Centre of Excellence
for Science and Innovation Studies

CESIS Electronic Working Paper Series

Paper No. 470

Directed Technical Change in Clean Energy: Evidence from the Solar Industry

Christopher F Baum
Luis Perez
Hans Lööf

August, 2018

The Royal Institute of technology
Centre of Excellence for Science and Innovation Studies (CESIS)
http://www.cesis.se

Directed Technical Change in Clean Energy: Evidence from the Solar Industry*

Hans Lööf† Luis Pérez‡ Christopher F Baum§

July 10, 2018

Abstract

This paper studies directed technical change and innovation in renewable energy. We construct panel data with micro- and macro observations from nearly 200 countries over a 20-year period and estimate how energy prices, government subsidies, financial markets, spillovers, and path dependence affect patenting in solar thermal and solar cells. Carbon taxes, R&D subsidies to solar technology and own-knowledge stocks have strong, significant positive effects on solar innovations. Subsidies to fossil energy have the adverse effect. We find no compelling evidence that the quality of financial markets and institutions has any consistent impact on the patenting activities of innovators in solar energy.

Keywords: Directed Technical Change, Climate Change, Innovation, Patents, Solar Energy.
JEL: O13, O3, P28, P47

*The authors thank Emil Wärnberg, from KTH's School of Computer Science, who helped with programming and data processing, and seminar audiences at the 7^{th} ZEW Conference on Economics of Innovation and Patenting, Mannheim June 2017, the International Workshop on Finance, Innovation and Green Growth, Seoul National University June 2017, the 10^{th} Conference on MEIDE Montevideo November 2017, and the Mistra Financial System International Research Conference on Sustainable Economic Development, Stockholm School of Economics March 2018. Finally, the authors gratefully acknowledge financial support from both the Swedish Foundation for Strategic Environmental Research (MISTRA) and Fundación Ramón Areces.

†KTH Royal Institute of Technology, Department of Industrial Economics and Management, Economics Unit, Lindstedtsvägen 30, Stockholm 114 28. email hans.loof@indek.kth.se

‡KTH Royal Institute of Technology, Department of Industrial Economics and Management. email luis.perez@indek.kth.se

§Department of Economics, Boston College and Department of Macroeconomics, DIW Berlin. email baum@bc.edu

1 Introduction

There is a need to better understand and manage nature's constraints to generate resources for the exponentially growing world production and to absorb its negative external effects. This largely applies to supply of cheap and reliable energy as an essential objective of socioeconomic development .

Scarcity of resources is at the heart of economics. The interest in devastation of irreplaceable natural assets goes back to Hotelling (1931), which emphasizes the need for regulations in order to prevent overexploitation of finite resources.

Beginning with Nordhaus et al. (1973), the economic literature has increasingly focused on the pivotal role of fossil resources for supplying the economy with abundant energy at low costs and simultaneously addressing the climate change caused by our growing consumption of coal, oil and natural gas.

There is a widespread view among economists that the primary mechanism to reduce carbon emissions is through technical change and innovation rather than via slower output growth. The challenge for green growth is to create market conditions that provide incentives for profit-maximizing firms to innovate in clean energy (Pizer and Popp, 2008).

Induced innovation from fossil fuels to renewables is often regarded as a necessary step for accomplishing this shift. The concept of induced innovation, which dates back to Hicks (1932), has been further developed in the past few decades. Recent theoretical advances in endogenous growth theory have incorporated induced innovation and directed technical change for analyzing sustainable development (see Acemoglu et al. (2012, 2016) and Aghion et al. (2016)). A critical assumption in these models, which allow profit-maximizing firms to decide whether to innovate in environmental technologies, is that carbon-intensive technologies, due to path dependence, benefit from an initial advantage.[1] As existing infrastructure and the stock of R&D capital represent prior investments in dirty technologies, marginal investments in the incumbent (dirty) sector are more profitable than investments in the emerging (clean) sector. From a policy standpoint, renewable sources will not replace dirty technologies without governmental intervention. The prospect of future climate disasters may therefore justify and require actions that aim at redirecting technological change and inducing clean innovations. Policy actions should be temporary and may include regulations and efficient price signals for phasing out wasteful consumption of fossil fuels and subsidies that compensate for the negative externalities associated with the production of clean energy.

Energy is needed for growth. The world economy is estimated to grow by an annual rate of around 3.5% through 2040 (OPEC, 2017). In a scenario based on existing policies and announced intentions, the International Energy Agency (IEA, 2017) estimates that the corresponding growth of energy demand will be close to 1% per year, with a continued increase of carbon dioxide (CO2) emissions.

In order to be compatible with the goal of stabilizing global temperature, a large-scale shift from fossil-based economic growth is required. Solar power, which currently accounts for less than 1% of the world energy supply, has a key role in the IEA's so-called Sustainable Scenario. The expectation is that the current explosive growth of solar power will continue, and produce around 10% of the energy supply by 2040. Recent literature suggests that such a shift of the global energy system may be challenging (Steves and Teytelboym, 2013). There are at least three critical sources of inertia hinder-

[1] A third category, "grey", that increases the efficiency of dirty technologies can also be introduced.

ing the transition: negative externalities, path dependence in the direction of technical change, and the long life-cycle of infrastructure, all accommodated by the endogenous models of a transition to clean technology.

Firms investing in fossil-energy technologies do not internalize the societal negative effects of climate change and may therefore choose to innovate more in these technologies than they would if they had to bear all associated environmental costs. Path dependence in the direction of technical change is explained by a higher marginal rate of return on investment in fossil technologies compared to renewables.[2] The existing infrastructure in the energy sector is characterized by long lifetimes. Investments in fossil power plants made today are likely to be operating and emitting CO2 for decades into the future.

Despite significant inertia and obstacles, the solar industry has experienced substantial growth and rapid technological development during the last decades. Data from the European Patent Office (EPO) shows that the solar industry has registered the greatest surge in renewable energy innovation over the past two decades. The number of high-value, solar patents increased by a factor of four between 2005 and 2010 (see Figure 1) and the costs of new solar photovoltaic cells decreased by 70% between 2010 and 2017. Thee average costs for solar cells are estimated to be cut by a further 40-70% by 2040.[3]

[Figure 1 about here.]

[Table 1 about here.]

[2]Fossil-based technologies, production, consumption and infrastructure are closely intertwined with the existing economic, financial, political and social system. They make up a large proportion of jobs, wages, profits, stock market valuation and pension fund assets (Ansar et al., 2013).

[3]See Reichelstein and Yorston (2013) for a comprehensive assessment of the cost competitiveness of solar power.

Aghion et al. (2016) were the first to conduct and empirical application of the endogenous theoretical framework on directed technical change and climate mitigation. They investigated the role of public intervention in redirecting car-manufacturers' innovation activities from internal combustion engines (ICE) towards innovations in electric and hybrid automobiles. Their results confirmed the ability of public intervention to direct innovation towards clean technologies.

Relying on main building blocks from the automotive study, this paper studies how directed technical change may affect innovation in solar technologies. First we construct a panel dataset with micro observations from nearly 200 countries over a 20-year period. We then apply count data models for estimating how prices, governmental subsidies, financial markets, spillovers, path dependence affect patenting in the solar industry. We also introduce some deviations to the empirical approach suggested by Aghion et al.. First, instead of a static weighting approach, we employ a dynamic weighting scheme,[4,5] with the implication that we can account for variation in the relative importance of markets over time.[6] Second, we accommodate research spillovers, which do not necessarily depend on location but rather on research efforts, i.e. knowledge flows that occur when a firm evaluates other firms' relevant inventions for its research purposes. Lastly, we use a

[4]Consider, for instance a company i whose patent portfolio consists of 10 patents in year $t = 0$ (5 filed at the USPTO and 5 at the JPO), and 20 patents in year $t = 10$ (4 at the EPO, 6 at the USPTO and 10 at JPO). Whilst firm i's exposure to the US and Japanese market at $t = 0$, the last year of the "pre-sample" period, is the same (=0.5) in both Aghion et al.'s and our approach, this would not hold true once we enter the regression period. Aghion et al.'s approach would still derive 0.5 as i's exposure to both the US and Japanese market in $t = 10$, ignoring the "EPO" market. Our approach would, however, calculate the exposure of firm i in year $t = 10$ to the US, Japanese and EPO market to be 0.3, 0.5 and 0.2, respectively.

