renewable technologies.

We also find evidence in support of research subsidies to reduce the innovation gap between fossil fuels and renewables. In fact, policymakers can foster new inventions in renewable technologies by increasing renewable research subsidies and/or reducing subsidies for general fossil fuel technologies.

Finally, a third mechanism to change the direction of innovation relates to historical research activity. Successful past research in fossil fuel technologies encourages more fossil fuel innovation in the future. Unfortunately, we do not observe such a relationship when we consider renewable energy innovation, potentially due to the absence of storable forms of renewable energy given the current state of technology. Finally, we find that economic growth policy can successfully enhance renewable innovation in the electricity sector through discouraging the development of fossil fuel technologies.

In short, our results suggest that regulations that raise the prices of all fossil fuels may be ineffective at fostering the invention of new renewable technologies in the electricity sector because of the imperfect substitution relationship between renewable energy and fossil fuels in electricity production. Researchers and policymakers interested in fostering renewable innovation in the electricity sector should consider this heterogeneity in their analysis.

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Appendix

A A directed technological change model of the electricity sector

In this section, we present a directed technological change model of the electricity sector where we distinguish between innovation in renewable and nonrenewable technologies. Our goal is to derive the equilibrium condition that explains firm-level innovation that guides our empirical analysis in section 4. Aghion et al. (2016) used the directed technological change framework by Acemoglu et al. (2012) to study innovation in the automobile industry. We follow a similar approach but focus instead on the electricity sector.

There are two types of agents in this economy: consumers and electricity producers. Consumers derive their utility from the consumption of goods and electricity:

$$U = c_0 + \frac{\beta}{\beta - 1}\left(\int_0^1 Y_i^{\frac{\sigma-1}{\sigma}}\, di\right)^{\frac{\sigma}{\sigma-1}\frac{\beta-1}{\beta}}, \tag{A.1}$$

where U denotes utility, c_0 is consumption good and Y_i is electricity purchased from retailer i. β is the elasticity of substitution between electricity and the consumption good while σ is the elasticity of substitution between electricity from different electricity retailers. Consumers allocate their budget between the consumption goods and electricity such that their utility is maximized. This maximization process yields the consumers' electricity demand function:

$$Y_i = P^{\sigma-\beta} P_i^{-\sigma}, \tag{A.2}$$

where Y_i is consumer electricity demand from retailer i, P_i is the price of electricity charged by retailer i, while P is the market price of electricity. In this model, we consider tax-inclusive electricity prices.

Two types of firms participate in the electricity sector: the generators and the retailers. Electricity generators produce electricity using either renewable or non-renewable resources while electricity retailers buy electricity from the generators and deliver it to the consumers. Let us start with electricity generators.

There are two types of electricity generators: renewable and nonrenewable. Renewable electricity generators produce electricity using renewable resources (r) while nonrenewable electricity generators use fossil fuels (f). At the beginning of each period, they engage in research to develop new electricity-generating technologies. Research efforts can improve firms' existing technology by $A_{i,j} = (1 + x_{i,j})A^0_{i,j}$, where $A_{i,j}$ measures generator i's advancement in technology j and $A^0_{i,j}$ is the firm's initial knowledge in technology j for $j = r, f$. At the end of the period, newly developed technologies are used to generate electricity, which is then sold to electricity retailers. All electricity generators engage in research, thus there exists a continuum of renewable and nonrenewable electricity generators with local market power, which allows them to seek monopoly rents from electricity retailers.[24]

Electricity retailers buy electricity from renewable and nonrenewable generators, which are substitutes. There are multiple electricity retailers and they take the consumer demand for electricity in equation (A.2) as given. Retailers maximize profits by choosing the amount of renewable and nonrenewable electricity to buy. The profit function for electricity retailers is given as:

$$\pi_i^R = \max_{y_{i,r},y_{i,f}} \{P_i Y_i - p_{i,r} y_{i,r} - p_{i,f} y_{i,f}\}, \tag{A.3}$$

where π_i^R are the profits of retailer i, P_i is the price of electricity that retailer i charges its consumers, $y_{i,j}$ $(j = r, f)$ is electricity purchased from renewable and nonrenewable sources, and $p_{i,j}$ $(j = r, f)$ are their corresponding prices. Electricity for final consumption, Y_i, combines electricity from renewable and nonrenewable sources:

$$Y_i \equiv \left(y_{i,r}^{\frac{\epsilon-1}{\epsilon}} + y_{i,f}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{A.4}$$

where ϵ is the ease of substitution between renewables and nonrenewables.[25] Retailers maximize profits in (A.3) and determine their demands for renewable and nonrenewable electricity: $y_{i,j} = Y_i \left(\frac{P_i}{p_{i,j}}\right)^{\epsilon}$ for $j = r, f$. Since electricity generators earn monopoly profits from their research by exerting their market power over the prices of electricity sold to retailers (i.e. $p_{i,j}$ for $j = r, f$), using (A.2), we rewrite the retailers' inverse demand function for electricity generated from source j $(j = r, f)$ in terms of prices as:

$$y_{i,j} = P^{\sigma-\beta} P_i^{\epsilon-\sigma} p_{i,j}^{-\epsilon}. \tag{A.5}$$

We consider two types of environmental policies: energy taxes and research subsidies. Energy taxes affect firms through the price of electricity (P) while research subsidies (τ_j) affect firms by reducing the cost of innovation.[26]

With the retailers' inverse demand function in place, we can calculate the profit maximization of electricity generators and their equilibrium level of investment in research.

[24] In reality, each electricity generator would be able to decide whether to conduct research at the beginning of each period. While this distinction is important to study the impact of policies on innovation from an empirical standpoint, note that there is no change in firms' level of technology when they choose not to conduct research or when they conduct unsuccessful research. In other words, from a theoretical standpoint, the economic outcome resulting from firms' decision not to engage in research is the same as those resulting from firms' unsuccessful research. Therefore, we assume that all electricity generators engage in research in our theoretical model while our empirical model separately analyzes the impact of policies on firms' decision to engage in research and on the probability that the research is successful.

[25] There is much debate about how ease it is to substitute renewable and nonrenewable technologies in electricity generation. While some people argue that they are easily substitutable, others find evidence for a complementary relationship.

[26] We can think of these subsidies as lowering the costs of doing research.

At the beginning of each period, electricity generator i invest $\frac{1}{2}\psi x_{i,j}$ of the consumption goods in research for technology type j ($j = r, f$). The equilibrium level of research $x_{i,j}$ maximizes:

$$\max_{x_{i,j}} \left\{ \pi_{i,j} - \frac{1}{2}\frac{\psi x_{i,j}}{\tau_j} \right\}, \tag{A.6}$$

where $\pi_{i,j}$ are generator i's expected profits from selling electricity generated by source j to the retailers and τ_j are research subsidies for technology type j ($j = r, f$). We calculate the equilibrium level of research backwards. First, we calculate electricity generators' equilibrium profits $\pi_{i,j}$ and second, we calculate their equilibrium level of research intensity $x_{i,j}$. Profit maximization becomes: $\pi_{i,j} = \max_{y_{i,j}}\{p_{i,j}y_{i,j} - \frac{1}{A_{i,j}}y_{i,j}\}$ where $p_{i,j}$ is the inverse demand function in equation (A.5). From this maximization problem, we obtain the equilibrium demand for renewable and nonrenewable electricity, $y_{i,j} = \left(\frac{\epsilon-1}{\epsilon}\right)^{\epsilon}$, their corresponding equilibrium prices, $p_{i,j} = \frac{\epsilon}{\epsilon-1}\frac{1}{A_{i,j}}$, and equilibrium profits, $\pi_{i,j} = \left(\frac{(\epsilon-1)^{\epsilon-1}}{\epsilon^{\epsilon}}\right) P_i^{\epsilon-\sigma} P^{\sigma-\beta} A_{i,j}^{\epsilon-1}$, for $j = r, f$. We use these equilibrium profits in (A.6) to calculate the equilibrium level of innovation.

