# Which Fossil fuel Taxes Promote Innovation in Renewable Electricity Generation?*

Itziar Lazkano† Linh Pham‡

**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 1963 to 2011, we find that the impact of fossil fuel taxes on renewable energy innovation varies with the type of fossil fuel. Specifically, a 10% increase in the coal price reduces innovation in renewable energy technologies by 3.6% while a higher natural gas price has no statistically significant impact on renewable energy innovation. The reason is that easily dispatchable energy sources (e.g., coal-fired power) need to complement renewable energy technologies (e.g., wind or solar) 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. 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. alone, 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 a 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 effort 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 1963 to 2011. Past work has focused on the aggregate impact of all energy prices on 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 and different fossil fuel technology innovation.

The directed technological change (DTC) framework of 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). While this may be true for aggregate measures of fossil fuel technologies, the substitution between different fossil fuel and renewable technologies in electricity generation varies with time and location. To capture this heterogeneity of the electricity market, we disaggregate both fossil fuel prices and technologies between coal, natural gas, and oil instead of employing an aggregate measure for fossil fuel technologies that summarizes them into one composite index.

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 an 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 cen-

as long as wind and solar energy cannot be efficiently stored for later use, they cannot replace fossil fuels 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 1963 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 3.6% 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

tury. Unfortunately, large hydroelectric plants are concentrated geographically and hydroelectric capacity 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. (2017) for an analysis of the role of electricity storage in the transition from fossil fuels to renewable sources in electricity generation.

play a significant role in shifting the direction of innovation in the electricity sector. Our 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 differs from these two 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 renewable, base- and peak-load fossil fuel 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. 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 varies considerably across the most innovative

[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.

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 heterogeneity 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. Overall, there are many sources used to generate

[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.

electricity with these technologies, however, their uses depend on regional electricity markets. Coal and nuclear power have been historically used to produce base-load electricity. Natural gas used to meet peak electricity load but since a new supply of natural gas from shale formations is available, it is now used in both base and peak-load electricity. Hydroelectric sources are used for both base-load and peak-load electricity in areas with abundant hydropower capacity. Other renewable resources such as wind and solar energy can potentially meet base-load electricity demand since once they are installed, the marginal cost of using them is zero. 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%). Non-hydro renewable resources 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.

| | | **Sources of electricity production (%)** | | | | | |
|---|---|---|---|---|---|---|---|
| **Region** | **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 has three implications. First, renewable energy technologies are imperfect substitutes for fossil fuel-burning technologies. Second, as of today, renewable energy is 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 distinctive features of the electricity sector are well understood, previous work that studies innovation incentives has been based on the underlying assumption that renewables and fossil fuels are substitutes. Indeed, the empirical literature has aggregated all fossil fuel prices into one composite price index and all fossil fuel technologies into one category. Thus, previous work has concluded that higher energy prices and taxes promote innovation in renewable technologies. While the assumption of a high elasticity of substitution between fossil fuels and renewable energy is appropriate for other sectors,[10] it 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 elasticity of substitution is sufficiently

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

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, and 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., 2015). Altogether, our data set spans 49 years (1963-2011) 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] We also account for the number of times a patent is cited to control for differences in the quality of patents.

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 In-

[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). In addition, we tackle the truncation due to the lag between application and granting following Hall et al. (2005). 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.

tellectual Property Office's (WIPO) IPC Green Inventory[14], while fossil fuel technologies are selected from the IPC codes used by Lanzi et al. (2011). Specifically, renewable energy patents are related to alternative energy production, which includes for example harnessing energy from manufactured waste, wind, solar, and geothermal energy. Fossil fuel technologies combine both general and efficiency-improving technologies. Moreover, we separate fossil fuel technologies into those used to generate base- or peak-load electricity. 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. We are the first at compiling a list of IPC codes to identify base- or peak-load electricity generation.[15] Specific descriptions of the IPC codes used to identify electricity-generating patents are presented in Tables B.3-B.7 in Appendix B.1.

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.[16] 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 innova-

[14]The IPC codes listed in the IPC Green Inventory have been compiled by the IPC Committee of Experts in concordance with the United Nations Framework Convention on Climate Change (UNFCCC). For more information, see http://www.wipo.int/classifications/ipc/en/est/.

[15]This classification presents several challenges because peak-load and base-load are sometimes separated by their flexibility at ramping production and other times the classification is based on their use at generating peak hour electricity generation. Moreover, electricity generation technologies vary considerably with time and location. A final challenge is that many of these technologies are inter connected and they draw on the same core knowledge.

[16]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.

tion 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.

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 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.

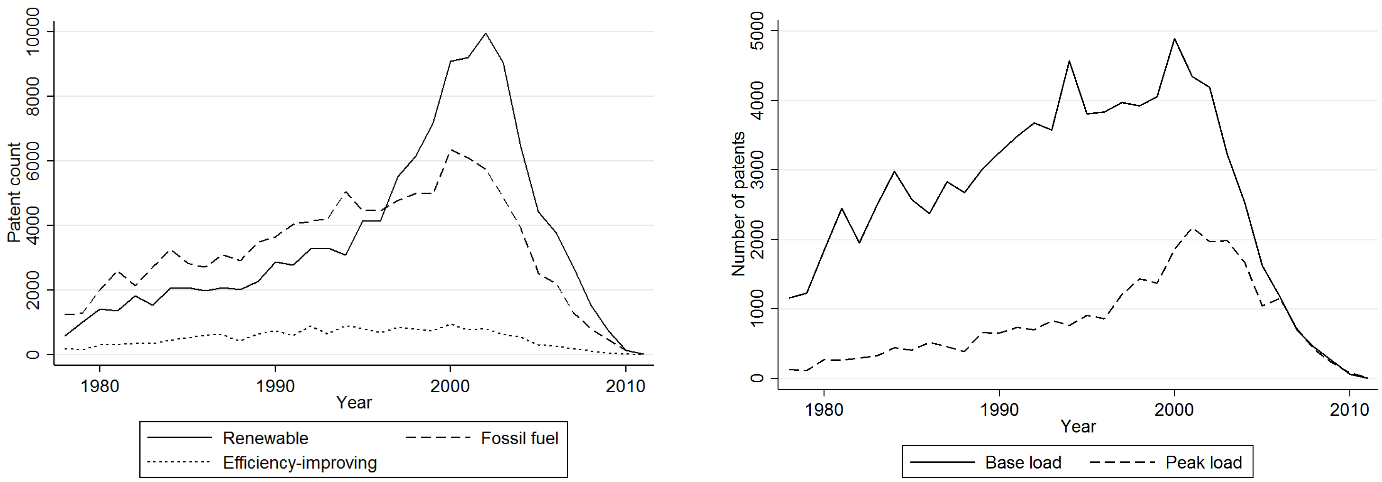
Another feature of our data set is that only some firms exist during the entire sample period. We account for this by including each firm in the data set from the first until the last year they applied for a patent. Thus, only active firms are accounted for in our panel data set.

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 49 years (1963-2011) and 26 countries (International Energy Agency, 2015c). This gives us the total amount of subsidies used 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., 2015). 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 1963 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 base-load and peak-load fossil fuel technologies into one category, but once we separate these two types of technologies, we have 89,425 and 27,121 base- and peak-load technologies, respectively. 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. 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 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




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

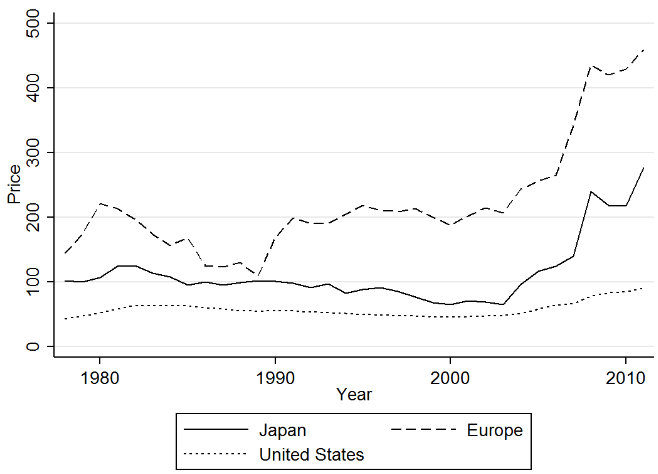
(b) Base- and peak-load fossil fuel patents.

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

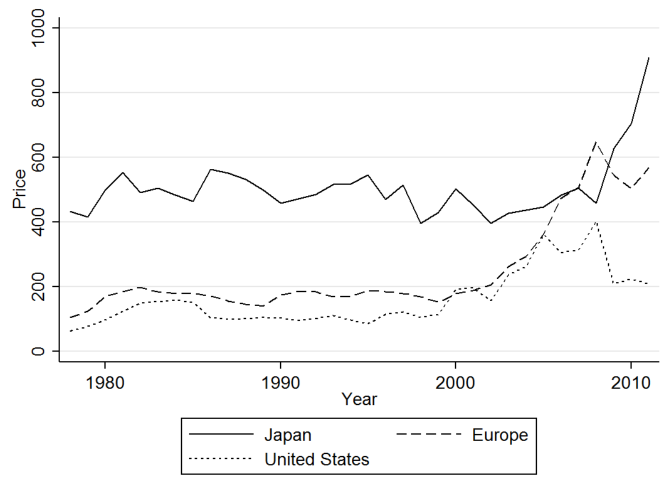
and 2009.[17] The reason for this downward trend is the lag from the application date to the actual granting of the patent at the USPTO which lasts from 18 months to five years (Popp, 2005). We account for this by skipping the last 2 years of the data set to run our estimations and by correcting for the truncation bias in the data.