[5]It should be noted that firms might be able to anticipate national policies and alter market exposures as response to decentralized environmental agendas. We address this potential endogeneity problem in the empirical section.

[6]It is well documented that firms vary their international strategies over time (Hitt et al., 1997; Milliman et al., 1991; Zahra et al., 2000).

wider set of controls that are *a fortiori* relevant to determine innovation intensity over time such as proxies for the technological frontier and size of the market.

Our main findings is that carbon taxes, as proxied by energy prices, have significant, sizable and positive effects on solar innovation. This is also the case for R&D subsidies to solar technology and own-knowledge stocks in both solar and other technologies. Subsidies to fossil energy have adverse effects. We find no compelling evidence that the quality of financial markets and institutions has any systematic impact on the patenting activities of innovators in solar energy. We challenge the validity of our results with the conclusion that they appear to be robust to model specification, estimation techniques, choice of energy prices and lag structures, depreciation rates of knowledge stocks, patent families, and weighting schemes.

The remainder of the paper is organized as follows. Section 2 presents the data. Section 3 explains the construction of variables and conducts an exploratory analysis of the data. Section 4 specifies the model and sets forth the empirical strategy. Section 5 reports results and robustness checks, while Section 6 concludes.

2 Data

There are three different data dimensions in our approach: organizations,[7] inventors and countries. Organizations file patent applications in different jurisdictions (i.e. patent offices, usually one per country) seeking legal protection. Inventors create technological blueprints either for their own exploitation or for some organization which remunerates this work. Coun-

[7]Organizations include state- and privately- owned firms, universities, research institutions, etc.

tries provide legal protection for intellectual property by granting temporary monopoly power to inventors and/or organizations through patent rights. These dimensions enter the model in different ways, all of them providing a rich amount of information. Organizations generate a yearly pool of technological breakthroughs, captured by the number of patents filed by organization-year. Inventors make possible organizations' patenting activities and also contribute, by their geographical location, to the diffusion of knowledge. Countries alter firms' incentives to innovate by implementing different fiscal, industrial and environmental policies, and also by the way in which institutions are regulated and intellectual property is protected.

2.1 Data Sources and Exploratory Analysis

2.1.1 European Patent Office (EPO)

Patent data come from the EPO's Worldwide Patent Statistical database (PATSTAT), which provides data at a highly-disaggregated technological level for more than 100 patent offices, sometimes starting as early as the nineteenth century. PATSTAT is the most comprehensive database on patents as it has almost full coverage and contains information regarding applications, legal status, patent families, priorities, applicants, inventors, publications, citations, and so on. To identify patents we use the Cooperative Patent Classification (CPC) system, which is an extension of the International Patent Classification (IPC) that extensively disaggregates technological groups and subgroups.[8]

We use the search strategies suggested by Haščič and Migotto (2015) for identification of environment-related technologies, which rely on previous work of the OECD and patent examiners of the EPO. In particular, we use

[8]Whilst the IPC has about 70,000 codes, the CPC has approximately 200,000.

the Y02 scheme introduced in Veefkind et al. (2012), which greatly facilitates the selection of solar energy technologies. Some examples of these codes are Y02E10/52 (PV systems with concentrators) and Y02E10/46 (conversion of thermal power into mechanical power). Table 17 at the end of the document lists all solar energy codes used in the analysis.

To measure innovation we use a count of patents by application-earliest-filing date,[9] noting that filing date is much closer in time to the patent's preparation than the date granted. Patenting has many advantages over other measures of innovation such as R&D expenditures. Firstly, extensive disaggregation by technological groups and subgroups allows easy and precise targeting. Secondly, patent data are complete, readily available and comparable across countries (Haščič and Migotto, 2015; Johnstone et al., 2010) whilst R&D expenditures are not; for instance, SMEs are not always required to report these expenditures. Thirdly, patent documents provide valuable information on other parts of the invention process such as identification of inter- and intra-firm knowledge flows. Finally, patents are a measure of intermediate innovation output, while R&D expenditures measure inputs (Acs and Audretsch, 2003) that do not necessarily capture the success of the research process; nevertheless, there is a strong relationship between the number of patents and R&D expenditures (Griliches, 1990). The main drawback of a patent count is that it is a partial measure of inventive activity because only a fraction of all inventions are patented, and not all innovations are patentable (Arundel and Kabla, 1998; Griliches, 1990; Horstmann et al., 1985). However, this problem is not homogeneous across sectors (Cohen et al., 2000), and patent protection is still the desired mechanism for general and special purpose machinery, which is the focus of our

[9]This is the mainstream approach in the empirical literature (see Aghion et al., 2016; Cincera et al., 1997; Dechezleprêtre et al., 2014; Hausman et al., 1984).

approach. In addition, it is plausible to assume that the most valuable inventions are patented since there are few examples of economically significant inventions that have not been patented (Van Pottelsberghe et al., 2001).

Assessing the quality of inventions has been an important issue in the literature that now can be better assessed through statistical methods and other techniques (Haščič et al., 2015). We focus on "biadic" and "triadic" patents. The former corresponds to Henderson and Cockburn (1996)'s original characterization, i.e. patents filed in at least two of the three main patent offices (EPO, JPO, USPTO); the latter considers patents that have been filed in all three main patent offices, and it is widely used in the current empirical literature.[10] As other patent offices have recently gained international importance, we extend patent categories and also consider "fouradic" and "fiveadic" patents. The former corresponds to triadic patents that are, in addition, filed either in the China Patent & Trademark Office (SIPO) or in the Korean Intellectual Property Office (KIPO); the latter considers patents filed in the five main patent offices (EPO, JPO, USPTO, SIPO, KIPO). Proceeding this way, we consider the most valuable inventions as it has been found that the greater the number of patent offices in which a patent seeks protection, the higher the quality of the invention (de la Potterie and Van Zeebroeck, 2008; Harhoff et al., 2003; Putnam, 1996).

Figure 2 depicts how the different patent categories have evolved over time in the solar industry. This figure is divided in figures 2a, 2b and 2c to improve readability of the y-axis. The reader might notice three things. First, filtering by the quality of inventions is important since the sample is substantially reduced and, thus, many low-quality inventions are discarded.

[10] See Aghion et al. (2016); Chang et al. (2013); Dechezleprêtre et al. (2014); Dernis and Khan (2004); Filippetti et al. (2016); Guellec and Van Pottelsberghe de la Potterie (2004).

Second, regardless of patent category, the number of patents has increased over time. Finally, there is truncation in the sample, [11] starting in 2010 for "all patents", and in 2009 for the rest of categories. These cut-off points indicate the final year of the time period for our regression analysis.

[Figure 2 about here.]

A critical issue with PATSTAT is that data are not clustered by corporate groups, implying that a multinational firm, e.g. Canon, will be counted (*at least*) as many times as subsidiaries it has. Not accounting for these sources of duplication has pernicious effects as it inflates both the dimensions of the regression panels and the measures of location-based knowledge spillovers.[12] Fortunately, the ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT) partially allows correcting for these problems. Another source of multiple counting is that spelling mistakes and typographical errors may lead to the inclusion of the same individual under different rubrics (e.g. personal identifications, *psn_id*).