Innovation intensity for each electricity generator satisfies the first order condition:

$$x_{i,j} = \left(\frac{\epsilon-1}{\epsilon}\right)^{\epsilon} \frac{\tau_j}{\psi} P_i^{\epsilon-\sigma} P^{\sigma-\beta} \left(\frac{A_{i,j}^0}{\left((1+x_{i,j})A_{i,j}^0\right)^{2-\epsilon}} \right). \tag{A.7}$$

Equation (A.7) describes each firm's incentives to innovate. This equation shows that the equilibrium innovation intensity depends on environmental policies, such as energy taxes and research subsidies, energy prices and firms' past research. More importantly, the impact of energy prices and taxes on the direction of innovation depends on the ease at which firms can substitute between electricity generated from fossil fuels and renewable energy (ϵ), as well as the ease at which consumers can substitute between electricity and the consumption good (β) and between electricity supplied by different producers (σ).

B Data appendix

Table B.1: Variables and sources of data.

Variable	Unit of measure	Source
Patents	Number of applications	OECD Triadic Patent Families Database
	Firms' name and location	OECD REGPAT Database
	Firms' name and location	OECD HAN database
Research subsidies	Constant 2005 national prices (in millions of 2005 U.S. $)	IEA Energy Technology RD&D Statistics
Energy prices including taxes	Constant 2005 national prices (in millions of 2005 U.S. $)	IEA Energy Prices & Taxes
Real GDP	Constant 2005 national prices (in millions of 2005 U.S. $)	Penn World Table
Population	Millions of people	Penn World Table
Population density	People per square km of land area	World Development Indicator

Table B.2: List of countries.

Patents:
Argentina, Australia, Austria, Bahamas, Barbados, Belgium, Belize, Bermuda, Brazil, Bulgaria, Canada, Cayman Islands, Chile, China, Colombia, Croatia, Cyprus, Czech Republic, Denmark, Dominica, Finland, France, Georgia, Germany, Greece, Hong Kong, Hungary, Iceland, Indonesia, India, Iran, Ireland, Italy, Israel, Japan, Jordan, Korea, Kenya, Kuwait, Lithuania, Luxembourg, Malaysia, Mauritius, Mexico, Netherlands, New Zealand, Norway, Panama, Philippines, Poland, Portugal, Russian Federation, Saudi Arabia, Seychelles, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, St. Kitts and Nevis, Sweden, Switzerland, Taiwan, Thailand, Turkey, Ukraine, United Arab Emirates, United Kingdom, United States of America, Venezuela.
Energy prices and research subsidies:
Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States of America.
Countries in the estimations:
Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States of America.

B.1 International patent classifications (IPC)

Table B.3: Patent classes for renewable electricity generation technologies.

IPC code	Description
H01M 4/86-4/98, 8/00-8/24, 12/00-12/08	**Fuel cells**
H01M 4/86-4/98	Electrodes
H01M 4/86-4/98	Inert electrodes with catalytic activity
H01M 2/00-2/04 , 8/00-8/24	Non-active parts
H01M 12/00-12/08	Within hybrid cells
C10B 53/00, C10J	**Pyrolysis or gasification of biomass**
	Harnessing energy from manmade waste
C10L 5/00	Agricultural waste
C10L 5/42, 5/44	Fuel from animal waste and crop residues
F23G 7/00, 7/10	Incinerators for field, garden or wood waste
C10J 3/02, 3/46, F23B 90/00, F23G 5/027	Gasification
B09B 3/00, F23G 7/00	Chemical waste
C10L 5/48, F23G 5/00, F23G 7/00	Industrial waste
C21B 5/06	Using top gas in blast furnaces to power pigiron production
D21C 11/00	Pulp liquors
A62D 3/02, C02F 11/04, 11/14	Anaerobic digestion of industrial waste
F23G 7/00, 7/10	Industrial wood waste
B09B 3/00, F23G 5/00	Hospital waste
B09B	Landfill gas
B01D 53/02, 53/04, 53/047, 53/14, 53/22, 53/24, C10L 5/46	Separation of components
F23G 5/00	Municipal waste
	Hydro energy
E02B 9/00-9/06	Water-power plants
E02B 9/08	Tide or wave power plants
F03B, F03C	Machines or engines for liquids
F03B 13/12-13/26	Using wave or tide energy
F03B 15/00-15/22	Regulating, controlling or safety means of machines or engines
B63H 19/02, 19/04	Propulsion of marine vessels using energy derived from water movement
F03G 7/05	**Ocean thermal energy conversion (OTEC)**
F03D	**Wind energy**
H02K 7/18	Structural association of electric generator with mechanical driving motor
B63B 35/00, E04H 12/00, F03D 11/04	Structural aspects of wind turbines
B60K 16/00	Propulsion of vehicles using wind power
B60L 8/00	Electric propulsion of vehicles using wind power
B63H 13/00	Propulsion of marine vessels by wind-powered motors
	Solar energy

Table B.3 – continued from previous page

IPC code	Description
H01L 27/142, 31/00 31/078, H01G 9/20, H02N 6	Devices adapted for the conversion of radiation energy into electrical energy
H01L 27/30, 51/42-51/48	Using organic materials as the active part
H01L 25/00, 25/03, 25/16, 25/18, 31/042	Assemblies of a plurality of solar cells
C01B 33/02, C23C 14/14, 16/24, C30B 29/06	Silicon; single-crystal growth
G05F 1/67	Regulating to the maximum power available from solar cells
F21L 4/00, F21S 9/03	Electric lighting devices with, or rechargeable with, solar cells
H02J 7/35	Charging batteries
H01G 9/20, H01M 14/00	Dye-sensitised solar cells (DSSC)
F24J 2/00-2/54	Use of solar heat
F24D 17/00	For domestic hot water systems
F24D 3/00, 5/00, 11/00, 19/00	For space heating
F24J 2/42	For swimming pools
F03D 1/04, 9/00, 11/04, F03G 6/00	Solar updraft towers
C02F 1/14	For treatment of water, waste water or sludge
F02C 1/05	Gas turbine power plants using solar heat source
H01L 31/058	Hybrid solar thermal-PV systems
B60K 16/00	Propulsion of vehicles using solar power
B60L 8/00	Electric propulsion of vehicles using solar power
F03G 6/00-6/06	Producing mechanical power from solar energy
E04D 13/00, 13/18	Roof covering aspects of energy collecting devices
F22B 1/00, F24J 1/00	Steam generation using solar heat
F25B 27/00	Refrigeration or heat pump systems using solar energy
F26B 3/00, 3/28	Use of solar energy for drying materials or objects
F24J 2/06, G02B 7/183	Solar concentrators
F24J 2/04	Solar ponds
	Geothermal energy
F01K, F24F 5/00, F24J 3/08, H02N 10/00, F25B 30/06	Use of geothermal heat
F03G 4/00-4/06, 7/04	Production of mechanical power from geothermal energy
F24J 1/00, 3/00, 3/06	Other production or use of heat, not derived from combustion, e.g. natural heat
F24D 11/02	Heat pumps in central heating systems using heat accumulated in storage masses
F24D 15/04	Heat pumps in other domestic- or space-heating systems
F24D 17/02	Heat pumps in domestic hot-water supply systems
F24H 4/00	Air or water heaters using heat pumps
F25B 30/00	Heat pumps
	Using waste heat
F01K 27/00	To produce mechanical energy
F01K 23/06-23/10, F01N 5/00, F02G 5/00-5/04, F25B 27/02	Of combustion engines
F01K 17/00;23/04	steam engine plants

Table B.3 – continued from previous page

IPC code	Description
F02C 6/18	Of gas-turbine plants
F25B 27/02	As source of energy for refrigeration plants
C02F 1/16	For treatment of water, waste water or sewage
D21F 5/20	Recovery of waste heat in paper production
F22B 1/02	For steam generation by exploitation of the heat content of hot heat carriers
F23G 5/46	Recuperation of heat energy from waste incineration
F24F 12/00	Energy recovery in air conditioning
F27D 17/00	Arrangements for using waste heat from furnaces, kilns, ovens or retorts
F28D 17/00-20/00	Regenerative heat-exchange apparatus
C10J 3/86	Of gasification plants
F03G 5/00-5/08	Devices for producing mechanical power from muscle energy

Source: IPC Green Inventory, World Intellectual Property Organization.