There is a large heterogeneity among firms. Most of the firms are located in the US, Japan, Germany, France and the UK as see in figure B.1. In terms of specialization, 54.56% of firms exclusively innovate in renewable technologies while 24.69% apply for both renewable and fossil fuel patents. Firms also vary in their age; the average age of the firms in our sample is 3.32 years whereas only 10.35% of them have been active for more than a decade in our sample. We take this heterogeneity of firms into account in our empirical analysis.

[17]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, 1978-2011.

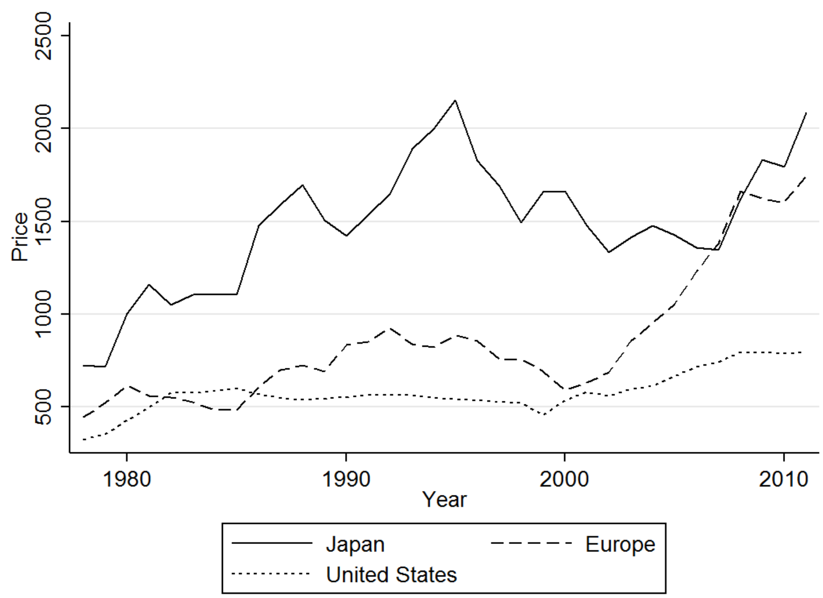



Figure 3: Electricity retail price (USD per MWh) in the most innovative regions, 1978-2011.

Figures 2 and 3 illustrate the evolution of coal, natural gas and electricity prices in the most innovative countries: U.S., Japan, and Europe.[18] 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 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. Table B.9 in the appendix summarizes the cross-correlation of energy prices in the most innovative regions. This table shows that the correlation between different energy prices varies considerable across regions. For example, the correlation between the coal and electricity price is 0.858 in Europe while 0.503 and 0.376 in the US and Japan, respectively. These table and figures illustrate in part some of the relationships between energy prices and innovation that our empirical work identifies in the next sections.

[18]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..

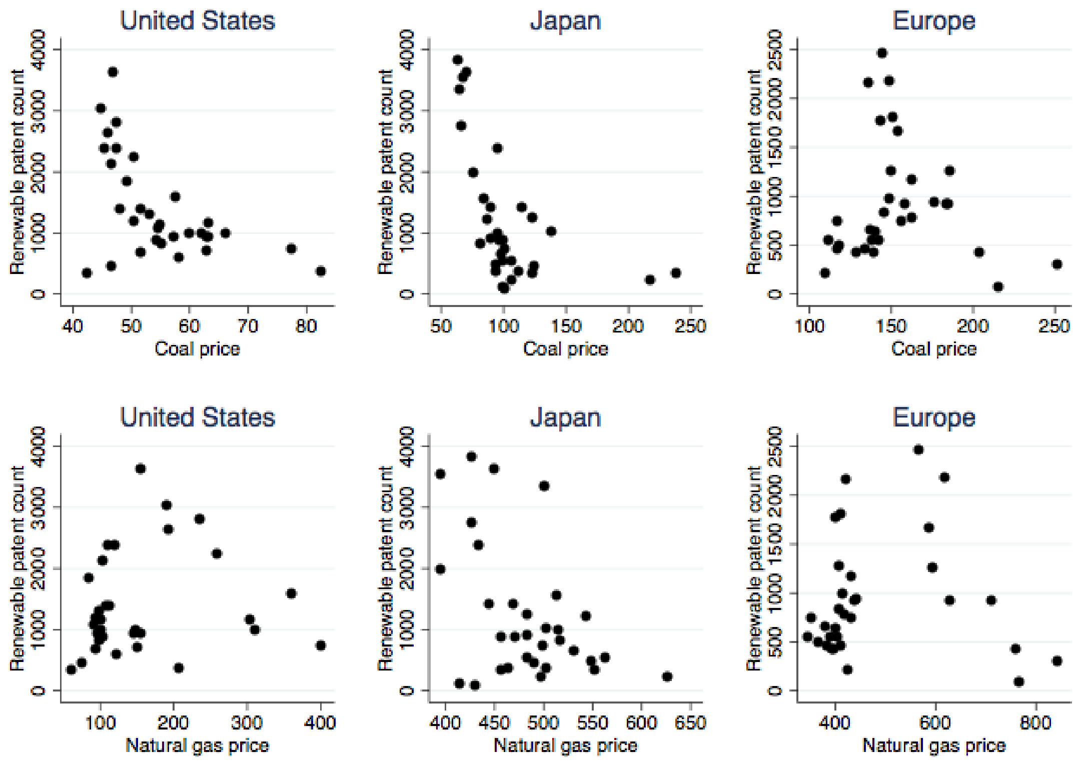



Figure 4: Renewable innovation and energy prices.

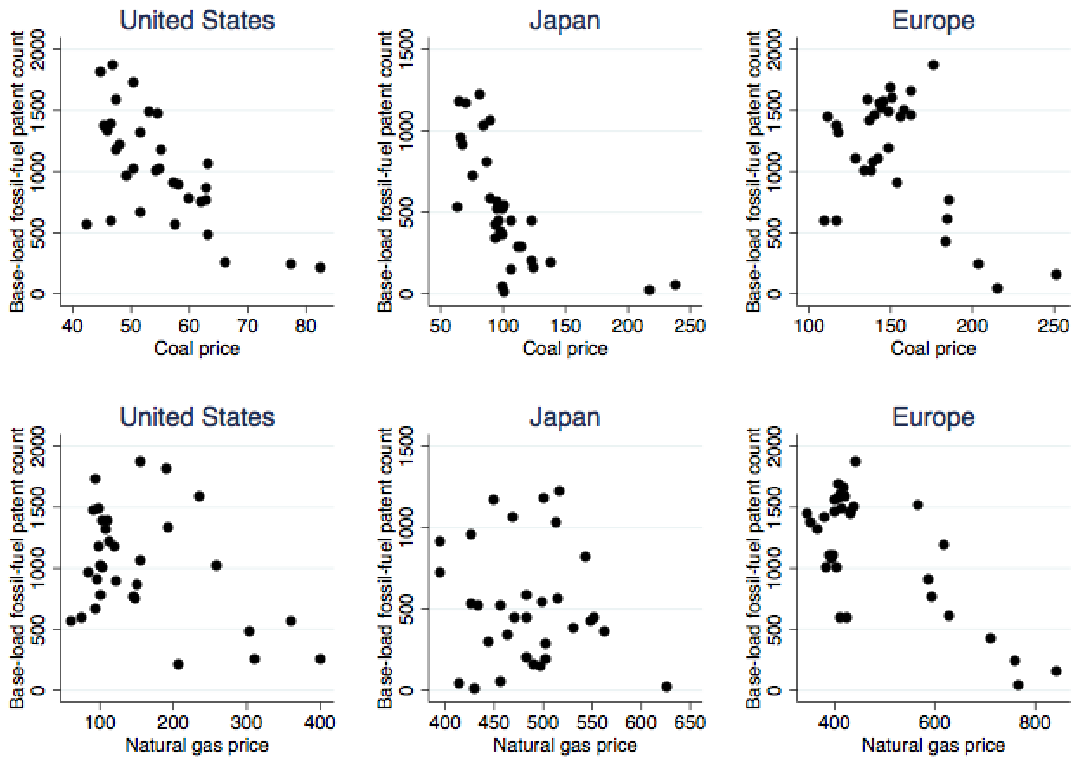



Figure 5: Base-load fossil fuel innovation and energy prices.