The EEE-PPAT table is the result of a joint project between EUROSTAT, ECOOM and Sogeti, which developed an algorithm that achieves patent-assignee name harmonization and assignee sector allocation.[13] The resulting unique patentee names are assigned a primary key, *hrm_l2_id*, that is used for empirical identification and which substantially reduces the number of duplicates, as may be seen in Table 2.

[Table 2 about here.]

[11] Patents are registered in PATSTAT with a delay. Thus, as we get closer in time to the actual date, the count of patents drops despite of changes in the pace of innovation.

[12] For instance, Hashimoto Haruhisa, with three distinct person_id's (9687207, 10884972 and 11452652), would enter into the regression panel as three different units; also, his inventions would be triple-counted in the spillover pool of Osaka, Japan.

[13] See Du Plessis et al. (2009), Magerman et al. (2006) and Peeters et al. (2010) for more information on how the EEE-PPAT table is constructed and, also, for descriptive statistics on patent assignees before and after harmonization.

Table 3 displays patentees' distribution across sectors for harmonized applicants. Not filtering by quality of inventions, we observe that most applicants are individuals[14] (76.64%), followed by companies (12.10%). These two categories add up to approximately 90% of the sample. About 2% of all patents are filed by universities and other governmental (research) institutions, and the rest have either unknown or non-allocated sectors.

[Table 3 about here.]

Table 4 reports applicants' distribution across sectors conditioning on quality of the invention. As expected, the number of applicants is a decreasing function of patent jurisdictions. The majority of applicants within each sample are still individuals, although the share of organizations increases with quality of invention (from nearly 17% in biadic patents to about 40% in fivadic patents). Organizations are mostly represented by private firms (approx. 85%), and unknown or non-allocated data is of relatively little importance (less than 1%).

[Table 4 about here.]

2.1.2 International Energy Agency (IEA)

Energy prices, taxes and R&D subsidies come from the IEA. The *Energy Prices and Taxes* dataset provides annual, quarterly and monthly data for 34 OECD countries for a period that spans from 1978 to 2016. We focus

[14] In order not to inflate the number of applicants, we account for legal differences in patent systems. In the US, for instance, inventors are required to be listed as applicants. For this purpose, we implement an algorithm that counts inventors as applicants if and only if they are applicants and no organization is involved in the filing process. When inspecting the data, however, we note that individuals still constitute the majority of the sample. We suspect that once inventors are listed as applicants in one patent office, they are tacitly listed in all other jurisdictions in which the patent is filed. To correct for this, and also because our main interest is on organizations, we exclude individuals for regression analysis.

on households, end-use tax-inclusive electricity prices and gasoline, diesel, natural gas and coal prices are used for robustness checks.

Figure 3 depicts energy prices and taxes by energy group. The left panel of the figure shows that energy prices have been steadily increasing since the late 1970s until 2012, when they reached its maximum and started to decline. This is true for all prices but for that of electricity, which violently boomed in 2014. Similar patterns are observed in the right panel for taxation, except in the case of coal, whose taxes, although increased over the sample period, were very volatile.

[Figure 3 about here.]

Looking at energy prices and taxes at the country level, we observe several interesting facts (see Figure 6 at the end of the document). First, prices and taxes are more homogeneous at the beginning of the time period. Second, given that some countries have much stricter environmental agendas than others,[15] heterogeneity in taxation is greater than in pricing. Third, although the general tendency is that of sustained increases, taxation levels are subject to abrupt changes over time.

R&D subsidies come from the Energy Technology RD&D database, which provides information on annual R&D budgets by energy technology group for 29 countries from 1974 to 2015. Figures of public sector research, development and demonstration (RD&D) are obtained by applying the RD&D

[15] To give a sense of how countries rank in terms of taxation efforts, consider the following information. While Turkey applies the highest fuel tax, followed by Hungary and the Slovak Republic, the United States, Mexico and Japan have the weakest taxation agendas. As regards natural gas taxation, Italy and the Netherlands apply the strictest policies while the United Kingdom, Luxembourg and Japan appear at the end of the list. Data for steam coal have extremely low coverage and it is in general meaningless to interpret; Denmark seems to tax this energy product more heavily than any other country. As regards electricity, all countries has experienced heavy increases in taxation over time, especially Germany and Denmark. A note of caution is due: the validity of inference is conditional on available data.

questionnaire in energy fields. As emphasized by the IEA, given the precise technical terms used in the questionnaire, the quality of the data strongly depends on the implication and information delivered by national data collectors. R&D budgets are calculated by identifying the relevant components of R&D activities and also by estimating R&D funding. R&D funding comes from public bodies mainly at the central or federal level but also at the country's first administrative subdivision level, i.e. state or regional government, when it is significant. The main problem of R&D data is always to set the cut-off point between allocations that really belong to these activities from those that do not. Although the questionnaire encompasses seven energy-related groups, we only focus on fossil fuels and renewable energy sources. These two broad groups are used to construct ratios and to analyze how much funding one sector receives in comparison to the other; our main interest is in solar energy (group 31). RD&D budgets are retrieved in USD using PPPs.

Figure 4 depicts sample average data. Figure 4a shows that fossil-fuel subsidies increased until 1980, significantly dropping until 2000 when they reached minimum levels; however, fossil-fuel subsidies have increased ever since. Figure 4b pictures the increase in renewable energy subsidies in the 1970s, which have stagnated until the late 2000s, when they increased again. Figure 4c portrays the evolution of solar subsidies, which have moved in line with renewable energy subsidies. Figure 4d depicts the ratio of renewable to fossil-fuel subsidies which, despite its general tendency to rise, has been very volatile and unpredictable. Finally, Figure 4e displays subsidies to solar energy which, in comparison to other renewables, have been decreasing since the beginning of the sample period.

[Figure 4 about here.]

Data at the country level is provided in Figure 7.The United States drives the sample-average subsidy in all categories, subsidizing energy products substantially more than any other country.[16] In contrast, when comparing relative measures such as the ratio of renewables to fossil-fuels R&D subsidies, Sweden has the highest average ratio which assigns greater importance to clean technologies. The share of R&D funds alloted to solar energy with respect to all other renewable energies has been declining since the beginning of the sample period, as shown in Figure 4e, although the speed and consistency of the trend have been very unequal across countries.[17]

2.1.3 International Monetary Fund (IMF)

From the IMF we retrieve data on the newly introduced Index of Financial Development (IFD), created as a response to the inadequacy of other financial measures[18] that proxy for financial development (Svirydzenka, 2016).

The IFD, which builds on Čihák et al. (2012), takes a multi-dimensional approach to assess the level of development of financial markets and institutions. The IFD is subdivided in two broad indexes, financial institutions (FI) and financial markets (FM), which in turn have three components each: depth, access and efficiency. The FI depth subindex considers private sector credit, pension fund assets, mutual fund assets, and insurance premiums, all as ratios to GDP. It is thus more comprehensive than the standard indicators used in the literature. The FI access subindex takes into account bank branches and ATMs per 100,000 adults. The FI efficiency subindex consists

[16]Note that subsidies are in absolute terms and, since we do not control for population size, larger countries are expected to drive the average subsidy.

[17]Although one can hardly appreciate any pattern in Figure 7e, a country-by-country graphical analysis, together with descriptive statistics, justifies this statement.

[18]Most empirical studies to date use measures of financial depth, such as the ratio of private credit or stock market capitalization to GDP, to approximate financial development.

of net interest margin, lending-deposits spread, non-interest income to total income, overhead costs to total assets, and returns on both assets and equity. Indicators for financial markets mainly focus on stocks and debt securities. The FM depth measure captures stock market capitalization, stocks traded, international debt securities of the government, and total debt securities of financial and non-financial corporations, all as ratios to GDP. The FM access category considers the percent of market capitalization outside the top 10 largest companies and the total number of debt issuers per 100,000 adults. Finally, FM efficiency is just measured as the stock turnover ratio.