Table B.4: Patent classes for efficiency-improving electricity generation technologies.

IPC code	Description
Coal gasification	
C10J3	Production of combustible gases containing carbon monoxide from solid carbonaceous fuels
Improved burners	[Classes listed below excluding combinations with B60,B68,F24,F27]
F23C1	Combustion apparatus specially adapted for combustion of two or more kinds of fuel simultaneously or alternately,at least one kind of fuel being fluent
F23C5/24	Combustion apparatus characterised by the arrangement or mounting of burners; disposition of burners to obtain a loop flame
F23C6	Combustion apparatus characterised by the combination of two or more combustion chambers
F23B10	Combustion apparatus characterised by the combination of two or more combustion chambers
F23B30	Combustion apparatus with driven means for agitating the burning fuel; combustion apparatus with driven means for advancing the burning fuel through the combustion chamber
F23B70	Combustion apparatus characterised by means for returning solid combustion residues to the combustion chamber
F23B80	Combustion apparatus characterised by means creating a distinct flow path for fluegases or for non-combusted gases given off by the fuel
F23D1	Burners for combustion of pulverulent fuel
F23D7	Burners in which drops of liquid fuel impinge on a surface
F23D17	Burners for combustion simultaneously or alternatively of gaseous or liquid or pulverulent fuel
Fluidised bed combustion	
B01J8/20-22	Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes; with liquid as a fluidising medium
B01J8/24-30	Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes; according to “fluidised-bed” technique
F27B15	Fluidised bed furnaces; Other furnaces using or treating finely divided materials in dispersion

Table B.4 – continued from previous page

IPC code	Description
F23C10	Apparatus in which combustion takes place in afluidised bed of fuel or other particles
Improved boilers for steam generation	
F22B31	Modifications of boiler construction, or of tube systems, dependent on installation of combustion apparatus; Arrangements or dispositions of combustion apparatus
F22B33/14-16	Steam generation plants,e.g.comprising steam boilers of different types in mutual association; combinations of low-and high-pressure boilers
Improved steam engines	
F01K3	Plants characterised by the use of steam or heat accumulators, or intermediate steam heaters, therein
F01K5	Plants characterised by use of means for storing steam in an alkali to increases team pressure,e.g. of Honigmann or Koenemann type
F01K23	Plants characterised by more than one engine delivering power external to the plant, the engines being driven by different fluids
Super-heaters	
F22G	Steam super heating characterised by heating method
Improved gas turbines	
F02C7/08-105	Features, component parts, details or accessories; heating air supply before combustion,e.g. by exhaust gases
F02C7/12-143	Features, component parts, details or accessories; cooling of plants
F02C7/30	Features, component parts, details or accessories; preventing corrosion in gas-swept spaces
Combined cycles	
F01K23/02-10	Plants characterised by more than one engine delivering power external to the plant, the engines being driven by different fluids; the engine cycles being thermally coupled
F02C3/20-36	Gas turbine plants characterised by the use of combustion products as the working fluid; using special fuel, oxidant or dilution fluid to generate the combustion products
F02C6/10-12	Plural gas-turbine plants; combinations of gas-turbine plants with other apparatus; supplying working fluid to a user,e.g. a chemical process, which returns working fluid to a turbine of the plant
Improved compressed-ignitionengines	
[Classes listed below excluding combinations with B60,B68,F24,F27]	
F02B1/12-14	Engines characterised by fuel-air mixture compression; with compression ignition
F02B3/06-10	Engines characterised by fuel-air mixture compression; with compression ignition
F02B7	Engines characterised by the fuel-air charge being ignited by compression ignition of an additional fuel
F02B11	Engines characterised by both fuel-air mixture compression and air compression, or characterised by both positive ignition and compression ignition,e.g.indifferent cylinders
F02B13/02-04	Engines characterised by the introduction of liquid fuel into cylinders by use of auxiliary fluid; compression ignition engines using air or gas for blowing fuel into compressed air in cylinder
F02B49	Methods of operating air- compressing compression-ignition engines involving introduction of small quantities of fuel in the form of a fine mist into the air in the engine's intake

Table B.4 – continued from previous page

IPC code	Description
Co-generation	
F01K17/06	Use of steam or condensate extracted or exhausted from steam engine plant; returning energy of steam, in exchanged form,to process,e.g. use of exhaust steam for drying solid fuel of plant
F01K27	Plants for converting heat or fluid energy into mechanical energy
F02C6/18	Plural gas-turbine plants; combinations of gas-turbine plants with other apparatus; using the waste heat of gas-turbine plants outside the plants themselves, e.g. gas-turbine power heat plants
F02G5	Profiting from waste heat of combustion engines
F25B27/02	Machines, plant, or systems, using particular sources of energy; using waste heat, e.g. from internal-combustion engines

Source: Lanzi et al. (2011).

Table B.5: Patent classes for general fossil-fuel technologies.

IPC code	**Description**
C10J	Production of fuel gases by carburetting air or other gases without pyrolysis
F01K	Steam engine plants; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles
F02C	Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants
F02G	Hot-gas or combustion-product positive-displacement engine; use of waste heat of combustion engines,not otherwise provided for
F22	Steam generation
F23	Combustion apparatus; combustion processes
F27	Furnaces; kilns; ovens; retorts

Source: Lanzi et al. (2011).

Table B.6: Patent classes for base load electricity generation technologies.

IPC code	**Description**
C10J3	Coal gassification–production from solid carbonaceous fuels
F23C1	Integrated coal gasification combined cycle (IGCC)
F23C5/24	Burners used for combustion are used in base load activities
F23C6	Burners used for combustion are used in base load activities
F23B10	Other coal-fire technology, in general
F23B30	Burners used for combustion are used in base load activities
F23B70	Burners used for combustion are used in base load activities
F23B80	Burners used for combustion are used in base load activities
F23D1	Pulverized coal combustion (PCC) in steam cycle
F23D7	Burners used for combustion are used in base load activities
F23D17	Integrated coal gasification combined cycle (IGCC)
B01J8/20-22	FBC burns coal or any combustable material. Coal is mainly used in base load operations
B01J8/24-30	FBC burns coal or any combustable material. Coal is mainly used in base load operations
F27B15	FBC burns coal or any combustable material. Coal is mainly used in base load operations
F23C10	FBC burns coal or any combustable material. Coal is mainly used in base load operations
F22B31	Used in steam generation. From p 24 ref 7 "baseload steam generating units (e.g., boilers)"
F22B33/14-16	Used in steam generation. From p 24 ref 7 "baseload steam generating units (e.g., boilers)"
F01K3	Steam engines used in base load ops
F01K5	Steam engines used in base load ops
F01K23	IGCC
F22G	PCC in steam cycle
F01K23/02-10	CCGT is the dominant gas-based technology for intermediate and base-load power generation
F02C3/20-36	CCGT is the dominant gas-based technology for intermediate and base-load power generation
F02C6/10-12	CCGT is the dominant gas-based technology for intermediate and base-load power generation

Source: own calculations.

Table B.7: Patent classes for peak load electricity generation technologies.

IPC code	Description
F02C7/08-105	Gas Turbines used in peak load operations
F02C7/12-143	Gas Turbines used in peak load operations
F02C7/30	Gas Turbines used in peak load operations
F02B1/12-14	Compressed-ignition engines (or diesel engines) are used in peak load production
F02B3/06-10	Compressed-ignition engines (or diesel engines) are used in peak load production
F02B7	Compressed-ignition engines (or diesel engines) are used in peak load production
F02B11	Compressed-ignition engines (or diesel engines) are used in peak load production
F02B13/02-04	Compressed-ignition engines (or diesel engines) are used in peak load production
F02B49	Compressed-ignition engines (or diesel engines) are used in peak load production
F01K17/06	Cogeneration is used dring peak load hours mainly using natural gases
F01K27	Cogeneration is used dring peak load hours mainly using natural gases
F02C6/18	Cogeneration is used dring peak load hours mainly using natural gases
F02G5	Cogeneration is used dring peak load hours mainly using natural gases
F25B27/02	Cogeneration is used dring peak load hours mainly using natural gases

Source: own calculations.