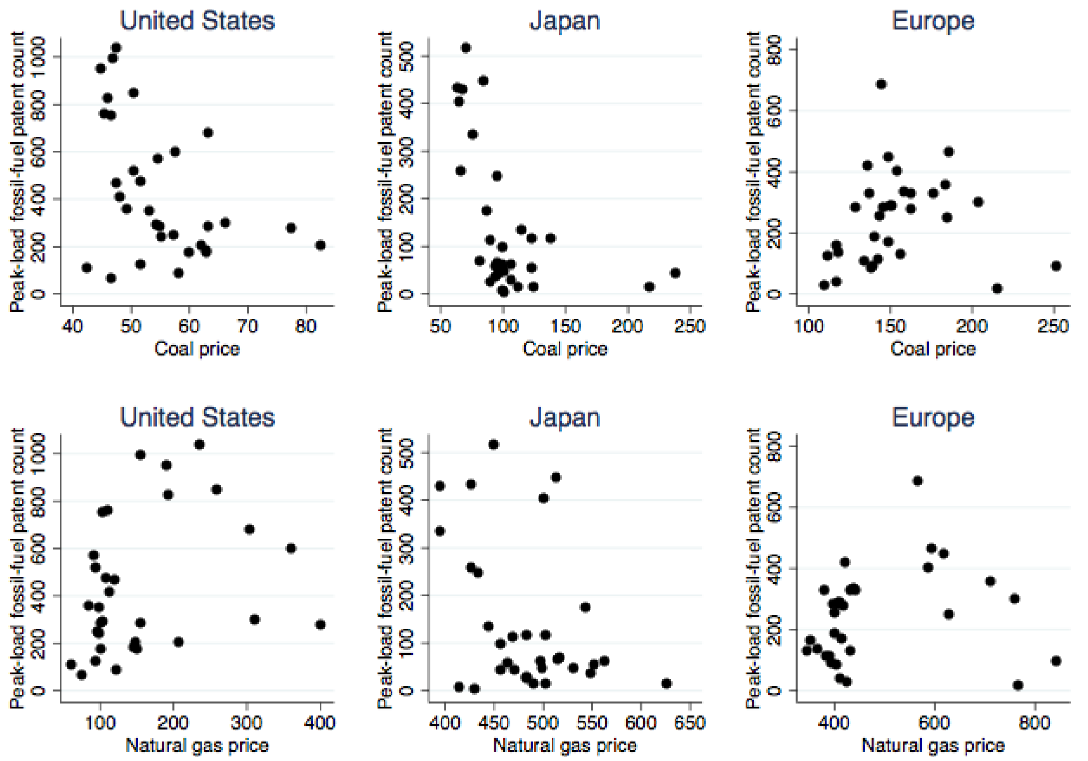



Figure 6: Peak-load fossil fuel innovation and energy prices.

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.

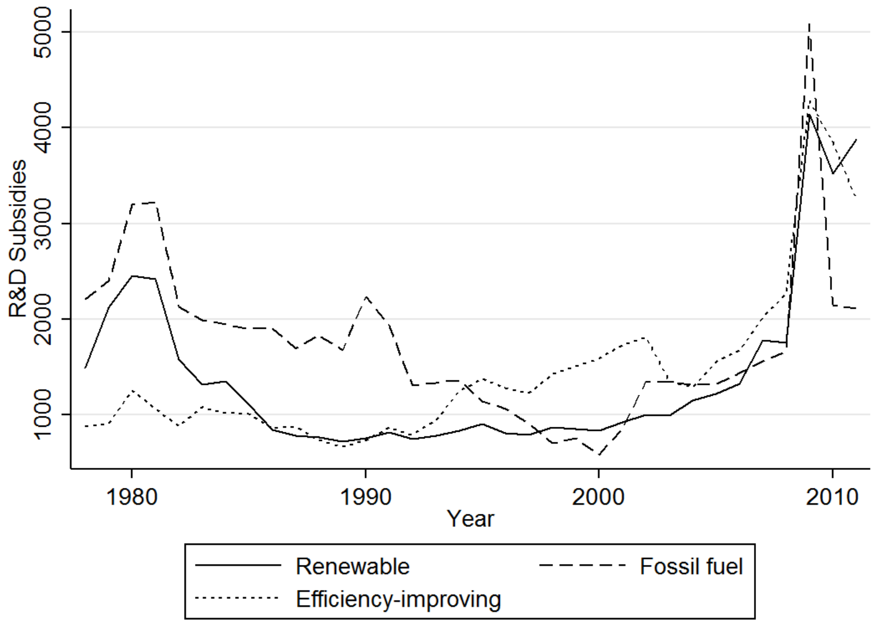



Figure 7: Global RD&D subsidies in million USD in renewable, general fossil fuel and efficiency-improving technologies, 1978-2011.

## 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 year 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 a parameter vector $\boldsymbol{\beta}$. 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:

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

where $j$ denotes the type of technology, while $i$, $n$ and $t$ represent firm, country and year. Technology type $j$ is renewable ($r$), base-load ($b$) or 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 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 into account the prices of both inputs and outputs in the electricity sector. Specifically, in our baseline estimations we use coal as a proxy for input prices in electricity generation and electricity prices to proxy for output prices. We use alternative measures such as natural gas and oil in our robustness analysis as well as addressing the potential endogeneity between coal and electricity prices. 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.

Another main determinant of innovation is given by 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.

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 potential issue to consider with a Poisson regression specification is unobserved heterogeneity. We account for the wide heterogeneity in firms' innovation success rate into consideration by controlling for firm-level patenting activity 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 ($Z_i$) for each firm. In addition, we use a dummy variable ($ID_i$) that equals 1 if the firm innovated in the pre-sample period (1963-1977).[19]

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.[20]

[19] In addition, we estimate our baseline specification with alternative definitions of patenting activity in the sampling period. In particular, we consider technology-specific patenting activity, 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.

[20] 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.

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 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).[21] 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 2-4. Standard errors in all estimations are clustered at the firm level for each technology.

Our baseline estimation in Table 2 includes firm and time fixed effects since our global data set contains a large number of countries and we are unable to control for country and

[21] One could argue that in our dynamic model with lagged dependent variables, the strict exogeneity of regressors is a strong assumption. If regressors are only weakly exogenous, which implies that future shocks are uncorrelated with current regressors, we can consider predetermined regressors that are correlated with past shocks, while still being uncorrelated with current and future shocks. In this case, the Poisson fixed effects estimator is inconsistent. A solution could be to use GMM estimation by eliminating fixed effects with a transformation. However, Blundell et al. (1995) show that the precision of this estimator is poor when the transformed regressors are persistent, which is the case with patent data. We therefore use an Poisson FE estimator that controls for pre-sample history of research firms instead of using a GMM regressor.

country-time fixed effects. In Table 3, however, we focus our attention to the five most innovative countries and we are able to control for country and country-times fixed effects in addition to time and firm fixed effects. As Table 3 shows, estimation results are robust to different fixed effects specifications and therefore, we are confident that our results in Table 2 using a global data set are robust. Finally, we use coal prices as a proxy for input prices in the electricity sector for our baseline estimation Table 2. In contrast, Table 4 uses alternative fossil fuel prices to proxy for the input price and analyzes the potential endogeneity between coal and electricity prices to understand the how energy prices affect innovation. Overall, these tables show that our main results are robust. In addition, we present multiple robustness checks in Section 6 to validate our results.

Overall, our estimation results show that energy prices, R&D subsidies, and past innovation significantly influence innovation in the electricity sector. Specifically, we find that a 10% increase in coal prices leads to a 3.6% decrease in the probability of applying for a renewable patent and a 4.1% decrease in the probability of applying for a base load fossil fuel patent. In contrast, we find that an increase in the price of natural gas does not significantly affect the probability to apply for a new patent in any technology type. Therefore, policies targeting coal prices can potentially direct innovation away from renewable energy. Next we discuss in detail the relationship between energy prices and innovation in the electricity sector.

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

The main estimation results in Tables 2-4 show that energy prices and taxes have a significant impact on firm-level innovation. Specifically, at the global level, a 10% increase in coal prices leads to a 3.6% decrease in the probability of applying for a renewable patent (Table 2). Similarly, in the five most innovative countries, a 10% increase in coal prices leads to a 3.1% decrease in the probability of applying for a renewable patent at the 12% significance level and controlling for firm, country, time and time-year fixed effects (Table 3).

This may sound counterintuitive at first and perhaps in contrast to the conclusion in previous empirical work that higher fossil fuel prices promote innovation in renewable technologies. Note, however, that this finding is in line with the theoretical predictions of the directed technological change literature that shows a negative effect of fossil fuel prices on renewables when renewable and fossil fuel technologies are complements. In the electricity sector, intermittent renewable sources are unable to supply electricity constantly and they rely on easily dispatchable fossil fuels like coal-fired plants to meet the electricity demand.[22] 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).[23] Thus, it is 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.[24]

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.

Table 4 further explores the relationship between coal and natural gas prices and innovation in renewable patents while Tables C.2 and C.3 present base- and peak-load fossil fuel patents. Specifically, we analyze: (1) Coal and electricity prices, (2) Coal prices only, (3) Natural gas prices and electricity prices, (4) Natural gas prices only, (5) Oil prices and electricity prices, (6) Coal and natural gas prices, (7) Coal and squared term of coal prices, (8) Gap between electricity and coal prices, and (9) Gap between electricity and natural gas prices.[25] These tables show that the impact of energy prices on innovation is robust

[22]Renewable technologies, such as wind and solar, cannot be used at all times to generate electricity because of the lack of well-developed large-scale energy storage to address the intermittency of renewable resources. Without the deployment of large-scale storage solutions, renewable energy such as the wind and sun cannot fully replace coal in base-load electricity generation.

[23]The role of natural gas in electricity generation has changed over the last several years due to its price change in response to the extraction of shale gas. The existence of cheaper natural gas has also led to a shift in the competition among fossil fuels to generate electricity. We control for these changes using country-time fixed effects.

[24]This finding is in line with the fact that coal is typically used in base-load electricity production, rather than in peak-load electricity generation.

[25]We omit electricity prices in specifications (2) and (4) to address a potential endogeneity issue as electricity output prices are affected by the prices of inputs such as coal or natural gas.

to alternative specifications of energy 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 theoretical prediction of the relationship between renewable and fossil fuel technologies when their elasticity of substitution is smaller than one (Acemoglu et al., 2012). In contrast, increasing natural gas prices is associated with a negative but statistically insignificant impact on innovation (columns (3)-(4) and (6) in Table 4). This insignificant impact of natural gas price on innovation can be due to the diverse role of natural gas in the electricity sector, and moreover, globally, coal still accounts for the largest share of electricity production (Table 1). In addition, 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). Finally, a larger gap between output and input prices has a positive but no statistically significant impact on innovation (columns (8) and (9) in Table 4).