The influence of the different subindices on the IFD is determined, at all levels of disaggregation, by application of principal component analysis (PCA), a statistical technique that assigns higher weights to the variables that cause larger within and between variations in the data.[19]

Data are available at the country level on an annual frequency for 1980–2013, with coverage over 183 countries. The main limitations of the dataset are the following: i) when series are completely not available for a country, it is assumed that there is no financial market for that country or that its quality is very poor; ii) not all financial intermediaries are included in the index; and iii) it does not include measures of regulatory or legal frameworks as such. Despite these limitations, this dataset is still more comprehensive and has better properties than any other alternative at hand.

2.1.4 The World Bank

All data for controls come from the World Bank. From the Sustainable-Energy-for-All database we retrieve energy measures that provide information on both the demand and supply side, e.g., electricity production from

[19] See Svirydzenka (2016) for more detailed information on weighting procedures, treatment of missing data, normalization of variables, and so on.

oil sources, renewable electricity, efficiency measures (transmission and distribution losses, energy intensity level, etc.), and electricity consumption. Climate change data on emissions and macroeconomic controls such as GDP, GDP per capita and population are taken from the World Development Indicators database.

3 Methodology

In this section we present the applied methodology, which builds on that of Aghion et al. (2016). An important feature of this approach is the ability to proxy for firms' exposure to different markets. For instance, when a firm i files a patent in country c, this firm gains access to the selected market,[20] either at time t or at some future date $t + p$. How a firm is affected by a given market depends on the relative number of patents that it has been granted in this market, i.e. on the share of patents that firm i has in market c as a share of its total patents. As noted earlier in section 1 we deviate from Aghion et al. by introducing a dynamic weighting scheme that more accurately calculates market exposures. Table 5 documents large differences between these two methods.

[Table 5 about here.]

3.1 Energy Prices

The vector of tax-inclusive energy prices, EP_{it}, is parameterized as follows:

$$EP_{it} = \beta_1 \ln ElectP_{it} + \beta_2 \ln FP_{it} + \beta_3 \ln NGP_{it} + \beta_4 \ln SCP_{it} \quad (1)$$

[20] Giuri et al. (2007) find that more than fifty percent of filed patents are exploited for commercial and industrial purposes. If not, 32% of the patents are either licensed or used to block competitors, implying that the firm is already present in that market.

where $ElectP_{it}$, FP_{it}, NGP_{it} and SCP_{it} are the electricity, fuel, natural gas, and steam coal prices for each firm, respectively. This is a time-varying weighted average of prices across the countries in which firm i operates. For simplicity we just specify the construction of fuel prices,

$$ElectP_{it} = \sum_{c} \omega_{ict}^{PP} ElectP_{ct}$$

where ω_{ict}^{PP} is a (dynamic) firm-specific weight that uses information on firm's i history of patenting for $t = \{1, 2, \ldots, T\}$, i.e. for the first year of the regression period, and then evolves according to how active firm i is in country c. More specifically, the weight ω_{ict}^{PP} is defined as the fraction of firm i's patents in country c at time t, and thus it may be easily thought of as the firm's patent portfolio in a given country at a specific point in time.[21] This procedure allows us to identify the relative importance of markets.[22]

3.2 Stock of Knowledge

The stock of knowledge is the accumulated result of prior internal and external efforts to generate new ideas and technologies. This concept captures the idea that firms stand on "the shoulders of giants". In this paper, the knowledge stock is defined as:

$$\begin{aligned} A_{it} = {} & \gamma_1 \ln K_{SE,it} + \gamma_2 \ln K_{NS,it} + \\ & \underbrace{\gamma_3 \ln GSPILL_{SE,it} + \gamma_4 \ln GSPILL_{NS,it} + \gamma_5 \ln RSPILL_{it}}_{\text{Knowledge Spillovers}} \end{aligned} \tag{2}$$

[21] A firm's exposure to a market is determined by considering all inventions patented in that market. Therefore we do not only consider solar patents but all type of patents.

[22] Given that some patent jurisdictions are regional offices and may grant protection in several markets, we construct artificial markets for these jurisdictions (See Appendix A.1).

where $GSPILL_{SE,it}$ and $GSPILL_{NS,it}$, and $RSPILL_{it}$, explained below, together capture all knowledge spillovers from which firm i benefits.[23] SE denotes solar and NS non-solar technologies, respectively. $K_{x,it}$ is the firm's own stock of innovation in technology x, calculated by applying the perpetual inventory method suggested by Griliches and Mairesse (1984):

$$K_{x,it} = PAT_{x,it} + (1 - \delta)K_{x,i,t-1}$$

where $\delta \in (0, 1)$ is the depreciation rate of existing technology. The existing literature often sets $\delta = 0.20$ or higher (see Bloch, 2003; Chan et al., 2001; Lev and Sougiannis, 1996; Sakai et al., 2016; Smith et al., 2004).

Knowledge spillovers in our setting should be understood as knowledge flows (Collins and Wyatt, 1988) that result from different knowledge transactions. Geographical spillovers, $GSPILL_{x,it}$, originate from non-codified knowledge transfers between inventors, either by employees' turnover across firms or by informal contacts between inventors. Let the knowledge spillovers, in technology x, from which firm i benefits at time t be defined as:

$$GSPILL_{x,it} = \sum_{c} w^{IP}_{ict} GSPILL_{x,ct}$$

where ω^{IP}_{ict} is the firm-specific inventors' portfolio, i.e. the relative number of firm's i inventors in country c, and $SPILL_{x,ct}$ is the total spillover of country c, defined as:

$$GSPILL_{x,ct} = \sum_{j \neq i} \omega^{IP}_{jct} K_{x,jt}$$

[23]Previous empirical studies that have relied on patent data to construct measures of knowledge spillovers are: Belenzon and Schankerman (2013); Cockburn et al. (2002); Dechezleprêtre et al. (2014); Gomes-Casseres et al. (2006); Jaffe et al. (1993); Maurseth and Verspagen (2002); Murata et al. (2014); Peri (2005); Thompson and Fox-Kean (2005), to just name a few.

so that the relevant spillover of country c for firm i depends on the exposure of other firms' inventors as well as the knowledge they have accumulated up to the present time.[24]

Given the richness of personal data that is obtained from combining PATSTAT with the EEE-PPAT table, we can obtain the exact geographical location of inventors. To identify the geolocation (latitude and longitude) of inventors we implement the following strategy. First, we maximize the quality of information, i.e. when we detect several addresses in the same region for one individual, we keep the address that provides more information. All addresses are queried in *Google Maps Geocoding API*'s system, which returns geographic coordinates. Figure 5 below depicts the geographical distribution of inventors.

[Figure 5 about here.]

Research spillovers, $RSPILL_{it}$, capture codified knowledge extracted from patent documents and *partly* correspond with Griliches (1991)'s "pure knowledge spillovers" formulation in which citations play a key role. However, citations are a noisy measure of knowledge spillovers (Jaffe et al., 2000) that do not necessarily reflect true spillovers, as a considerable number of citations are added by patent examiners,[25] and inventors are, to a great extent, unaware of them. Furthermore, a share of total citations does not represent knowledge flows as they refer to patents filed by the same inventor(s), i.e. self-citations. For these reasons, we characterize research

[24]Implicit in this approach, firm i's inventors are assumed to interact with probability one with the inventors of other firms and, also, to fully absorb their knowledge. Although this is obviously far from perfect, it can still serve as an approximation to the knowledge transfer process.