B.2 Summary statistics

Table B.8: Total number of patents in each renewable and fossil fuel technology.

Technology	Global
Renewables	
Geothermal	2,123
Hydro	6,337
Natural heat	2,351
Solar	59,905
Thermal	43
Waste	17,361
Waste heat	2,351
Wind	5,770
Fuel cells	22,994
Biomass	808
Muscle energy	16
Total	*120,059*
Fossil fuels	
Base load (coal and natural gas)	89,425
Peak load (natural gas and diesel)	27, 121
Total	*116,546*

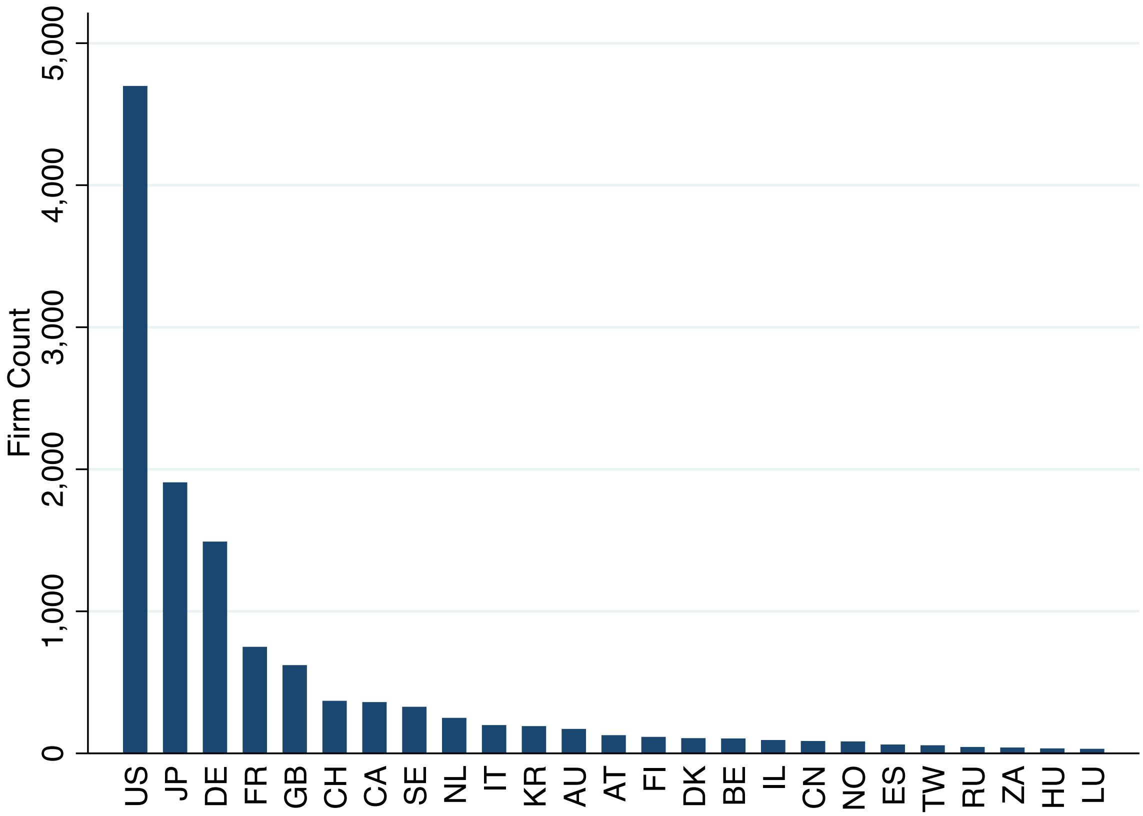

Figure B.1: Innovating firms by country.

C Robustness analysis

This section presents the detailed estimation results of the robustness analysis discussed in section 6. Specifically, tables C.1 and C.2 show the zero-inflated Poisson and negative binomial estimates while Table C.3 shows additional fossil fuel prices. In tables C.4 and C.5 we consider alternative lag structures of past innovation and table C.6 presents the estimation results using the five geographical regions as an alternative definition of regional spillovers. Table C.7 controls for additional macroeconomic indicators while Table C.8 considers only firms in France, Germany, Japan, United Kingdom and United States, the five most innovative countries in the dataset. Table C.9 separates firms between large and small firms while table C.10 separates them between specialized and mixed firms. Finally, tables C.11 and C.12 looks at different definitions of base load and peak load technologies.

Table C.1: Zero-inflated Poisson estimates of the determinants of firm-level innovation in renewable and non-renewable technologies using global data from 1978 to 2011.

	Dependent variable: firm-level number of patents			
	Probability to apply for a patent (Poisson – intensive margin)		Probability to engage in research (Logit – extensive margin)	
	Renewable (1)	Fossil fuel (2)	Renewable (3)	Fossil fuel (4)
Energy prices including taxes				
L1.Coal price	-.36010***	-.30060*	-.05183	-.16450***
	(.10370)	(.16440)	(.04318)	(.04526)
L1.Electricity price	-.50680***	-.72890***	-.10040*	.01906
	(.10470)	(.18690)	(.05896)	(.06581)
Research subsidies				
L1.Renewable	.08301***	.04699	-.02661	-.06508***
	(.03033)	(.05693)	(.01890)	(.02014)
L1.Fossil fuel	-.10610***	-.04926	-.01698	-.00639
	(.02006)	(.03995)	(.01332)	(.01473)
L1.Efficiency-improving	.03313	.06965	.03944*	.06440***
	(.03131)	(.06131)	(.02245)	(.02431)
Past innovation				
L1.Renewable knowledge	.00345***	.00007	-.01313***	.00055
	(.00018)	(.00068)	(.00082)	(.00049)
L1.Renewable spillovers	-.00002***	-.00003*	-.00002***	-.00000
	(.00001)	(.00001)	(.00000)	(.00000)
L1.Fossil-fuel knowledge	.00004	.00054***	.00068***	-.00792***
	(.00006)	(.00007)	(.00017)	(.00092)
L1.Fossil-fuel spillover	.00003***	.00003**	.00000	.00000
	(.00001)	(.00001)	(.00000)	(.00000)
Macroeconomic indicators				
L1.GDP	-.00629	-.00417	.01788	.03257
	(.05982)	(.1028)	(.02037)	(.022)
L1.GDP per capita	.12320	-2.8430***	-.10140	.87870***
	(.35030)	(.68200)	(.12240)	(.13720)
Constant term	55.55000*	-36.84000	2.96400**	-7.34800***
	(29.40000)	(53.14000)	(1.26300)	(1.38500)
Firm pre-sample FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	30597	30597	30597	30597

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.
Numbers in parentheses are standard errors.

Table C.2: Negative binomial estimates of the determinants of firm-level innovation in renewable, base load and peak load technologies in the five most innovative countries.