In addition to input prices, firm-level innovation also depends on electricity prices; however, we only find a significant impact of electricity prices on fossil fuel innovation. Column (4) of Table 2 suggests that a 10% increase in electricity prices increases the probability of applying for a patent in fossil fuel by 5%. 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 5% 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 insignificant. These effects are not surprising because coal, which is used in base-load electricity generation, contributes 41.1% of global electricity generation (International Energy Agency, 2015b). Using data on the most innovative countries, we find that higher electricity prices promote the application of new patents in both base- and peak-load fossil fuel technologies (Table 3).

To summarize, we find evidence that increasing coal prices discourages innovation not only in base-load fossil-fuel electricity generation technologies, but also in renewable 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. Taxing natural gas, however, does not significantly affect innovation in renewable and peak-load technologies. Finally, more expensive electricity prices promote innovation in base- and peak-load fossil fuel 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 in research subsidies towards those technologies. In particular, a 10% increase in renewable research subsidies increases the number of patents in renewable energy by 1.5% (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 0.9%, while a 10% increase in subsidies for efficiency-improving fossil fuel technologies increases the number of peak-load fossil fuel patents by 3.2%. The results are robust to alternative specifications of energy prices (Tables 4 and C.1-C.3).

In Table C.4, we classify all fossil fuel technologies into general fossil fuel and efficiency-improving technologies.[26] After we separate these technologies, we find that general fossil fuel research subsidies promote the development of efficiency-improving technologies. Specifically, a 10% increase in general fossil fuel research subsidies increases the number of efficiency improving patents by 1.02%. 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

[26]Ideally, we would like to classify fossil-fuel technologies into general fossil fuel and efficiency-improving technologies for base-load and peak-load technologies separately. However, doing so would yield a small number of observations for each category, which makes it difficult for our Poisson fixed effect model to converge.

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 C.4 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 to support fossil-fuel research is larger than that of renewable-energy research. 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 not easily substitutable 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 patents 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. 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.[27] We find that a firm located in a region with a larger stock of fossil fuel inno-

[27] In our baseline results, we calculate regional knowledge spillovers using the World Bank income classifi-

vations by other firms is less likely to apply for a renewable patent (Column (1) of table 2). Moreover, the negative impact of base-load fossil-fuel knowledge spillovers on renewable innovation is smaller and less significant than that of peak-load fossil-fuel knowledge spillovers (Column (3) of Table 2). This is in line with the heterogeneous relationships among different electricity generating technologies, as discussed in section 2

Note that in most cases, the coefficients on the spillover variables are not statistically significant, 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.[28] We will discuss the details of these robustness analyses in section 6.

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 base load technology in the most innovative countries. When we classify fossil fuel technologies into general fossil fuel patents and efficiency-improving technologies (Table C.4), our results show that a 1% increase in GDP decreases a firm's incentive to conduct efficiency-improving fossil-fuel research by 1.449%.

cation 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.

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

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 | -.322* | -.2975† | -.3657** | -.4104*** | -.4374 |
| | (.1786) | (.1948) | (.1644) | (.1515) | (.3451) |
| L1.Electricity price | .2311 | .4347* | .2177 | .5045** | .1856 |
| | (.2235) | (.2309) | (.2) | (.204) | (.3666) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1621** | .09869 | .1518** | .0478 | .1973 |
| | (.07221) | (.1041) | (.07295) | (.08212) | (.1861) |
| L1.Fossil fuel | -.0039 | .07875 | -.0086 | .09121† | .04258 |
| | (.03891) | (.05728) | (.04105) | (.0597) | (.08147) |
| L1.Efficiency-improving | -.00501 | .05636 | .00296 | .00055 | .3279*** |
| | (.04012) | (.07027) | (.03932) | (.05699) | (.1082) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00055*** | -.00048 | -.00049*** | -1.3e-05 | -.00079 |
| | (.00013) | (.00042) | (.00016) | (.00052) | (.00059) |
| L1.Fossil fuel | 4.6e-05 | .00025*** | | | |
| | (.00017) | (4.5e-05) | | | |
| L1.Baseload | | | -.00101*** | -.00065*** | .00043 |
| | | | (.00026) | (.00022) | (.00047) |
| L1.Peakload | | | .001*** | .00076*** | .00012 |
| | | | (.0002) | (.00017) | (.0003) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -3.0e-05† | -4.0e-05† | -3.0e-05† | -2.6e-05 | -5.6e-05 |
| | (2.1e-05) | (2.5e-05) | (1.9e-05) | (2.5e-05) | (4.7e-05) |
| L1.Fossil fuel | -4.0e-05*** | -4.6e-06 | | | |
| | (1.5e-05) | (1.7e-05) | | | |
| L1.Baseload | | | -1.2e-05 | 1.6e-05 | 4.8e-05 |
| | | | (1.9e-05) | (2.8e-05) | (4.6e-05) |
| L1.Peakload | | | -8.6e-05* | -7.5e-05 | -3.3e-05 |
| | | | (4.5e-05) | (5.5e-05) | (8.9e-05) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.02804 | -.00925 | -.00867 | -.06246 | -.1219 |
| | (.09642) | (.1121) | (.09543) | (.1198) | (.1645) |
| L1.GDP per capita | -.6718 | .3993 | -.2137 | .9325 | -.1283 |
| | (.7155) | (.6116) | (.6695) | (.7057) | (1.354) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Year dummy | Yes | Yes | Yes | Yes | Yes |
| Observations | 39314 | 27236 | 39314 | 25179 | 9772 |

Significance levels: ***: 1% **: 5% *: 10% †: 15%

Numbers in parentheses are standard errors.

Table 3: Fixed-effect specification using data on the most innovative countries, i.e. France, Germany, Japan, UK, and US.

| | **Dependent variable: firm-level number of patents** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Renewable | | | Fossil fuel base load | | | Fossil fuel peak load | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Energy prices including taxes* | | | | | | | | | |
| L1.Coal price | -.5219$^{**}$ | -.5377$^{***}$ | -.3153$^{\dagger}$ | -.4405$^{**}$ | -.4179$^{**}$ | -.05761$^{\dagger}$ | .1044 | .1105 | 1.315$^{*}$ |
| | (.2039) | (.2056) | (.2225) | (.1936) | (.1957) | (.4657) | (.4184) | (.4248) | (.7145) |
| L1.Electricity price | .3433$^{\dagger}$ | .3444$^{\dagger}$ | .4078 | .772$^{***}$ | .7651$^{***}$ | 2.131$^{***}$ | -.4095 | -.4086 | 2.203$^{***}$ |
| | (.2376) | (.2392) | (.3066) | (.28) | (.2829) | (.4594) | (.4179) | (.4229) | (.5319) |
| *Research subsidies* | | | | | | | | | |
| L1.Renewable | .143$^{*}$ | .1382$^{*}$ | .08968 | .05976 | .05118 | .06013 | .1808 | .1806 | -.5073 |
| | (.08224) | (.08299) | (.164) | (.09762) | (.0982) | (.2474) | (.1976) | (.1958) | (.4368) |
| L1.Fossil fuel | .02052 | .0238 | -.1242 | .1394$^{**}$ | .135$^{**}$ | .3472$^{***}$ | -.06422 | -.06346 | .253$^{**}$ |
| | (.04842) | (.04901) | (.09679) | (.0686) | (.06872) | (.1189) | (.08444) | (.08563) | (.1222) |
| L1.Efficiency-improving | -.022 | -.02137 | .0367 | -.00207 | -.00725 | .2119 | .4363$^{***}$ | .4301$^{***}$ | .8849$^{***}$ |
| | (.04166) | (.04138) | (.1066) | (.05982) | (.05957) | (.2101) | (.106) | (.1062) | (.2588) |
| *Past innovation knowledge* | | | | | | | | | |
| L1.Renewable | -.00046$^{**}$ | -.00046$^{**}$ | -.00046$^{**}$ | 1.7e-05 | 2.7e-05 | 2.6e-05 | -.00082 | -.00082 | -.00101 |
| | (.00018) | (.00018) | (.00019) | (.00052) | (.00053) | (.00049) | (.00066) | (.00066) | (.00085) |
| L1.Fossil fuel base load | -.00106$^{***}$ | -.00105$^{***}$ | -.001$^{***}$ | -.00066$^{**}$ | -.00068$^{**}$ | -.00076$^{**}$ | .00051 | .00051 | .00094 |
| | (.00028) | (.00028) | (.00033) | (.00028) | (.00029) | (.00032) | (.00056) | (.00056) | (.00067) |
| L1.Fossil fuel peak load | .00102$^{***}$ | .00102$^{***}$ | .00107$^{***}$ | .00073$^{***}$ | .00076$^{***}$ | .001$^{***}$ | .00016 | .00016 | .0003 |
| | (.0002) | (.00021) | (.00024) | (.00022) | (.00023) | (.00039) | (.00036) | (.00035) | (.00101) |
| *Past innovation spillovers* | | | | | | | | | |
| L1.Renewable | -2.8e-05 | -2.8e-05 | 6.0e-06 | -1.7e-05 | -2.3e-05 | -1.7e-07 | -9.2e-05$^{\dagger}$ | -9.4e-05$^{\dagger}$ | -.00019 |
| | (2.3e-05) | (2.3e-05) | (3.6e-05) | (4.0e-05) | (4.0e-05) | (.00013) | (5.9e-05) | (6.0e-05) | (.00046) |
| L1.Fossil fuel base load | -1.4e-05 | -1.5e-05 | 6.0e-06 | 4.8e-05 | 4.0e-05 | -8.7e-06 | 4.1e-05 | 3.8e-05 | 2.0e-05 |
| | (2.4e-05) | (2.4e-05) | (2.9e-05) | (3.8e-05) | (3.8e-05) | (.0001) | (5.3e-05) | (5.5e-05) | (.00025) |
| L1.Fossil fuel peak load | -9.0e-05$^{*}$ | -8.8e-05$^{*}$ | 2.4e-05 | -.00013$^{*}$ | -.00012$^{*}$ | .00012 | 8.3e-06 | 1.2e-05 | .00054 |
| | (5.0e-05) | (5.1e-05) | (9.3e-05) | (7.5e-05) | (7.4e-05) | (.00031) | (9.6e-05) | (9.8e-05) | (.00095) |
| *Macroeconomic indicators* | | | | | | | | | |
| L1.GDP | -.1451 | -.1481 | -.0395 | -.2323$^{\dagger}$ | -.2172 | -.4398$^{*}$ | -.2553 | -.2446 | .1869 |
| | (.1206) | (.1211) | (.1278) | (.1603) | (.159) | (.2462) | (.2379) | (.255) | (.337) |
| L1.GDP per capita | -.08693 | -.13 | -.237 | 1.319 | .9728 | -.6575 | .1984 | .1188 | -2.342 |
| | (.8297) | (.8384) | (.9131) | (1.004) | (.9676) | (1.503) | (1.797) | (1.898) | (3.182) |
| 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 |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country dummy | N | Yes | Yes | N | Yes | Yes | N | Yes | Yes |
| Country×Year dummy | N | N | Yes | N | N | Yes | N | N | Yes |
| Observations | 33646 | 33646 | 33646 | 21366 | 21366 | 21366 | 8508 | 8508 | 8508 |