[25]Alcacer and Gittelman (2006)'s empirical study concludes that 40% of all patents have all citations added by patent examiners; also, about two-thirds of citations in the average patent are added by examiners.

spillovers as knowledge flows that originate from direct surveying of other firms' relevant inventions for firm i's invention, and parameterize them as follows:

$$RSPILL_{it} = NPL_{it} + PL_{it} \times I_C(x), \quad \text{where } I_C(x) = \begin{cases} 0 & x \in C \\ 1 & \text{otherwise} \end{cases}$$

where NPL_{it} is the number of different non-patent literature documents reviewed by firm i at time t, PL is the number of different patent documents, and $I_C(x)$ is an indicator function that takes the value 1 when citations are added by other than the patent examiner or by the same inventor, i.e. when $x \notin C$; and 0 otherwise. This approach thus controls for self-learning.[26]

3.3 Financial Markets

When firms file patents in certain jurisdictions they mainly aim to capture and secure market demand. This is the reason why many firms seek for legal protection in countries with large markets. Patenting in other countries may also have additional advantages such as access to a wider pool of financial resources. For instance, once a firm has been granted a patent it might be eligible for governmental R&D subsidies, tax deductions, or may be able to pledge the granted patent as collateral to obtain resources from country's c financial institutions (Amable et al., 2010; Hochberg et al., 2014; Munari

[26] Recent literature (Dechezleprêtre et al., 2014; Lukach and Lukach, 2007; Shaffer, 2011) uses measures, such as the PatentRank algorithm, to determine the relevance of patent documents by examining quality and number of (backward- and forward-) citations. Whilst this method proves fruitful for determining the importance of some inventions in the development of a technological field, it is not clear that it is appropriate for the construction of firm-specific research spillovers.

et al., 2011). A priori, we expect firms exposed to stronger financial markets to patent more intensively.

We compute the effect of financial systems, FS_{it}, on firm i at time t as:

$$FS_{it} = \sum_{c} \omega_{ict}^{PP} IFD_{ct} \tag{3}$$

where ω_{ict}^{PP} is the patent portfolio of the firm in country c defined above, and IFD_{ct} is the Index of Financial Development of country c, corresponding with the newly-developed index in Svirydzenka (2016).

3.4 Controls

The set of controls include public R&D funding for the development of clean technologies, a market size measure (i.e., the size of the renewable sector compared to non-renewable energy), a measure of efficiency in solar technologies (a proxy for the technology frontier in the industry), climate change regulation measures such as CO_2 or greenhouse emissions, and macroeconomic controls such as GDP, GDP per capita or population.

4 Empirical Strategy

4.1 Model

Consider the following structural-form model:

$$\text{PAT}_{SE,it} = \exp\left(EP_{i,t-p} + A_{i,t-p} + \phi FS_{i,t-p} + \psi_m X_{it} + \lambda T\right) \xi_i + u_{it} \tag{4}$$

where $\text{PAT}_{SE,it}$ is the number of patents applied for in the solar industry sector by firm i in year t; EP_{it} is a vector of energy prices lagged p periods; A_{it} is the firm's knowledge stock, which depends on both past (firm-specific) innovation and knowledge spillovers from other institutions and inventors; FS_{it} is the strength of the representative financial system to which firm i is exposed; X_{it} is a vector of controls; T is a set of time dummies; ξ_i are firm-specific effects; and u_{it} is the usual idiosyncratic error term in the regression. Substituting equations (1) and (2) into equation (4) yields equation (5), which is the baseline model for estimation:

$$\begin{aligned} \mathrm{PAT}_{SE,it} = \exp\big(&\beta_1 \ln ElectP_{i,t-p} + \beta_2 \ln FP_{i,t-p} + \beta_3 \ln NGP_{i,t-p} \\ &+ \beta_4 \ln SCP_{i,t-p} + \gamma_1 \ln K_{SE,i,t-1} + \gamma_2 \ln K_{NS,i,t-1} \\ &+ \gamma_3 \ln GSPILL_{SE,i,t-1} + \gamma_4 \ln GSPILL_{NS,i,t-1} \\ &+ \gamma_5 \ln RSPILL_{i,t-1} + \phi FS_{i,t-p} + \psi_m X_{it} + \lambda T\big)\, \xi_i + u_{it} \end{aligned} \tag{5}$$

Coefficient expectations are: (i) $\beta_i > 0$ for $i = \{1, 2, 3, 4\}$, i.e. as energy prices (electricity, fuel, natural gas and coal) increase the number of patents in solar energy should increase given that clean energy generation becomes cheaper in relative terms;[27] (ii) $\gamma_1 > \gamma_2 > 0$, implying that the firms' internal accumulated knowledge in solar energy is more important than other internally accumulated knowledge; (iii) $\gamma_3 > \gamma_4 > 0$, assuming that external knowledge spillovers from solar technology are more relevant than other spillovers; (iv) $\gamma_5 > 0$, so that organizations benefit from codified knowledge embedded in patent documents outside the firm; and (v) $\phi > 0$, indicating that organizations with access to stronger financial markets benefit from greater opportunities to finance their innovations and activities.

The number of lags p of energy prices is optimally determined by the number of former periods which influence firms' production decisions. If firm i makes the decision to develop a new product in year $t-3$, the optimal

[27] In particular, we expect electricity prices to have a larger effect than any other energy price on fostering solar-related innovations, i.e. $\beta_1 > \beta_2, \beta_3, \beta_4$, given that solar energy is a direct substitute for electricity generation.

number of lags should be three. However, given the large heterogeneity between firms, it is in practice difficult to decide upon this number. Also, the greater the number of lags, the larger the reduction in the dimensions of the panel. Thus, it appears convenient to decide upon the optimal number of lags by taking as a reference the time dimensions of the data. Finally, as noted by Aghion et al., firms' own stocks of innovation and spillovers are lagged one period to be consistent with the path dependency hypothesis.

4.2 Estimation

From the set of nonlinear panel data models our preferred specification is the Poisson fixed-effects model. The Poisson panel estimator is consistent provided that the conditional mean is correctly specified, even when the errors are not distributed as Poisson. However, in the presence of overdispersion, i.e. the conditional variance is larger than the conditional mean, the estimated standard errors will considerably understate true standard errors. If this is the case, there are two alternatives: (i) either to apply a more appropriate estimator that explicitly accommodates overdispersion, such as the Negative Binomial; or ii) to use the Poisson estimator with cluster-robust standard errors, which are roughly twice as large as default standard errors (Cameron and Trivedi, 2013). The former has the advantage to bring efficiency gains, whilst the latter relies on weaker distributional assumptions. Since the Negative Binomial model brings only slight efficiency gains when compared to the Poisson with cluster-robust standard errors, it is beneficial to implement the Poisson fixed-effects estimator considering that is more robust under uncertainty in distributional assumptions.

5 Summary Statistics and Empirical Results

Our baseline results are estimated from the sample with biadic patents. While the triadic region consisting of the United States Patent and Trademark Office (USPTO), Japanese Patent Office (JPO), and European Patent Office (EPO) accounted for the majority of global patent applications in the 1990s, their share decreased to less than 50% by 2013 (OECD 2015) suggesting a trend towards decentralization of the regional areas for intellectual property protection. To account for the possibility that this trend is relevant also for solar inventions, we consider triadic patents as well as biadic and patents filed in one or more regions. We also report results for fouradic patents (triadic plus China or Korea). While the triadic sample contains 4,545 patent observations, the number is almost double in the biadic sample (8,849), and five times higher in the sample with all patents (22,664). Assuming that a larger market for intellectual property protection can be considered as a proxy for patent quality, we consider the biadic sample as the most optimal tradeoff between quantity and quality. The result section also include fouradic patents (triadic plus China or Korea).