	Dependent variable: firm-level number of patents		
		Fossil fuel	
	Renewable	Base load	Peak load
Energy prices including taxes			
L1.Coal price	-.4939***	-.4275***	-.3169*
	(.06604)	(.09596)	(.1721)
L1.Electricity price	-.00157	.0215	-.1107
	(.07439)	(.1032)	(.1803)
Research subsidies			
L1.Renewable	.01648	.03532	.03243
	(.0292)	(.03803)	(.07431)
L1.Fossil fuel	.04571**	.02959	-.02929
	(.02059)	(.02778)	(.05324)
L1.Efficiency-improving	.04731***	.00883	.1616***
	(.01664)	(.02333)	(.04631)
Past innovation knowledge			
L1.Renewable	.00072***	.00063***	.00115***
	(5.5e-05)	(.00011)	(.00019)
L1.Base load	.00046***	.00135***	.00055***
	(.0001)	(.00011)	(.00017)
L1.Peak load	2.8e-05	-.00048***	6.0e-05
	(.0001)	(.0001)	(.00013)
Past innovation spillovers			
L1.Renewable	1.2e-05	2.4e-05*	1.1e-05
	(7.6e-06)	(1.3e-05)	(2.1e-05)
L1.Base load	-3.6e-05***	-6.0e-05***	-3.1e-05
	(8.9e-06)	(1.4e-05)	(2.5e-05)
L1.Peak load	8.1e-05***	7.0e-05**	4.7e-05
	(1.8e-05)	(2.9e-05)	(4.8e-05)
Macroeconomic indicators			
L1.GDP	-.8157***	-.7045***	-.4787***
	(.04811)	(.05605)	(.108)
L1.GDP per capita	.7797**	1.275***	.5734
	(.3149)	(.4848)	(.8579)
Constant term	2.69	-5.711	-1.588
	(3.382)	(5.33)	(9.151)
Pre-sample history	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	196903	100955	31494

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C.3: Fossil fuel price effect in base load and peak load technologies using global data from 1978 to 2009 (firms with more than 10 patents – top 22% innovators).

	Dependent variable: firm-level number of patents								
	Renewable			Base load			Peak load		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Energy prices including taxes									
L1.Coal price	-.8366			.5183			.3937		
	(.6063)			(.5667)			(.8791)		
L1.Coal price squared	.9411			-1.661			-1.866		
	(1.236)			(1.151)			(1.593)		
L1.Oil price		.03736			.1095			.2135	
		(.2032)			(.2426)			(.3715)	
L1.Electricity price		.03578			.1439			-.2071	
		(.2612)			(.2195)			(.3621)	
L1.Elec-coal price gap			.5675**			.6421***			.4826
			(.23)			(.2405)			(.5954)
Research subsidies									
L1.Renewable	.1335*	.1106	.1156	-.03796	-.03609	-.03989	.1625	.1661	.1591
	(.07896)	(.07847)	(.0785)	(.08523)	(.08647)	(.08577)	(.2126)	(.2099)	(.2125)
L1.Fossil fuel	.00747	-.01113	.0197	.04053	.0531	.06869	.04789	.02528	.06499
	(.04556)	(.04263)	(.04456)	(.05576)	(.0606)	(.05687)	(.07685)	(.08678)	(.07989)
L1.Efficiency-improving	.04536	.05442	.04606	.01864	.01824	.00855	.3811***	.3864***	.3819***
	(.04251)	(.04163)	(.04222)	(.05867)	(.05716)	(.05868)	(.1092)	(.1076)	(.1057)
Past innovation knowledge									
L1.Renewable	-.00041**	-.0004**	-.0004**	7.6e-05	.00012	.0001	-.00068	-.00059	-.00059
	(.00017)	(.00017)	(.00017)	(.00051)	(.00053)	(.00052)	(.00059)	(.0006)	(.00062)
L1.Fossil-fuel	-.00098***	-.00096***	-.00097***	-.00079***	-.0007***	-.00074***	.00031	.00037	.0004
	(.00027)	(.00028)	(.00026)	(.00022)	(.00023)	(.00023)	(.00049)	(.00046)	(.00048)
L1.Peak load	.00101***	.001***	.00099***	.00088***	.0008***	.00083***	.00022	.00015	.00012
	(.0002)	(.00021)	(.0002)	(.00017)	(.00018)	(.00018)	(.00031)	(.0003)	(.00031)
Past innovation spillovers									
L1.Renewable	-1.1e-05	-1.2e-05	-4.0e-06	-2.5e-05	-1.9e-05	-1.8e-05	-6.0e-05	-5.0e-05	-4.3e-05
	(1.9e-05)	(2.0e-05)	(1.9e-05)	(2.1e-05)	(2.1e-05)	(2.2e-05)	(5.1e-05)	(5.0e-05)	(5.1e-05)
L1.Base load	1.3e-05	1.3e-05	2.0e-05	1.7e-05	1.8e-05	1.8e-05	5.2e-05	5.2e-05	6.3e-05*
	(2.3e-05)	(1.9e-05)	(2.4e-05)	(2.3e-05)	(2.3e-05)	(2.3e-05)	(3.9e-05)	(3.9e-05)	(3.8e-05)
L1.Peak load	-.00011**	-.00012**	-.00013**	-8.9e-05	-9.7e-05*	-9.5e-05*	-2.1e-05	-2.0e-05	-4.1e-05
	(5.4e-05)	(4.8e-05)	(5.7e-05)	(5.5e-05)	(5.7e-05)	(5.5e-05)	(9.8e-05)	(.0001)	(9.9e-05)
Macroeconomic indicators									
L1.GDP	-.2366**	-.1505	-.196**	-.2274**	-.1188	-.1754*	-.5012***	-.3641*	-.3744**
	(.09645)	(.09981)	(.09779)	(.09345)	(.09634)	(.09547)	(.1872)	(.1906)	(.1788)
L1.GDP per capita	.5374	.5634	.4427	1.551**	1.552**	1.42**	.6351	.7471	.6453
	(.842)	(.7767)	(.8344)	(.6495)	(.6648)	(.6434)	(1.638)	(1.6)	(1.661)
Pre-sample history	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21433	21433	21433	17801	17801	17801	7730	7730	7730

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C.4: Estimates with second lags of explanatory variables.

	Dependent variable: firm-level number of patents				
				Fossil fuel	
	Renewable	Fossil fuel	Renewable	Base load	Peak load
	(1)	(2)	(3)	(4)	(5)
Energy prices including taxes					
L1.Coal price	-.4123**	-.3538*	-.3801**	-.4599***	-.5508
	(.1621)	(.2064)	(.1481)	(.1652)	(.3651)
L1.Electricity price	.2079	.3064	.1687	.3595	-.2256
	(.2098)	(.2732)	(.187)	(.2313)	(.3913)
Research subsidies					
L1.Renewable	.1538**	.04959	.1668**	-.0118	.1749
	(.07187)	(.113)	(.06896)	(.08075)	(.2059)
L1.Fossil fuel	.00717	.05446	-.00955	.0623	.06368
	(.03757)	(.05815)	(.03977)	(.05977)	(.08687)
L1.Efficiency-improving	.00229	.03965	-.0096	-.02493	.3045***
	(.03686)	(.06079)	(.03812)	(.0544)	(.09123)
Past innovation knowledge					
L2.Renewable	-.00104***	-.00079	-.00095***	-5.9e-05	-.00104
	(.00014)	(.00054)	(.00012)	(.00066)	(.0007)
L2.Fossil fuel	-1.8e-06	.00019***			
	(.0002)	(6.4e-05)			
L2.Base load			-.0011***	-.00125***	.00031
			(.0003)	(.0003)	(.00057)
L2.Peak load			.00105***	.00114***	.00023
			(.00025)	(.00022)	(.00036)
Past innovation spillovers					
L2.Renewable	-2.3e-05	-1.4e-05	-2.9e-05*	-3.7e-05	-7.7e-05
	(1.6e-05)	(2.4e-05)	(1.7e-05)	(2.3e-05)	(5.4e-05)
L2.Fossil fuel	-3.9e-05**	-5.4e-06			
	(1.5e-05)	(1.5e-05)			
L2.Base load			-3.5e-05**	4.9e-06	8.9e-06
			(1.6e-05)	(2.0e-05)	(3.0e-05)
L2.Peak load			-3.7e-05	-3.0e-05	7.8e-05
			(4.4e-05)	(5.5e-05)	(8.9e-05)
Macroeconomic indicators					
L1.GDP	-.1764*	-.1321	-.1792*	-.2485***	-.6646***
	(.09771)	(.1077)	(.1015)	(.08802)	(.1872)
L1.GDP per capita	-.4653	.4265	-.6343	.7695	.4334
	(.7823)	(.8231)	(.7311)	(.6287)	(1.466)
Pre-sample history	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	46590	31316	46620	28779	9782

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C.5: Estimates with third lags of explanatory variables.