Significance levels: $^{***}$: 1% $^{**}$: 5% $^{*}$: 10%

Numbers in parentheses are standard errors.

Table 4: Fixed-effect Poisson estimates of fossil fuel price effect in renewable technologies using global data.

| | Dependent variable: firm-level number of patents | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Renewable | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Energy prices including taxes* | | | | | | | | | |
| L1.Coal price | -.3657$^{**}$ | -.3059$^{*}$ | | | | -.2982$^{\dagger}$ | -.6812 | | |
| | (.1644) | (.1843) | | | | (.1842) | (.5229) | | |
| L1.Electricity price | .2177 | | .1562 | | .05637 | | | | |
| | (.2) | | (.2374) | | (.2491) | | | | |
| L1.Natural gas price | | | -.1774 | -.1185 | | -.02835 | | | |
| | | | (.1292) | (.136) | | (.1325) | | | |
| L1.Oil price | | | | | .03255 | | | | |
| | | | | | (.1943) | | | | |
| L1.Coal price squared | | | | | | | .7519 | | |
| | | | | | | | (1.081) | | |
| L1.Diff. electricity coal price | | | | | | | | .1106 | |
| | | | | | | | | (.1758) | |
| L1.Diff. electricity nat gas price | | | | | | | | | .1306 |
| | | | | | | | | | (.1639) |
| 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 |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 39314 | 39314 | 39314 | 39314 | 39314 | 39314 | 39314 | 39314 | 38381 |

Significance levels: $^{***}$: 1% $^{**}$: 5% $^{*}$: 10% $^{\dagger}$: 15%

Numbers in parentheses are standard errors.

*Note*: Full table presented in Table C.1.

## 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, and sample selection issues, such as quality of patents, the selection of 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.5 presents zero-inflated Poisson estimation results for the baseline specification in equation (3). 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.[29] These results confirm our main findings.[30]

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. We reduce the over-dispersion problem in our data as we control for entry and exit of firms in the market; therefore, our baseline estimates use a Poisson fixed effects estimator. However, one might argue that firms in our unbalanced

[29] 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.

[30] The zero-inflated Poisson estimator is not an ideal estimator in our analysis because the same variables have been used to explain both the extensive and intensive margins.

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 2011. The fully balanced panel data exhibits an over-dispersion problem; therefore, we use a negative binomial specification. Poisson estimates are used as a starting point for the negative binomial estimation. Table C.6 shows that our main results are robust to a negative binomial specification.[31]

In addition to considering alternative estimators, we address the truncation bias that arises because of the lag between the time of patent application and the time a patent is granted. This is a relevant issue in our data due to the lag in the USPTO as seen in figures 1a-1b. Following Hall et al. (2005), we correct for the truncation bias in three steps. We first calculate the application-grant distribution of patents. From this, we obtain the share of patents granted after each lag, and finally, we use these weights to scale up the number of patent applications during the last years of our data set. Specifically, each year a patent application is scaled up as: $\hat{P}_t = \frac{P_t}{\sum_{s=0}^{2011-t} w_s}, \quad 2004 < t < 2011$, where $\hat{P}_t$ is adjusted patent count, $P_t$ is the number of patent applications in year $t$ and $w_s$ are the weights calculated in the second step. Table C.7 shows that our main results are robust to the truncation bias in our data.

Another common issue with patent data relates to the quality of patents. Popp (2002) finds that not controlling for patent quality underestimates the relationship between energy prices and patent applications. Our baseline estimates use data on Triadic patents, which we expect to represent high quality patents since they are applied for in the three main patent offices. Even though this is a sign of high innovation quality, it does not directly control for the vast heterogeneity in triadic patents. We tackle this issue using patent citation data.[32] Following Hall et al. (2005), we calculate citation-adjusted knowledge stocks: $\text{Knowledge stock}_t = \frac{\text{Citations}_t}{\text{Patents}_t}$, where citations are calculated in two steps. First, using past citation stocks we calculate the total citation stocks per year and patent application, and then, we correct for the truncation problem using the distribution of citation lags in years. Table C.8 shows that our main results are robust to using citation data.

Next, we choose alternative variables to represent past innovations and macroeconomic

[31]Note that the negative binomial estimator is not able to handle fixed effects, which are crucial in our global analysis. For this reason, we consider a fixed-effects Poisson estimator a better choice for our main estimations.

[32]Citation data are only available for the EPO and USPTO and therefore we have incomplete citation data for our sample. Note, however, that summary statistics provide no evidence that citation data is missing for any specific technology, firm or country.

indicators. First, we analyze past innovation in more detail. One might 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.9 and C.10. 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 five 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. Overall, Table C.11 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.12 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.

In addition to considering different specifications of our main equation, we categorize our data into sub-groups to identify whether different types of firms behave systematically differently. First, we analyze the the choice of firms. Our data contain a diverse set of 13,054 firms. We separate these firms into large and small research firms in Table C.13. 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.13, and we exclude them from the Appendix. Finally, we categorize firms as specialized or mixed firms in Table C.14. 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.14 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.

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.[33] Columns (3)-(5) of Table C.4 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.

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.15. 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.16, 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 rely on 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. Table 5 provides a summary of our findings. Our results suggest heterogeneity in the responses of innovation to changes in energy prices in the electricity sector. Specifically, because renewable energies like the sun or wind rely on 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. Finally, our results also show that to effectively promote innovation in renewable energy, a combination of tax and research subsidy policies is desirable.

[33] 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.

Table 5: Summary of the determinants of innovation in the electricity sector.

| Determinants | Empirical evidence | Explanations and implications |
|---|---|---|
| Energy prices | Increasing coal prices negatively affects the development of both renewable and fossil-fuel base-load technologies. The impact of natural gas price on innovation is negative but insignificant. | Renewable energies are imperfect substitutes for fossil fuels in electricity generation. The substitution relationship between renewable technologies and various types of fossil fuel technologies is heterogeneous. |
| Research subsidies | Research subsidies have a positive impact on innovation. | 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. |
| Past innovation | A larger knowledge stock of fossil-fuel technologies increases the likelihood of current fossil-fuel innovation while a larger knowledge stock of renewable technologies negatively impacts the development of new renewable technologies. | Unlike fossil fuels, many renewable energies supply electricity intermittently and storage technologies for renewable energies are still at their early stage of development. Thus, the lack if cheap, large-scale storage solutions may hinder further innovation in renewable technologies. |

# 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 heterogeneity 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. Specifically, we find that a 10% increase in the price of coal decreases the probability of applying for a renewable patent by 3.6%. This implies that until we are able to replace the use of coal from base-load electricity generation, renewable energy sources rely on coal-fired plants 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. Last but not least, 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 $i$. $\beta$ is the elasticity of substitution between electricity and the consumption good while $\sigma$ 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 $A_{i,j} = (1 + x_{i,j})A_{i,j}^0$, where $A_{i,j}$ measures generator $i$'s advancement in technology $j$ and $A_{i,j}^0$ 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.[34]

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 $\pi_i^R$ 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 $\epsilon$ is the ease of substitution between renewables and nonrenewables.[35] 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 $(\tau_j)$ affect firms by reducing the cost of innovation.[36]

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.

[34] 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.

[35] 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.

[36] 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 $\tau_j$ 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 ($\epsilon$), as well as the ease at which consumers can substitute between electricity and the consumption good ($\beta$) and between electricity supplied by different producers ($\sigma$).