We first present the descriptive statistics before estimating equation (5) and conducting sensitivity tests. Summary statistics and correlations for the sample consisting of biadic patents are reported in Table 6 and Table 7. The baseline regression results appear in Table 8, and robustness checks are presented in Tables 9–15.

5.1 Summary Statistics

Table 6 reports the summary statistics for biadic patents, the panel of which is not balanced. The number of observations for solar patents, ($\text{PAT}_{SE,it}$) is considerably larger than for any other variable because when patents are not registered, this number is set to zero, reflecting no patenting activity in that year. Unfortunately this cannot be done for other variables as the data would be arbitrarily modified. Also, the data for steam coal price ($\ln \mathrm{SC}_{it}$) are poor, which is the motivation why this variable is discarded for analysis. The average number of biadic patents by firm-year is 0.37 with a standard deviation of 2.07, indicating the presence of overdispersion. The two variables for knowledge stocks shows that the log of firms' average stock of non-solar inventions is 1.51 (4.54 patents) compared to 0.33 (1.39 patents) for solar inventions. Taking the antilog of the energy subsidies, the table reveals that fossil fuel energy is four times more subsidized than solar energy.

[Table 6 about here.]

Table 7 below displays the correlation matrix. As expected, energy prices are highly collinear, creating challenges for estimation. Instead of estimating with a vector of energy prices, we focus on electricity prices, $\ln \mathrm{ElecP}_{it}$, which are *a priori* more important for innovation in solar energy than any other energy price.[28]

[Table 7 about here.]

5.2 Baseline Results

Table 8 reports the results for the biadic sample. Column 1 shows the impact of energy prices on solar patents, controlling for a time trend and fixed effects. Column 2 adds firms' own patent stocks to the model, while Column 3 also considers R&D subsidies. The full model is reported in Column 4, also considering the impact of access to external financial sources. It should be

[28]To ensure that our results do not depend on electricity prices, robustness checks are performed for the different energy prices.

noted that energy prices are closely associated with carbon taxes, suggesting that the former can be considered as a proxy for the latter.

Lagged values of energy prices in the first column are quite precisely estimated at 3.293. The implication is this result is that a 1% increase in price of electricity or carbon taxes is associated with about 3% more solar patents. The corresponding estimate in Aghion et al. (2014) is around unity when the dependent variable is patents in the electric car industry.

The estimated effect of our proxy for carbon taxes is reduced to 1.7 in the second column that include lagged knowledge stocks in the regression. Knowledge spillovers from prior inventions have a significant and positive impact on current patenting activity in solar energy. The point estimate is 0.436 and highly significant. The estimated effect is about the same for prior patents in other technologies (0.365).

The point estimate for R&D subsidies to solar energy in the third column is 0.133 and highly significant. In their study, Aghion et al (2014) find no effect of research support to clean technology. Column 3 also report the effect of fossil fuel energy subsidies, which are five times larger than subsidies to solar energy. The estimate is -0.114, not distinguishable from zero.

The results for the full model are provided in Column 4. The regression results suggest that 1% higher carbon taxes increase solar innovations with 2%, and that the impact of a 1% increase in knowledge stocks is 0.4% more solar patents. The positive impact of research subsidies to renewable energy in Column 3 is confirmed in Column 4. When estimating the full model, the negative effect of subsidies to carbon-intensive energy is significant at the 5% level. Contrary to expectations, stronger financial markets do not stimulate solar innovations, with the estimated effect of the lagged financial variable of -0.777. How can this be explained? First, the country index of Financial

Development shows almost no within-variation in our sample, rendering the fixed effects estimator inefficient. Second, as pointed out by Svirydzenka, when financial indices are already high, having a larger index might reflect stricter regulations rather than flexibility, so that being exposed to stronger financial systems might not be beneficial.

[Table 8 about here.]

5.3 Robustness Checks

In this subsection we investigate whether the main results are sensitive to model specifications, energy prices, the depreciation rates of knowledge stocks, estimation techniques, patent families, and markets.

Table 9 tests different lag structures of the carbon taxes and finds that they are positively related to solar innovation in lagged periods. The parameter estimate for the contemporaneous effect is 4.292, falling to 2.230 with four lagged periods. The baseline results are not sensitive to choice of the lag structure of energy prices.

[Table 9 about here.]

Following Aghion et al. (2014) we use energy prices as a proxy for carbon taxes, and we consider electricity prices in the baseline model. Table 10 reports results for different energy prices. The table shows that solar technology is also an increasing function of lagged prices of both natural gas and fuel. The only difference compared to electricity is that the highly significant point estimates are smaller. This is in accordance with our assumption that taxing electricity is more relevant for solar technology than taxing natural gas prices or fuel prices, i.e. $\beta_1 > \beta_3 > \beta_2$, although increasing taxation on all carbon-intensive energy sources stimulates the development of clean energy, i.e. $\beta_i > 0$.

[Table 10 about here.]

Next we check that the baseline results are not sensitive to depreciation rates of the knowledge stocks (see Table 11). In the regression we change the assumed depreciation rate from $\delta = 0.20$ to $\delta = 0.15$. As evidenced in the table, our estimates are not affected by depreciation rates.

[Table 11 about here.]

Our baseline results are estimated by the nonlinear Poisson fixed effects count data model, assuming the equidispersion property of the Poisson distribution. However, Table 6 reported that the equidispersion property is violated as the mean value of the patent variable is 0.37 and its standard error 2.070. An alternative estimator is the negative binomial (NB) model which is more general than the Poisson model since is accommodates overdispersion of observations with zero patents. Table 12 compare the baseline estimates with the fixed effects NB model. The table also presents random effects estimates for the two models.

If we first look at Column 2 and the estimate from Poisson RE, we find that the most significant difference to the baseline results relates to the financial variable. It is not significant in the RE model, which suggests that the result in the baseline model is driven by the low degree of variation in the financial indexes we use. It can also be noted that the significance level of the two subsidy estimates decreases from 5% in the FE model to 10% in the RE model.

Column 3 and 4 reports the NB model's results. The estimated impact of carbon taxes is similar to the baseline results, with the exception that the point estimate for the financial markets variable is not distinguishable from zero.

[Table 12 about here.]

We then estimate equation 5 for the four different samples, where Table 13 compares the results. The most divergent results are shown in the sample of all patents in column (2), where the estimates are insignificant for both firms' own knowledge base in solar energy and subsidies for carbon-intensive energy sources. Our interpretation of these estimated effects is that they are data driven. The quality of the model's estimates is lower when based on our sample with all patents.

[Table 13 about here.]

An important robustness check is whether our results are sensible to different weighting schemes, which express firms' exposure to different markets. In table 14, we report these results. Column (1) displays our baseline estimates. Column (2) uses static weighting from the last year of the pre-sample period (1989), as in Aghion et al. (2016)'s approach, so that only exogenous sources of variation are exploited in the data. Column (3), using semi-static weighting, updates weights once every six years. Column (4) uses placebo (dynamic) weights that are randomly selected from a normalized uniform distribution.[29]

There is obviously a trade-off between weighting schemes. On the one hand, dynamic weighting introduces semi-endogenous sources of variation in the data, as firms may vary their market exposures in accordance to the

[29]Note that the number of observations more than doubles in comparison to our baseline estimates. This is explained by the imposed restrictions in the randomization process, namely, in order to take advantage of all information in the sample we randomize across the set of countries for which full data are available.

underlying socioeconomic processes in these markets, but correctly identifies exposures to markets. Static weighting, on the other hand, makes variables exogenous but at the high cost of miscalculating market exposures (see Table 5). We believe that dynamic weighting presents more advantages than limitations in comparison to the static scheme. As regardless of the weighting scheme that is used, th einterpretation of coefficients seems more reliable when market exposures are accurately computed. Columns (3) and (4) present further robustness checks. Especially important is column (4), which utilizes placebo weighting and tests for model overfitting. Although all variables are significant, the results are generally not in line with prior results and coefficient expectations. For instance, non-solar related stocks become more important than solar-related (own) stocks of innovation. Most surprisingly, fossil-fuel subsidies spur innovation in solar technologies while solar subsidies hinder it. As these coefficients do not conform with prior results and *a priori* expectations, we may conclude that placebo weighting renders, as expected, inadequate results, and that there is no model overfitting.