	Dependent variable: firm-level number of patents				
				Fossil fuel	
	Renewable	Fossil fuel	Renewable	Base load	Peak load
	(1)	(2)	(3)	(4)	(5)
Energy prices including taxes					
L1.Coal price	-.4294***	-.3924**	-.4012***	-.4787***	-.5158
	(.1496)	(.1959)	(.1383)	(.1662)	(.3949)
L1.Electricity price	.2292	.3448	.2845	.3623*	-.2149
	(.199)	(.2579)	(.179)	(.2201)	(.3932)
Research subsidies					
L1.Renewable	.1512**	.04769	.1408**	.00381	.1709
	(.06923)	(.109)	(.06488)	(.07456)	(.2099)
L1.Fossil fuel	.01373	.05483	.00358	.06109	.07089
	(.0378)	(.05881)	(.04003)	(.05967)	(.0935)
L1.Efficiency-improving	-.00734	.01646	-.00943	-.04462	.2936***
	(.0357)	(.06259)	(.03483)	(.05181)	(.08994)
Past innovation knowledge					
L3.Renewable	-.00148***	-.00103*	-.00134***	-7.6e-05	-.00093
	(.00027)	(.0006)	(.0002)	(.00078)	(.00065)
L3.Fossil fuel	-7.0e-05	.00015*			
	(.00024)	(8.1e-05)			
L3.Base load			-.00123***	-.00174***	.00018
			(.00038)	(.00035)	(.00058)
L3.Peak load			.00106***	.00147***	.00029
			(.00032)	(.00027)	(.00038)
Past innovation spillovers					
L3.Renewable	-2.8e-05	-8.7e-06	-1.6e-05	-3.8e-05*	-7.7e-05
	(1.7e-05)	(2.7e-05)	(1.9e-05)	(2.2e-05)	(6.1e-05)
L3.Fossil fuel	-3.6e-05**	-9.1e-06			
	(1.6e-05)	(1.9e-05)			
L3.Base load			-9.5e-06	-2.5e-06	7.1e-06
			(1.7e-05)	(2.2e-05)	(3.5e-05)
L3.Peak load			-9.4e-05*	-9.9e-06	1.0e-04
			(4.9e-05)	(6.0e-05)	(.00011)
Macroeconomic indicators					
L1.GDP	-.1981*	-.1141	-.1734*	-.2491***	-.6602***
	(.112)	(.1196)	(.1037)	(.09158)	(.1985)
L1.GDP per capita	-.4775	.3075	-.3941	.6358	.4153
	(.7639)	(.8435)	(.7155)	(.62)	(1.498)
Pre-sample history	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	53642	35200	53676	32180	9782

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C.6: Alternative definition of regional spillovers: five regions.

	Dependent variable: firm-level number of patents				
				Fossil fuel	
	Renewable	Fossil fuel	Renewable	Base load	Peak load
	(1)	(2)	(3)	(4)	(5)
Energy prices including taxes					
L1.Coal price	-.3964**	-.2992	-.4168**	-.4081**	-.5841
	(.1809)	(.2168)	(.1664)	(.1703)	(.3599)
L1.Electricity price	.1641	.2415	.2467	.3653	-.02527
	(.2259)	(.2857)	(.194)	(.2404)	(.3832)
Research subsidies					
L1.Renewable	.1567**	.0485	.1288*	-.0253	.1756
	(.07383)	(.1129)	(.07403)	(.08381)	(.2168)
L1.Fossil fuel	.00263	.0551	.02039	.06659	.06384
	(.03797)	(.05722)	(.03945)	(.05826)	(.08065)
L1.Efficiency-improving	.00187	.06258	.0385	-.00404	.3642***
	(.0406)	(.06928)	(.04008)	(.05664)	(.1052)
Past innovation knowledge					
L1.Renewable	-.00056***	-.00049	-.00045***	4.3e-05	-.00077
	(.00013)	(.00044)	(.00016)	(.00053)	(.00062)
L1.Fossil-fuel	4.4e-05	.00025***			
	(.00017)	(4.9e-05)			
L1.Base load			-.001***	-.00076***	.00036
			(.00027)	(.00024)	(.0005)
L1.Peak load			.00098***	.00082***	.00016
			(.0002)	(.00018)	(.00032)
Past innovation spillovers					
L1.Renewable	-2.6e-05	-3.6e-05	-6.0e-06	-1.4e-05	-5.0e-05
	(2.3e-05)	(3.2e-05)	(2.1e-05)	(3.1e-05)	(5.6e-05)
L1.Fossil-fuel	-4.3e-05***	-1.1e-05			
	(1.5e-05)	(1.6e-05)			
L1.Base load			2.2e-05	2.1e-05	5.9e-05
			(2.3e-05)	(3.0e-05)	(3.8e-05)
L1.Peak load			-.00013***	-.0001*	-3.7e-05
			(5.0e-05)	(6.0e-05)	(9.4e-05)
Macroeconomic indicators					
L1.GDP	-.1662*	-.1112	-.1941**	-.1636*	-.4713**
	(.09153)	(.1016)	(.09364)	(.09356)	(.1953)
L1.GDP per capita	-.3539	.5974	.2637	1.255**	.7033
	(.8199)	(.8274)	(.7974)	(.6389)	(1.634)
Pre-sample history	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39293	27233	39317	25194	9782

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C.7: Baseline estimates with additional macroeconomic indicators (population density).

	Dependent variable: firm-level number of patents				
				Fossil fuel	
	Renewable	Fossil fuel	Renewable	Base load	Peak load
	(1)	(2)	(3)	(4)	(5)
Energy prices including taxes					
L1.Coal price	-.3871*	-.2869	-.403**	-.4036**	-.5892
	(.1986)	(.2195)	(.1798)	(.1695)	(.347)
L1.Electricity price	.1767	.2685	.2707	.3659	-.03229
	(.2265)	(.2847)	(.1989)	(.2412)	(.39)
Research subsidies					
L1.Renewable	.1575**	.04417	.126*	-.03284	.1754
	(.07461)	(.1154)	(.07477)	(.08704)	(.2151)
L1.Fossil fuel	.0012	.05684	.0213	.06772	.06437
	(.03916)	(.05764)	(.04196)	(.05867)	(.0804)
L1.Efficiency-improving	.01003	.06804	.03807	.00048	.366***
	(.04124)	(.0738)	(.04069)	(.0585)	(.1142)
Past innovation knowledge					
L1.Renewable	-.00055***	-.00046	-.00045***	5.4e-05	-.00077
	(.00013)	(.00043)	(.00016)	(.00053)	(.00062)
L1.Fossil-fuel	4.8e-05	.00025***			
	(.00017)	(4.9e-05)			
L1.Base load			-.001***	-.00076***	.00036
			(.00027)	(.00023)	(.00049)
L1.Peak load			.00098***	.00082***	.00017
			(.0002)	(.00017)	(.00031)
Past innovation spillovers					
L1.Renewable	-2.3e-05	-3.0e-05	-5.1e-06	-1.4e-05	-5.2e-05
	(2.0e-05)	(2.7e-05)	(1.8e-05)	(2.2e-05)	(5.1e-05)
L1.Fossil-fuel	-3.7e-05***	-5.7e-06			
	(1.4e-05)	(1.6e-05)			
L1.Base load			2.5e-05	2.2e-05	5.5e-05
			(2.0e-05)	(2.4e-05)	(3.5e-05)
L1.Peak load			-.00013***	-9.9e-05*	-2.6e-05
			(5.0e-05)	(5.9e-05)	(9.5e-05)
Macroeconomic indicators					
L1.GDP	-.1374	-.1152	-.1765*	-.1622*	-.4801**
	(.09599)	(.09859)	(.1038)	(.09144)	(.1942)
L1.GDP per capita	-.3662	.6039	.2445	1.287**	.6931
	(.8814)	(.819)	(.8643)	(.6551)	(1.53)
L1.Pop. density	-.00289	-.03837	-.03412	.00132	.00953
	(.07262)	(.1259)	(.08817)	(.1257)	(.2721)
Pre-sample history	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39099	27020	39123	24981	9767

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C.8: Five most innovative countries: France, Germany, Japan, United Kingdom, United States.