# 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 |
| | Number of citations | OECD Citation 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.

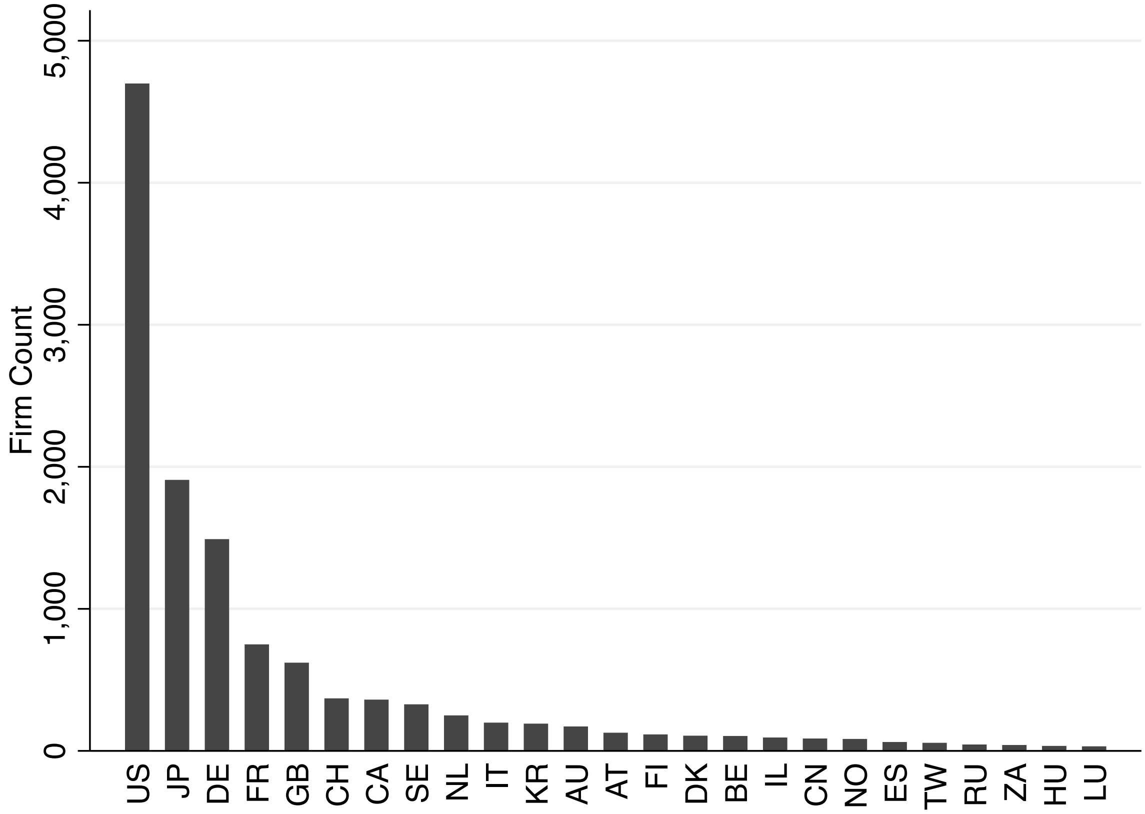


Figure B.1: Innovating firms by country.

## 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* |

Table B.9: Cross-correlation table of energy prices in the most innovative regions.

**United States**

| | Coal price | Natural gas price | Oil price | Electricity price |
|---|---|---|---|---|
| Coal price | 1.000 | | | |
| Natural gas price | 0.503 | 1.000 | | |
| Oil price | 0.766 | 0.867 | 1.000 | |
| Electricity price | 0.769 | 0.779 | 0.775 | 1.000 |

**Europe**

| | Coal price | Natural gas price | Oil price | Electricity price |
|---|---|---|---|---|
| Coal price | 1.000 | | | |
| Natural gas price | 0.858 | 1.000 | | |
| Oil price | 0.902 | 0.921 | 1.000 | |
| Electricity price | 0.961 | 0.913 | 0.902 | 1.000 |

**Japan**

| | Coal price | Natural gas price | Oil price | Electricity price |
|---|---|---|---|---|
| Coal price | 1.000 | | | |
| Natural gas price | 0.376 | 1.000 | | |
| Oil price | 0.858 | 0.206 | 1.000 | |
| Electricity price | -0.014 | 0.386 | 0.164 | 1.000 |

# C Robustness analysis

This section presents the detailed estimation results of the robustness analysis discussed in section 6. Specifically, tables C.1-C.3 show alternative energy price specifications in renewable, base- and peak-load technologies while table C.4 separates fossil fuel technologies between general and efficiency-improving technologies. Tables C.5 and C.6 show the zero-inflated Poisson and negative binomial estimates. In table C.7 we correct for the patent truncation bias whereas table C.8 includes patent citations. Tables C.9 and C.10 consider alternative lag structures of past innovation and table C.11 presents the estimation results using the five geographical regions as an alternative definition of regional spillovers. Table C.12 controls for additional macroeconomic indicators while Table C.13 separates firms between large and small firms while table C.14 separates them between specialized and mixed firms. Finally, tables C.15 and C.16 looks at different definitions of base load and peak load technologies.

Table C.1: Alternative energy price specifications in renewables.

| | Dependent variable: firm-level number of renewable patents | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Energy prices including taxes* | | | | | | | | | |
| L1.Coal price | -.3657$^{**}$ | -.3059$^{*}$ | | | | -.2982$^{\dagger}$ | -.6812 | | |
| | (.1644) | (.1843) | | | | (.1842) | (.5229) | | |
| L1.Electricity price | .2177 | | .1562 | | .05637 | | | | |
| | (.2) | | (.2374) | | (.2491) | | | | |
| L1.Natural gas price | | | -.1774 | -.1185 | | -.02835 | | | |
| | | | (.1292) | (.136) | | (.1325) | | | |
| L1.Oil price | | | | | .03255 | | | | |
| | | | | | (.1943) | | | | |
| L1.Coal price squared | | | | | | | .7519 | | |
| | | | | | | | (1.081) | | |
| L1.Gap elec-coal | | | | | | | | .1106 | |
| | | | | | | | | (.1758) | |
| L1.Gap elec-nat | | | | | | | | | .1306 |
| | | | | | | | | | (.1639) |
| *Research subsidies* | | | | | | | | | |
| L1.Renewable | .1518$^{**}$ | .1509$^{**}$ | .13$^{*}$ | .1343$^{*}$ | .1412$^{*}$ | .1492$^{**}$ | .1542$^{**}$ | .1392$^{*}$ | .1406$^{*}$ |
| | (.07295) | (.07391) | (.07301) | (.07341) | (.07263) | (.07312) | (.07351) | (.07317) | (.07457) |
| L1.Fossil fuel | -.0086 | -.02737 | -.0439 | -.05144 | -.04075 | -.02935 | -.02331 | -.03552 | -.03416 |
| | (.04105) | (.04342) | (.04261) | (.04307) | (.04141) | (.0456) | (.04343) | (.04154) | (.0421) |
| L1.Efficiency-improving | .00296 | .01692 | .02125 | .02719 | .01747 | .01855 | .01457 | .01391 | .01085 |
| | (.03932) | (.04063) | (.03924) | (.04068) | (.03801) | (.04185) | (.04068) | (.03871) | (.03893) |
| *Past innovation knowledge* | | | | | | | | | |
| L1.Renewable | -.00049$^{***}$ | -.00049$^{***}$ | -.00049$^{***}$ | -.00049$^{***}$ | -.00048$^{***}$ | -.00049$^{***}$ | -.00049$^{***}$ | -.00048$^{***}$ | -.00048$^{***}$ |
| | (.00016) | (.00016) | (.00016) | (.00016) | (.00016) | (.00016) | (.00016) | (.00016) | (.00017) |
| L1.Baseload | -.00101$^{***}$ | -.00103$^{***}$ | -.001$^{***}$ | -.00101$^{***}$ | -.001$^{***}$ | -.00103$^{***}$ | -.00102$^{***}$ | -.00099$^{***}$ | -.00102$^{***}$ |
| | (.00026) | (.00026) | (.00027) | (.00026) | (.00027) | (.00026) | (.00026) | (.00026) | (.00027) |
| L1.Peakload | .001$^{***}$ | .00104$^{***}$ | .00104$^{***}$ | .00105$^{***}$ | .00101$^{***}$ | .00104$^{***}$ | .00102$^{***}$ | .001$^{***}$ | .00103$^{***}$ |
| | (.0002) | (.0002) | (.00021) | (.0002) | (.00021) | (.0002) | (.0002) | (.0002) | (.0002) |
| *Past innovation spillovers* | | | | | | | | | |
| L1.Renewable | -3.0e-05$^{\dagger}$ | -4.0e-05$^{**}$ | -4.8e-05$^{**}$ | -5.0e-05$^{***}$ | -3.9e-05$^{**}$ | -4.1e-05$^{**}$ | -3.8e-05$^{**}$ | -3.8e-05$^{**}$ | -4.1e-05$^{**}$ |
| | (1.9e-05) | (1.9e-05) | (2.0e-05) | (1.9e-05) | (1.9e-05) | (1.9e-05) | (1.9e-05) | (1.9e-05) | (1.8e-05) |
| L1.Baseload | -1.2e-05 | -1.7e-05 | -1.8e-05 | -2.0e-05 | -1.9e-05 | -1.7e-05 | -1.7e-05 | -1.7e-05 | -1.6e-05 |
| | (1.9e-05) | (2.1e-05) | (1.8e-05) | (2.0e-05) | (1.9e-05) | (2.0e-05) | (2.1e-05) | (1.9e-05) | (1.8e-05) |
| L1.Peakload | -8.6e-05$^{*}$ | -6.9e-05$^{\dagger}$ | -4.7e-05 | -4.5e-05 | -7.3e-05$^{*}$ | -6.4e-05 | -6.9e-05$^{\dagger}$ | -7.7e-05$^{*}$ | -7.0e-05$^{\dagger}$ |
| | (4.5e-05) | (4.7e-05) | (4.6e-05) | (4.6e-05) | (4.4e-05) | (5.0e-05) | (4.7e-05) | (4.5e-05) | (4.6e-05) |
| *Macroeconomic indicators* | | | | | | | | | |
| L1.GDP | -.00867 | -.02003 | .04874 | .0413 | .08181 | -.02427 | -.01756 | .07788 | .06018 |
| | (.09543) | (.09271) | (.08858) | (.08849) | (.09392) | (.0923) | (.09151) | (.09221) | (.09292) |
| L1.GDP per capita | -.2137 | -.03925 | .08731 | .1386 | -.04987 | -.01014 | -.02617 | -.06211 | -.1016 |
| | (.6695) | (.6899) | (.658) | (.6549) | (.6341) | (.6544) | (.692) | (.6709) | (.6742) |
| 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 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 39314 | 39314 | 39314 | 39314 | 39314 | 39314 | 39314 | 39314 | 38381 |