[Table 14 about here.]

In the final robustness check, we test for sensitivity of organizations such as universities and governmental non-profits being included in the sample. Columns (1) and (2) in table 15 report our baseline results for organizations with depreciation rates, δ, of twenty and fifteen percent, respectively. Columns (3) and (4) report the same results for only firms. Interesting results emerge: on the one hand, firms are more sensitive to government intervention when it comes to taxation and financial markets. Governmental non-profit organizations or universities, on the other hand, rely more heavily on subsidies as it is more difficult for them to internally finance their activities since they are not primarily focused on commercialization of their inventions.

[Table 15 about here.]

6 Conclusion

Recent literature on economic growth and directed technical change addresses climate change by endogenous market-based approaches in which profit-maximizing firms can decide whether to innovate in environmental-friendly or carbon-intensive technologies.

Empirical tests of predictions from endogenous models on the transport sector confirm that regulations and subsidies may alter relative returns on investments and redirect firms' innovations from conventional vehicles to hybrid or electric vehicles (Aghion et al. (2016)).

Relying on building blocks from the automotive study, this paper studies how directed technical change affects innovation in patenting in solar thermal and solar cells. Using a panel data with micro and macro observations from nearly 200 countries over a 20-year period, we find that carbon taxes, R&D subsidies to solar technology, and the size of firms' own knowledge stocks have significant positive effects on solar innovations. R&D subsidies to fossil energy have the adverse effect, while the role of financial markets and financial institutions are negligible. The results are robust to a number of sensitivity tests.

Despite explosive growth over the recent decade, solar electricity accounts for less than 1% of world energy supply. To be compatible with the 2015 Paris Agreement and the U.N. Sustainable Energy goal, this fraction must increase tenfold by 2040. Further research should address whether current policy interventions and commercial activities are sufficiently comprehensive for this ambition to be achievable.

References

Acemoglu, D., Aghion, P., Bursztyn, L. and Hemous, D. (2012). The environment and directed technical change, *American Economic Review* **102**(1): 131–66.

Acemoglu, D., Akcigit, U., Hanley, D. and Kerr, W. (2016). Transition to clean technology, *Journal of Political Economy* **124**(1): 52–104.

Acs, Z. J. and Audretsch, D. B. (2003). *Innovation and technological change*, Springer.

Aghion, P., Dechezleprtre, A., Hmous, D., Martin, R. and Reenen, J. V. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry, *Journal of Political Economy* **124**(1): 1–51.

Alcacer, J. and Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations, *The Review of Economics and Statistics* **88**(4): 774–779.

Amable, B., Chatelain, J.-B. and Ralf, K. (2010). Patents as collateral, *Journal of Economic Dynamics and Control* **34**(6): 1092–1104.

Ansar, A., Caldecott, B. and Tilbury, J. (2013). Stranded assets and the fossil fuel divestment campaign: what does divestment mean for the valuation of fossil fuel assets, *Stranded Assets Programme, SSEE, University of Oxford* pp. 1–81.

Arundel, A. and Kabla, I. (1998). What percentage of innovations are patented? empirical estimates for european firms, *Research policy* **27**(2): 127–141.

Belenzon, S. and Schankerman, M. (2013). Spreading the word: Geography, policy, and knowledge spillovers, *Review of Economics and Statistics* **95**(3): 884–903.

Bloch, C. (2003). The effect of r&d expenditures on stock market returns for danish firms, *AFSK WP* **6**.

Cameron, A. C. and Trivedi, P. K. (2013). *Regression analysis of count data*, Vol. 53, Cambridge university press.

Chan, L. K., Lakonishok, J. and Sougiannis, T. (2001). The stock market valuation of research and development expenditures, *The Journal of Finance* **56**(6): 2431–2456.

Chang, C.-L., Chen, S.-P. and McAleer, M. (2013). Globalization and knowledge spillover: international direct investment, exports and patents, *Economics of Innovation and New Technology* **22**(4): 329–352.

Čihák, M., Demirgüç-Kunt, A., Feyen, E. and Levine, R. (2012). Benchmarking financial systems around the world.

Cincera, M. et al. (1997). Patents, r&d, and technological spillovers at the firm level: some evidence from econometric count models for panel data, *Journal of Applied Econometrics* **12**(3): 265–280.

Cockburn, I. M., Kortum, S. and Stern, S. (2002). Are all patent examiners equal? the impact of examiner characteristics, *Technical report*, National Bureau of Economic Research.

Cohen, W. M., Nelson, R. R. and Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why us manufacturing firms patent (or not), *Technical report*, National Bureau of Economic Research.

Collins, P. and Wyatt, S. (1988). Citations in patents to the basic research literature, *Research Policy* **17**(2): 65–74.

de la Potterie, B. v. P. and Van Zeebroeck, N. (2008). A brief history of space and time: The scope-year index as a patent value indicator based on families and renewals, *Scientometrics* **75**(2): 319–338.

Dechezleprêtre, A., Martin, R. and Mohnen, M. (2014). Knowledge spillovers from clean and dirty technologies.

Dernis, H. and Khan, M. (2004). Triadic patent families methodology.

Du Plessis, M., Van Looy, B., Song, X. and Magerman, T. (2009). Data production methods for harmonized patent indicators: Assignee sector allocation, *Luxembourg: EUROSTAT Working Paper and Studies* .

Filippetti, A., Frenz, M. and Ietto-Gillies, G. (2016). The impact of internationalization on innovation at countries? level: the role of absorptive capacity, *Cambridge Journal of Economics* p. bew032.

Giuri, P., Mariani, M., Brusoni, S., Crespi, G., Francoz, D., Gambardella, A., Garcia-Fontes, W., Geuna, A., Gonzales, R., Harhoff, D. et al. (2007). Inventors and invention processes in europe: Results from the patval-eu survey, *Research policy* **36**(8): 1107–1127.

Gomes-Casseres, B., Hagedoorn, J. and Jaffe, A. B. (2006). Do alliances promote knowledge flows?, *Journal of Financial Economics* **80**(1): 5–33.

Griliches, Z. (1990). Patent statistics as economic indicators: a survey, *Technical report*, National Bureau of Economic Research.

Griliches, Z. (1991). The search for r&d spillovers, *Technical report*, National Bureau of Economic Research.

Griliches, Z. and Mairesse, J. (1984). *Productivity and R&D at the Firm Level*, National Bureau of Economic Research Cambridge, Mass., USA, pp. 339–374.

Guellec, D. and Van Pottelsberghe de la Potterie, B. (2004). From r&d to productivity growth: Do the institutional settings and the source of funds of r&d matter?, *Oxford Bulletin of Economics and Statistics* **66**(3): 353–378.

Harhoff, D., Scherer, F. M. and Vopel, K. (2003). Citations, family size, opposition and the value of patent rights, *Research policy* **32**(8): 1343–1363.

Haščič, I. and Migotto, M. (2015). Measuring environmental innovation using patent data.

Haščič, I., Silva, J. and Johnstone, N. (2015). The use of patent statistics for international comparisons and analysis of narrow technological fields.

Hausman, J. A., Hall, B. H. and Griliches, Z. (1984). Econometric models for count data with an application to the patents-r&d relationship.