	Dependent variable: firm-level number of patents				
				Fossil fuel	
	Renewable	Fossil fuel	Renewable	Base load	Peak load
	(1)	(2)	(3)	(4)	(5)
Energy prices including taxes					
L1.Coal price	-.5212**	-.0764	-.6175***	-.3273	.02017
	(.2215)	(.2669)	(.208)	(.2093)	(.4524)
L1.Electricity price	.2901	.06645	.5866**	.5353	-.5389
	(.2539)	(.3515)	(.229)	(.3435)	(.4916)
Research subsidies					
L1.Renewable	.1383*	.06597	.1274	.02422	.1783
	(.08316)	(.1258)	(.08085)	(.0935)	(.2117)
L1.Fossil fuel	.02769	.06799	.07531	.115*	-.05627
	(.04436)	(.06448)	(.04806)	(.06856)	(.08894)
L1.Efficiency-improving	-.02535	.09217	.01101	-.00632	.4546***
	(.04325)	(.06963)	(.04223)	(.05709)	(.1068)
Past innovation knowledge					
L1.Renewable	-.00053***	-.00059	-.00041**	-1.7e-05	-.00086
	(.00014)	(.00044)	(.00018)	(.00051)	(.00067)
L1.Fossil-fuel	4.2e-05	.00029***			
	(.00017)	(4.7e-05)			
L1.Base load			-.00101***	-.00066**	.00048
			(.00028)	(.00027)	(.00056)
L1.Peak load			.00095***	.00078***	.00018
			(.00021)	(.00022)	(.00036)
Past innovation spillovers					
L1.Renewable	-2.4e-05	-6.1e-05*	1.2e-05	-1.7e-05	-8.4e-05
	(2.4e-05)	(3.5e-05)	(2.4e-05)	(4.0e-05)	(6.6e-05)
L1.Fossil-fuel	-4.4e-05***	-3.1e-06			
	(1.5e-05)	(1.7e-05)			
L1.Base load			4.4e-05	3.8e-05	5.6e-05
			(2.7e-05)	(3.9e-05)	(5.3e-05)
L1.Peak load			-.00018***	-.00012	-1.7e-05
			(5.8e-05)	(8.6e-05)	(.00011)
Macroeconomic indicators					
L1.GDP	-.2038*	-.1909	-.2624**	-.1796	-.3594*
	(.1196)	(.1759)	(.1271)	(.1184)	(.1837)
L1.GDP per capita	-.3636	.8395	.2975	.3559	.6358
	(.9212)	(.8435)	(.9344)	(.8418)	(1.557)
Pre-sample history	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	33586	23139	33652	21394	8525

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C.9: Baseline estimates with large and small firms.

	Dependent variable: firm-level number of patents					
	Large firms (> 15 total patents)			Small firms (< 15 total patents)		
	Renewable	Base load	Peak load	Renewable	Base load	Peak load
	(1)	(2)	(3)	(4)	(5)	(6)
Energy prices including taxes						
L1.Coal price	-.4436**	-.4003**	-.5758	.09776	.00012	-.5506
	(.1832)	(.1785)	(.3713)	(.2114)	(.3373)	(1.074)
L1.Electricity price	.2726	.3507	-.02502	.06325	1.397***	1.441
	(.2116)	(.2488)	(.3782)	(.2339)	(.4325)	(1.312)
Research subsidies						
L1.Renewable	.1324*	-.02993	.184	.01987	-.1885	.2159
	(.08045)	(.08819)	(.2226)	(.09456)	(.1535)	(.3421)
L1.Fossil fuel	.02327	.071	.06291	.00138	-.07014	.1345
	(.04323)	(.06038)	(.08314)	(.06061)	(.09505)	(.2693)
L1.Efficiency-improving	.04037	-.00082	.3782***	-.08224	.064	-.1454
	(.04303)	(.0603)	(.109)	(.05443)	(.09466)	(.287)
Past innovation knowledge						
L1.Renewable	-.00039**	.00012	-.00072	-.6293***	-.2323***	-.2383
	(.00017)	(.00052)	(.00062)	(.03314)	(.08897)	(.1725)
L1.Base load	-.00098***	-.00071***	.00036	-.03261	-.9332***	-.4581
	(.00028)	(.00023)	(.00049)	(.05756)	(.07653)	(.3674)
L1.Peak load	.001***	.00081***	.00018	-.139	-.5253*	-1.434***
	(.00021)	(.00017)	(.00032)	(.0958)	(.3102)	(.2648)
Past innovation spillovers						
L1.Renewable	1.1e-06	-1.3e-05	-4.9e-05	-9.4e-05**	.00015**	-.00024
	(2.0e-05)	(2.2e-05)	(5.3e-05)	(3.7e-05)	(7.7e-05)	(.00016)
L1.Base load	2.4e-05	2.0e-05	5.9e-05	.00011***	.00038***	.00015
	(2.1e-05)	(2.3e-05)	(3.6e-05)	(3.1e-05)	(6.6e-05)	(.00026)
L1.Peak load	-.00014***	-.0001*	-3.4e-05	-2.4e-05	7.7e-05	-.00035
	(5.3e-05)	(5.7e-05)	(9.7e-05)	(.00013)	(.0003)	(.00207)
Macroeconomic indicators						
L1.GDP	-.2284**	-.1731*	-.4857**	.5648	.8201**	-24.85
	(.1015)	(.0953)	(.1963)	(.3449)	(.3744)	(111.1)
L1.GDP per capita	.3592	1.344**	.6504	.7158	.523	23.17
	(.8471)	(.6641)	(1.669)	(1.547)	(2.657)	(110.9)
Pre-sample history	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18064	15544	7028	20736	9250	2601

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C.10: Baseline estimates with specialized and mixed firms.

	Dependent variable: firm-level number of patents					
	Specialized firms			Mixed firms		
	Renewable	Base load	Peak load	Renewable	Base load	Peak load
	(1)	(2)	(3)	(4)	(5)	(6)
Energy prices including taxes						
L1.Coal price	-.802***	-.2684	-3.039*	-.2009	-.3744**	-.5976
	(.3003)	(.3301)	(1.843)	(.1433)	(.1854)	(.364)
L1.Electricity price	-.5917*	.2668	5.37***	.4349**	.3449	-.02659
	(.3043)	(.3646)	(1.938)	(.2196)	(.2579)	(.3743)
Research subsidies						
L1.Renewable	.1288	-.1609	-1.347	.1171	-.01907	.1965
	(.1047)	(.1403)	(.9019)	(.0888)	(.09345)	(.2183)
L1.Fossil fuel	.123**	-.04512	.1831	-.01608	.09057	.06972
	(.0604)	(.08581)	(.5875)	(.05007)	(.06612)	(.08219)
L1.Efficiency-improving	-.01507	.2294**	-.04686	.03205	-.01894	.3669***
	(.07171)	(.1059)	(.8053)	(.04585)	(.06322)	(.1085)
Past innovation knowledge						
L1.Renewable	-.00315**			-.00036*	.00016	-.00076
	(.0014)			(.00021)	(.00052)	(.00062)
L1.Base load		-.04717***		-.00096***	-.00065***	.00036
		(.01288)		(.00028)	(.00023)	(.0005)
L1.Peak load			-.327	.00098***	.00078***	.00018
			(.2278)	(.00021)	(.00018)	(.00031)
Past innovation spillovers						
L1.Renewable	-7.5e-05**	9.7e-05**	-.00038	5.0e-06	-9.1e-06	-5.0e-05
	(3.2e-05)	(5.0e-05)	(.00029)	(2.3e-05)	(2.4e-05)	(5.1e-05)
L1.Base load	.00012**	.00016***	.00026	2.4e-06	1.5e-05	5.6e-05
	(5.0e-05)	(4.7e-05)	(.00017)	(1.9e-05)	(2.5e-05)	(3.5e-05)
L1.Peak load	-.00014	-.00031*	1.5e-05	-.00014**	-.0001*	-2.7e-05
	(9.0e-05)	(.00017)	(.00107)	(5.6e-05)	(6.0e-05)	(9.5e-05)
Macroeconomic indicators						
L1.GDP	.095	.2788	-10.43	-.2037*	-.2012**	-.4989**
	(.1785)	(.7883)	(81.37)	(.1089)	(.09996)	(.1954)
L1.GDP per capita	-1.713	.2664	20.45	.7907	1.316*	.5791
	(1.496)	(2.998)	(86.99)	(.8294)	(.6796)	(1.651)
Pre-sample history	Yes	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21223	7187	891	18094	18007	8891

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C.11: FE Poisson estimates for top five innovating countries excluding hydro, geothermal, and biomass from renewable technologies.