Table C.2: Alternative energy price specifications in base load fossil fuels.

| | Dependent variable: firm-level number of baseload patents | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Energy prices including taxes* | | | | | | | | | |
| L1.Coal price | -.4104$^{***}$ | -.2696$^{*}$ | | | | -.2613$^{\dagger}$ | .2161 | | |
| | (.1515) | (.1472) | | | | (.1637) | (.5697) | | |
| L1.Electricity price | .5045$^{**}$ | | .36$^{*}$ | | .341$^{*}$ | | | | |
| | (.204) | | (.1921) | | (.2028) | | | | |
| L1.Natural gas price | | | -.1178 | -.08849 | | -.02974 | | | |
| | | | (.1084) | (.1346) | | (.1629) | | | |
| L1.Oil price | | | | | .00377 | | | | |
| | | | | | (.2413) | | | | |
| L1.Coal price squared | | | | | | | -1.012 | | |
| | | | | | | | (1.163) | | |
| L1.Gap elec-coal | | | | | | | | .4025$^{**}$ | |
| | | | | | | | | (.1587) | |
| L1.Gap elec-nat | | | | | | | | | .1704 |
| | | | | | | | | | (.1665) |
| *Research subsidies* | | | | | | | | | |
| L1.Renewable | .0478 | .05295 | .03124 | .04122 | .02921 | .05327 | .04812 | .02727 | .04091 |
| | (.08212) | (.08417) | (.08059) | (.08206) | (.08097) | (.08418) | (.08395) | (.07994) | (.08494) |
| L1.Fossil fuel | .09121$^{\dagger}$ | .06762 | .06404 | .05302 | .07287 | .06501 | .06288 | .07854 | .04681 |
| | (.0597) | (.05826) | (.05986) | (.05821) | (.05961) | (.05772) | (.05931) | (.06027) | (.06349) |
| L1.Efficiency-improving | .00055 | .02347 | .02788 | .03781 | .02535 | .02458 | .02475 | .0193 | .01936 |
| | (.05699) | (.05509) | (.05478) | (.05426) | (.05382) | (.05493) | (.05508) | (.0551) | (.05553) |
| *Past innovation knowledge* | | | | | | | | | |
| L1.Renewable | -1.3e-05 | -9.6e-05 | 3.6e-05 | -4.0e-05 | 1.3e-05 | -8.9e-05 | -9.9e-05 | 3.4e-05 | 1.5e-05 |
| | (.00052) | (.0005) | (.00055) | (.00053) | (.00053) | (.00051) | (.0005) | (.00054) | (.00054) |
| L1.Baseload | -.00065$^{***}$ | -.00062$^{***}$ | -.00063$^{***}$ | -.00062$^{***}$ | -.00059$^{***}$ | -.00063$^{***}$ | -.00065$^{***}$ | -.00063$^{***}$ | -.00067$^{***}$ |
| | (.00022) | (.00021) | (.00024) | (.00022) | (.00022) | (.00021) | (.0002) | (.00023) | (.00025) |
| L1.Peakload | .00076$^{***}$ | .00079$^{***}$ | .00078$^{***}$ | .0008$^{***}$ | .00073$^{***}$ | .0008$^{***}$ | .00081$^{***}$ | .00074$^{***}$ | .00081$^{***}$ |
| | (.00017) | (.00017) | (.00019) | (.00019) | (.00017) | (.00018) | (.00016) | (.00018) | (.0002) |
| *Past innovation spillovers* | | | | | | | | | |
| L1.Renewable | -2.6e-05 | -3.7e-05$^{\dagger}$ | -3.6e-05 | -4.2e-05$^{\dagger}$ | -2.9e-05 | -3.9e-05 | -3.9e-05$^{\dagger}$ | -2.8e-05 | -3.9e-05 |
| | (2.5e-05) | (2.6e-05) | (2.6e-05) | (2.7e-05) | (2.4e-05) | (2.7e-05) | (2.5e-05) | (2.5e-05) | (2.7e-05) |
| L1.Baseload | 1.6e-05 | 1.6e-05 | 1.5e-05 | 1.5e-05 | 1.9e-05 | 1.5e-05 | 1.6e-05 | 1.7e-05 | 1.1e-05 |
| | (2.8e-05) | (2.8e-05) | (2.9e-05) | (2.9e-05) | (2.8e-05) | (2.8e-05) | (2.8e-05) | (2.9e-05) | (3.2e-05) |
| L1.Peakload | -7.5e-05 | -6.7e-05 | -5.2e-05 | -5.1e-05 | -7.9e-05 | -6.0e-05 | -6.8e-05 | -7.9e-05 | -5.1e-05 |
| | (5.5e-05) | (5.7e-05) | (6.2e-05) | (6.5e-05) | (5.5e-05) | (6.6e-05) | (5.7e-05) | (5.6e-05) | (6.4e-05) |
| *Macroeconomic indicators* | | | | | | | | | |
| L1.GDP | -.06246 | -.09808 | -.01329 | -.05371 | .0064 | -.1014 | -.1067 | -.00971 | -.02584 |
| | (.1198) | (.1347) | (.115) | (.1219) | (.123) | (.1293) | (.1358) | (.1114) | (.1262) |
| L1.GDP per capita | .9325 | 1.32$^{*}$ | 1.221$^{*}$ | 1.422$^{**}$ | 1.264$^{*}$ | 1.311$^{*}$ | 1.309$^{*}$ | 1.182$^{*}$ | 1.105 |
| | (.7057) | (.6868) | (.6935) | (.709) | (.6552) | (.7115) | (.7148) | (.6606) | (.8019) |
| 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 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 25179 | 25179 | 25179 | 25179 | 25179 | 25179 | 25179 | 25179 | 24564 |

Table C.3: Alternative energy price specifications in peak load fossil fuels.

| | Dependent variable: firm-level number of peakload patents | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Energy prices including taxes* | | | | | | | | | |
| L1.Coal price | -.4374 | -.4026 | | | | -.3767 | .2766 | | |
| | (.3451) | (.3273) | | | | (.3251) | (.8343) | | |
| L1.Electricity price | .1856 | | .1142 | | .1119 | | | | |
| | (.3666) | | (.3517) | | (.3678) | | | | |
| L1.Natural gas price | | | -.1962 | -.1834 | | -.1076 | | | |
| | | | (.1776) | (.1856) | | (.1802) | | | |
| L1.Oil price | | | | | -.1007 | | | | |
| | | | | | (.3324) | | | | |
| L1.Coal price squared | | | | | | | -1.283 | | |
| | | | | | | | (1.607) | | |
| L1.Gap elec-coal | | | | | | | | .1323 | |
| | | | | | | | | (.3148) | |
| L1.Gap elec-nat | | | | | | | | | -.226 |
| | | | | | | | | | (.2962) |
| *Research subsidies* | | | | | | | | | |
| L1.Renewable | .1973 | .1919 | .1605 | .16 | .1577 | .1887 | .1784 | .1653 | .1761 |
| | (.1861) | (.1886) | (.1781) | (.1782) | (.1783) | (.1879) | (.1838) | (.1779) | (.1719) |
| L1.Fossil fuel | .04258 | .02909 | -.00032 | -.00622 | .00909 | .02077 | .01399 | .01579 | -.02992 |
| | (.08147) | (.08373) | (.08738) | (.0887) | (.08278) | (.08558) | (.07913) | (.08269) | (.0878) |
| L1.Efficiency-improving | .3279*** | .3358*** | .3483*** | .3516*** | .3373*** | .3414*** | .341*** | .3382*** | .3489*** |
| | (.1082) | (.1039) | (.09873) | (.09749) | (.09973) | (.103) | (.1034) | (.103) | (.09989) |
| *Past innovation knowledge* | | | | | | | | | |
| L1.Renewable | -.00079 | -.00082 | -.00069 | -.00071 | -.00067 | -.00082 | -.00078 | -.00067 | -.00072 |
| | (.00059) | (.0006) | (.00059) | (.0006) | (.00059) | (.00061) | (.00058) | (.00059) | (.0006) |
| L1.Baseload | .00043 | .00042 | .00041 | .00041 | .00043 | .0004 | .00038 | .00044 | .00032 |
| | (.00047) | (.00047) | (.00046) | (.00046) | (.00045) | (.00048) | (.00048) | (.00045) | (.00048) |
| L1.Peakload | .00012 | .00014 | .00016 | .00017 | .00011 | .00017 | .00017 | 9.8e-05 | .0002 |
| | (.0003) | (.00029) | (.0003) | (.00029) | (.00029) | (.0003) | (.0003) | (.00029) | (.00031) |
| *Past innovation spillovers* | | | | | | | | | |
| L1.Renewable | -5.6e-05 | -6.1e-05 | -7.0e-05$^{\dagger}$ | -7.2e-05$^{\dagger}$ | -6.1e-05 | -6.8e-05 | -6.7e-05 | -5.7e-05 | -7.1e-05 |
| | (4.7e-05) | (4.8e-05) | (4.6e-05) | (4.7e-05) | (4.7e-05) | (4.7e-05) | (5.0e-05) | (4.7e-05) | (5.1e-05) |
| L1.Baseload | 4.8e-05 | 4.8e-05 | 4.1e-05 | 4.0e-05 | 4.4e-05 | 4.5e-05 | 4.6e-05 | 4.5e-05 | 2.6e-05 |
| | (4.6e-05) | (4.7e-05) | (4.9e-05) | (4.9e-05) | (4.8e-05) | (4.6e-05) | (4.6e-05) | (4.9e-05) | (4.9e-05) |
| L1.Peakload | -3.3e-05 | -2.7e-05 | 2.1e-05 | 2.3e-05 | -1.6e-05 | -1.9e-06 | -2.4e-05 | -2.3e-05 | 9.8e-06 |
| | (8.9e-05) | (9.7e-05) | (9.9e-05) | (.0001) | (9.4e-05) | (9.3e-05) | (9.6e-05) | (9.4e-05) | (.00011) |
| *Macroeconomic indicators* | | | | | | | | | |
| L1.GDP | -.1219 | -.1265 | -.06715 | -.07237 | -.04306 | -.1328 | -.1394 | -.04985 | -.06705 |
| | (.1645) | (.1671) | (.1588) | (.1583) | (.1541) | (.1668) | (.1645) | (.1547) | (.1709) |
| L1.GDP per capita | -.1283 | .02759 | .08004 | .1505 | .1318 | .00029 | .0671 | .0853 | -.2573 |
| | (1.354) | (1.349) | (1.297) | (1.292) | (1.347) | (1.318) | (1.352) | (1.349) | (1.316) |
| 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 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 9772 | 9772 | 9772 | 9772 | 9772 | 9772 | 9772 | 9772 | 9526 |

Table C.4: Fixed-effect Poisson estimates of innovation in general and efficiency-improving fossil fuel technologies using global data.

| | 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.

Table C.5: 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 | Fossil fuel | Renewable | Fossil fuel |
| | (1) | (2) | (3) | (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.6: 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.7: Baseline specification with correction for patent truncation bias.

| | Dependent variable: firm-level number of patents | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable | Fossil fuel | Renewable | Base load | Peak load |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.3352* | -.3566* | -.4102** | -.5178*** | -.4425† |
| | (.1831) | (.1821) | (.1716) | (.1582) | (.2927) |
| L1.Electricity price | .172 | .3432 | .2012 | .4367** | .05563 |
| | (.2148) | (.2407) | (.1911) | (.2109) | (.3831) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1679** | .04728 | .1499** | .00767 | .1538 |
| | (.07208) | (.1017) | (.07419) | (.08175) | (.1827) |
| L1.Fossil fuel | -.01664 | .07015 | -.01082 | .08885† | .04155 |
| | (.03831) | (.05759) | (.03905) | (.05841) | (.08433) |
| L1.Efficiency-improving | .00068 | .05062 | .00768 | -.00256 | .297*** |
| | (.04134) | (.07017) | (.04138) | (.05644) | (.1005) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00055*** | -.00055 | -.00049*** | -3.6e-05 | -.0008 |
| | (.00013) | (.00041) | (.00016) | (.00051) | (.00061) |
| L1.Fossil fuel | 5.3e-05 | .00026*** | | | |
| | (.00017) | (4.7e-05) | | | |
| L1.Baseload | | | -.00099*** | -.00067*** | .00031 |
| | | | (.00026) | (.00019) | (.0005) |
| L1.Peakload | | | .00099*** | .0008*** | .00022 |
| | | | (.0002) | (.00015) | (.00031) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -2.2e-05 | -4.1e-05* | -2.0e-05 | -2.8e-05 | -6.4e-05 |
| | (2.0e-05) | (2.4e-05) | (1.8e-05) | (2.3e-05) | (4.9e-05) |
| L1.Fossil fuel | -4.1e-05*** | -8.1e-06 | | | |
| | (1.4e-05) | (1.4e-05) | | | |
| L1.Baseload | | | -1.3e-05 | 1.1e-05 | 3.4e-05 |
| | | | (1.6e-05) | (2.6e-05) | (3.1e-05) |
| L1.Peakload | | | -9.2e-05** | -6.6e-05 | -3.7e-05 |
| | | | (4.5e-05) | (5.6e-05) | (8.1e-05) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.1488† | -.09727† | -.1522† | -.1516* | -.3522** |
| | (.09922) | (.06151) | (.09451) | (.08666) | (.1375) |
| L1.GDP per capita | -.1252 | .2446 | .3599 | .7846* | -.00505 |
| | (.7587) | (.4935) | (.7234) | (.4348) | (1.29) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 39309 | 27247 | 39309 | 25190 | 9774 |

Table C.8: Baseline specification with citation-adjusted knowledge stocks.

| | Dependent variable: firm-level number of patents | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable | Fossil fuel | Renewable | Base load | Peak load |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.2848† | -.3263† | -.3027* | -.4059*** | -.3994 |
| | (.178) | (.2017) | (.1672) | (.1464) | (.3748) |
| L1.Electricity price | .1451 | .35† | .1906 | .3679* | .1358 |
| | (.2328) | (.2424) | (.2133) | (.2159) | (.3405) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1339† | .04312 | .129† | .01367 | .1489 |
| | (.0819) | (.09834) | (.08066) | (.09493) | (.1695) |
| L1.Efficiency-improving | -.00791 | .02065 | .00375 | -.00086 | .2808*** |
| | (.04095) | (.06844) | (.04111) | (.05596) | (.1037) |
| L1.Fossil fuel | -.00911 | .07776 | .00708 | .08643 | .1013 |
| | (.03924) | (.05838) | (.03917) | (.06785) | (.08619) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -8.7e-05*** | -1.9e-05 | -8.6e-05*** | -1.7e-05 | -2.9e-05 |
| | (2.6e-05) | (3.5e-05) | (2.5e-05) | (4.2e-05) | (3.0e-05) |
| L1.Fossil fuel | -2.0e-05 | 7.4e-05** | | | |
| | (8.9e-05) | (2.9e-05) | | | |
| L1.Baseload | | | -.00032** | -.00023*** | .00037** |
| | | | (.00014) | (7.2e-05) | (.00018) |
| L1.Peakload | | | .00033** | .00032*** | -.00016 |
| | | | (.00016) | (6.9e-05) | (.00014) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -3.8e-05 | -3.7e-05 | -2.9e-05 | -4.7e-05 | -4.1e-05 |
| | (3.3e-05) | (3.2e-05) | (3.2e-05) | (3.6e-05) | (6.9e-05) |
| L1.Fossil fuel | -6.0e-05*** | -2.6e-05 | | | |
| | (2.3e-05) | (2.6e-05) | | | |
| L1.Baseload | | | -1.8e-05 | -1.7e-05 | 5.1e-05 |
| | | | (2.9e-05) | (4.2e-05) | (6.9e-05) |
| L1.Peakload | | | -.00013** | -4.7e-05 | -4.4e-05 |
| | | | (6.9e-05) | (9.6e-05) | (.00018) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | .0172 | -.00967 | .0112 | -.03946 | -.1914 |
| | (.1136) | (.1054) | (.1042) | (.09769) | (.2027) |
| L1.GDP per capita | -.3211 | .843* | .2016 | 1.102** | .2826 |
| | (.9647) | (.4755) | (.934) | (.4524) | (1.359) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 33354 | 23529 | 33354 | 21736 | 8110 |

Significance levels: ***: 1% **: 5% *: 10% †: 15%

Numbers in parentheses are standard errors.

Table C.9: 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 |
| 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.10: Estimates with third lags of explanatory variables.

| | 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 | -.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 |
| 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.11: Alternative definition of regional spillovers: one region.

| | 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 | -.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 |
| 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.12: Baseline estimates with additional macroeconomic indicators (population density).

| | **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 | -.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 |
| 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.13: 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 (1) | Base load (2) | Peak load (3) | Renewable (4) | Base load (5) | Peak load (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 |
| 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.14: Baseline estimates with specialized and mixed firms.

| | Dependent variable: firm-level number of patents | | | | | |
|---|---|---|---|---|---|---|
| | Specialized firms | | | Mixed firms | | |
| | Renewable (1) | Base load (2) | Peak load (3) | Renewable (4) | Base load (5) | Peak load (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 |
| 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.15: 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.16: 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 |
| Year FE | Yes | Yes |
| Observations | 27660 | 40011 |

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

Numbers in parentheses are standard errors.