	Dependent variable: firm-level number of patents				
				Fossil fuel	
	Renewable	Fossil fuel	Renewable	Base load	Peak load
	(1)	(2)	(3)	(4)	(5)
Energy prices including taxes					
L1.Coal price	-.525**	-.03552	-.6438***	-.5085**	-.05094
	(.2237)	(.2706)	(.2142)	(.2105)	(.4438)
L1.Electricity price	.2791	.1139	.4469*	.4667	-.6124
	(.2621)	(.3462)	(.2359)	(.3284)	(.5269)
Research subsidies					
L1.Renewable	.1353	.0826	.1429*	.0567	.1857
	(.08524)	(.1266)	(.08516)	(.1024)	(.197)
L1.Fossil fuel	.03507	.04622	.06106	.07373	-.04772
	(.04678)	(.06331)	(.04904)	(.06969)	(.08827)
L1.Efficiency-improving	-.04022	.05854	-.02912	-.01993	.4737***
	(.04234)	(.07206)	(.0424)	(.05729)	(.1115)
Past innovation knowledge					
L1.Renewable	-.00055***	-.00068	-.00047***	6.4e-05	-.00087
	(.00015)	(.00044)	(.00018)	(.00057)	(.00069)
L1.Fossil-fuel	7.6e-08	.00029***			
	(.00018)	(4.3e-05)			
L1.Base load			-.00108***	-.00086**	.00047
			(.00028)	(.00034)	(.00057)
L1.Peak load			.00098***	.00097***	.00018
			(.00021)	(.00025)	(.00035)
Past innovation spillovers					
L1.Renewable	-2.3e-05	-6.0e-05*	-1.3e-05	-5.0e-05	-6.8e-05
	(2.4e-05)	(3.6e-05)	(2.2e-05)	(3.4e-05)	(5.8e-05)
L1.Fossil-fuel	-4.8e-05***	-1.4e-05			
	(1.6e-05)	(1.6e-05)			
L1.Base load			2.7e-07	-1.9e-05	7.1e-05
			(2.6e-05)	(3.8e-05)	(5.7e-05)
L1.Peak load			-.00012**	-1.7e-07	-3.4e-05
			(5.6e-05)	(7.8e-05)	(.0001)
Macroeconomic indicators					
L1.GDP	-.271**	-.07988	-.1046	-.4305***	-.6013**
	(.1292)	(.1968)	(.1409)	(.1445)	(.2375)
L1.GDP per capita	-.3806	.1371	-.3618	-.2393	.6567
	(.9774)	(.9394)	(.9623)	(.851)	(1.768)
Pre-sample history	Yes	Yes	Yes	Yes	Yes
Pre-sample active	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	32134	22914	32124	21167	8393

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C.12: All patents separated between base load and peak load technologies.

	Dependent variable: firm-level number of patents	
	Base load	Peak load
Energy prices including taxes		
L1.Coal price	-.3075*	-.2522
	(.165)	(.1795)
L1.Electricity price	.3366	.1447
	(.2217)	(.1772)
Research subsidies		
L1.Renewable	.0294	.149*
	(.08583)	(.07837)
L1.Fossil fuel	.07615	.03047
	(.05487)	(.03866)
L1.Efficiency-improving	.02353	.09496**
	(.05639)	(.04487)
Past innovation knowledge		
L1.Base load	-.00062**	.00037
	(.00025)	(.00037)
L1.Peak load	.00065***	-.00013
	(.00016)	(.00021)
Past innovation spillovers		
L1.Base load	8.3e-06	5.4e-06
	(2.0e-05)	(1.7e-05)
L1.Peak load	-2.9e-05*	-2.6e-05
	(1.7e-05)	(1.8e-05)
Macroeconomic indicators		
L1.GDP	-.1686	-.2283*
	(.1375)	(.119)
L1.GDP per capita	1.359**	.2075
	(.665)	(.6933)
Pre-sample history	Yes	Yes
Pre-sample active	Yes	Yes
Firm FE	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	27660	40011

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C.13: Baseline estimates without pre-sample patenting activity.

	Dependent variable: firm-level number of patents				
				Fossil fuel	
	Renewable (1)	Fossil fuel (2)	Renewable (3)	Base load (4)	Peak load (5)
Energy prices including taxes					
L1.Coal price	-.3891**	-.344*	-.4584***	-.4162***	-.4352
	(.1825)	(.2087)	(.1675)	(.1539)	(.3699)
L1.Electricity price	.1098	.4099*	.2111	.3791	.00688
	(.2178)	(.2434)	(.1965)	(.2337)	(.4163)
Research subsidies					
L1.Renewable	.1465*	.07793	.1423*	.00574	.1372
	(.07475)	(.1089)	(.07332)	(.08518)	(.1997)
L1.Fossil fuel	.00359	.06335	.01328	.0859*	.05623
	(.03823)	(.05416)	(.03941)	(.05561)	(.08003)
L1.Efficiency-improving	.01639	.05165	.03249	-.00465	.3396***
	(.04148)	(.07135)	(.04022)	(.05517)	(.1128)
Past innovation knowledge					
L1.Renewable	-.00054***	-.00046	-.00047***	3.6e-05	-.00083
	(.00013)	(.00043)	(.00016)	(.00054)	(.0006)
L1.Fossil-fuel	4.4e-05	.00024***			
	(.00017)	(4.4e-05)			
L1.Base load			-.00098***	-.00075***	.0004
			(.00027)	(.00023)	(.0005)
L1.Peak load			.00097***	.00085***	.00011
			(.0002)	(.00016)	(.00031)
Past innovation spillovers					
L1.Renewable	-2.3e-05	-3.6e-05	-1.3e-05	-3.7e-05*	-4.9e-05
	(2.1e-05)	(2.8e-05)	(1.7e-05)	(2.2e-05)	(4.6e-05)
L1.Fossil-fuel	-3.5e-05**	-1.0e-05			
	(1.4e-05)	(1.6e-05)			
L1.Base load			6.3e-06	2.0e-06	6.9e-05
			(2.0e-05)	(2.9e-05)	(5.0e-05)
L1.Peak load			-.00011**	-4.9e-05	-9.2e-05
			(4.8e-05)	(5.8e-05)	(9.5e-05)
Macroeconomic indicators					
L1.GDP	-.1322	-.07117	-.04709	-.00821	-.1083
	(.08913)	(.1212)	(.09775)	(.1007)	(.1636)
L1.GDP per capita	-.03711	.8073	.3347	.6445	.7332
	(.8216)	(.7256)	(.7642)	(.65)	(1.462)
Pre-sample history	No	No	No	No	No
Pre-sample active	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39303	27240	39319	25183	9774

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

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Norges
Handelshøyskole

Norwegian School of Economics

NHH
Helleveien 30
NO-5045 Bergen
Norway

Tlf/Tel: +47 55 95 90 00
Faks/Fax: +47 55 95 91 00
nhh.postmottak@nhh.no
www.nhh.no