Henderson, R. and Cockburn, I. (1996). Scale, scope, and spillovers: the determinants of research productivity in drug discovery, *The Rand journal of economics* pp. 32–59.

Hicks, J. R. (1932). The theory of wages (2nd.

Hitt, M. A., Hoskisson, R. E. and Kim, H. (1997). International diversification: Effects on innovation and firm performance in product-diversified firms, *Academy of Management journal* **40**(4): 767–798.

Hochberg, Y. V., Serrano, C. J. and Ziedonis, R. H. (2014). Patent collateral, investor commitment, and the market for venture lending, *Technical report*, National Bureau of Economic Research.

Horstmann, I., MacDonald, G. M. and Slivinski, A. (1985). Patents as information transfer mechanisms: To patent or (maybe) not to patent, *Journal of Political Economy* **93**(5): 837–858.

Hotelling, H. (1931). The economics of exhaustible resources, *Journal of political Economy* **39**(2): 137–175.

IEA (2017). World energy outlook 2017, *Technical report*, International Energy Agency, Paris.

Jaffe, A. B., Trajtenberg, M. and Fogarty, M. S. (2000). Knowledge spillovers and patent citations: Evidence from a survey of lnventors, *NBER/Sloan* p. 21.

Jaffe, A. B., Trajtenberg, M. and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations, *the Quarterly journal of Economics* **108**(3): 577–598.

Johnstone, N., Haščič, I. and Popp, D. (2010). Renewable energy policies and technological innovation: evidence based on patent counts, *Environmental and resource economics* **45**(1): 133–155.

Lev, B. and Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of r&d, *Journal of accounting and economics* **21**(1): 107–138.

Lukach, R. and Lukach, M. (2007). Ranking uspto patent documents by importance using random surfer method (pagerank).

Magerman, T., Van Looy, B. and Song, X. (2006). Data production methods for harmonized patent statistics: Patentee name harmonization.

Maurseth, P. B. and Verspagen, B. (2002). Knowledge spillovers in europe: a patent citations analysis, *The Scandinavian journal of economics* **104**(4): 531–545.

Milliman, J., Von Glinow, M. A. and Nathan, M. (1991). Organizational life cycles and strategic international human resource management in multinational companies: Implications for congruence theory, *Academy of management review* **16**(2): 318–339.

Munari, F., Odasso, M. C. and Toschi, L. (2011). 12. patent-backed finance, *The Economic Valuation of Patents: Methods and Applications* p. 309.

Murata, Y., Nakajima, R., Okamoto, R. and Tamura, R. (2014). Localized knowledge spillovers and patent citations: A distance-based approach, *Review of Economics and Statistics* **96**(5): 967–985.

Nordhaus, W. D., Houthakker, H. and Solow, R. (1973). The allocation of energy resources, *Brookings papers on economic activity* **1973**(3): 529–576.

OPEC (2017). Opec world oil outlook 2040, *Technical report*, Organization of the Petroleum Exporting Countries, Vienna, Austria.

Peeters, B., Song, X., Callaert, J., Grouwels, J. and Van Looy, B. (2010). Harmonizing harmonized patentee names: an exploratory assessment of top patentees.

Peri, G. (2005). Determinants of knowledge flows and their effect on innovation, *Review of Economics and Statistics* **87**(2): 308–322.

Pizer, W. A. and Popp, D. (2008). Endogenizing technological change: Matching empirical evidence to modeling needs, *Energy Economics* **30**(6): 2754–2770.

Putnam, J. D. (1996). *The value of international patent rights*, Yale University Yale.

Reichelstein, S. and Yorston, M. (2013). The prospects for cost competitive solar pv power, *Energy Policy* **55**: 117–127.

Sakai, H. et al. (2016). Depreciation rate of r&d capital: panel data analysis of listed firms in japanese r&d-intensive industries, *Asian Economic and Financial Review* **6**(4): 196–205.

Shaffer, M. J. (2011). *Entrepreneurial innovation: Patent rank and marketing science*, PhD thesis, Washington State University.

Smith, V., Dilling-Hansen, M., Eriksson, T. and Madsen, E. S. (2004). R&d and productivity in danish firms: some empirical evidence, *Applied Economics* **36**(16): 1797–1806.

Steves, F. and Teytelboym, A. (2013). Political economy of climate change policy.

Svirydzenka, K. (2016). Introducing a new broad-based index of financial development.

Thompson, P. and Fox-Kean, M. (2005). Patent citations and the geography of knowledge spillovers: A reassessment, *American Economic Review* pp. 450–460.

Van Pottelsberghe, B., Denis, H., Guellec, D. et al. (2001). Using patent counts for cross-country comparisons of technology output, *Technical report*, ULB–Universite Libre de Bruxelles.

Veefkind, V., Hurtado-Albir, J., Angelucci, S., Karachalios, K. and Thumm, N. (2012). A new epo classification scheme for climate change mitigation technologies, *World Patent Information* **34**(2): 106–111.

Zahra, S. A., Ireland, R. D. and Hitt, M. A. (2000). International expansion by new venture firms: International diversity, mode of market entry, technological learning, and performance, *Academy of Management journal* **43**(5): 925–950.

A Appendix

A.1 Regional patent offices and other application authorities

Although there are several regional patent offices,[30] Table 16 lists only those offices that have registered at least one patent from our sample. Given that there is no correspondence between these offices and macroeconomic units, an identification hassle emerges. We solve this problem by creating aggregated macroeconomic variables. For instance, the African Regional Intellectual Property Organization (ARIPO) has 19 member states[31], each of them influencing the aggregated macroeconomic variables from earliest date of membership (in this case determined by the Lusaka Agreement) onwards. The same approach is followed for all other regional offices.

[Table 16 about here.]

Aggregated macroeconomic variables are mostly population-weigthed (e.g., GDP per capita, energy prices and taxes, energy efficiency measures, financial indexes, etc.), capturing the general conditions to which firms with patents in those jurisdictions are exposed. However, in the case of population and R&D subsidies, we simply sum over member states of the regional patent office in question. This choice is motivated by the fact that when firms file patents in regional offices they secure larger markets and, also, because having access to a greater number of markets makes firms eligible for subsidies in more countries.

Finally, there is an additional complication with patent offices that, if not properly accounted for, could bias the calculation of market exposures, namely: some patent offices that were in place in the past either no longer operate today or have changed names.[32] On the one hand, and in order to be consistent with our weighting scheme, where patent offices were renamed,

[30] Access http://www.wipo.int/directory/en/urls.jsp to see the full list.

[31] See https://goo.gl/DwU3Tb.

[32] Examples of patent offices that changed names are the African Intellectual Property Organization (OAPI), which was renamed African Regional Intellectual Property Organization (ARIPO) in 2005; and also, the patent office associated to the German Democratic Republic which, after the unification with the Federal Republic of Germany, became part of the German Patent and Trade Mark Office (DPMA). Examples of patent offices that ceased operations when their countries broke apart are USSR Gospatent and those linked to the former Socialist Federal Republic of Yugoslavia (SFRY) and Czechoslovakia.

we added the weights of the office's former and current name by applicant-year. On the other hand, despite having tagged some patent offices as "no longer operative", we still (artificially) followed them over time. This is so because, by construction, granted patents enter into firms' patent portfolios not only at the year of filing but also in all future periods, implying that the market(s) associated with a given jurisdiction will always affect those firms with at least one invention in that jurisdiction. Assuming that firms keep on innovating, extinguished jurisdictions' relative importance in patent portfolios will decline proportionally to firms' patenting intensity, in most cases becoming negligible.

Auxiliary figures and tables

[Figure 6 about here.]

[Figure 7 about here.]

[Table 17 about here.]

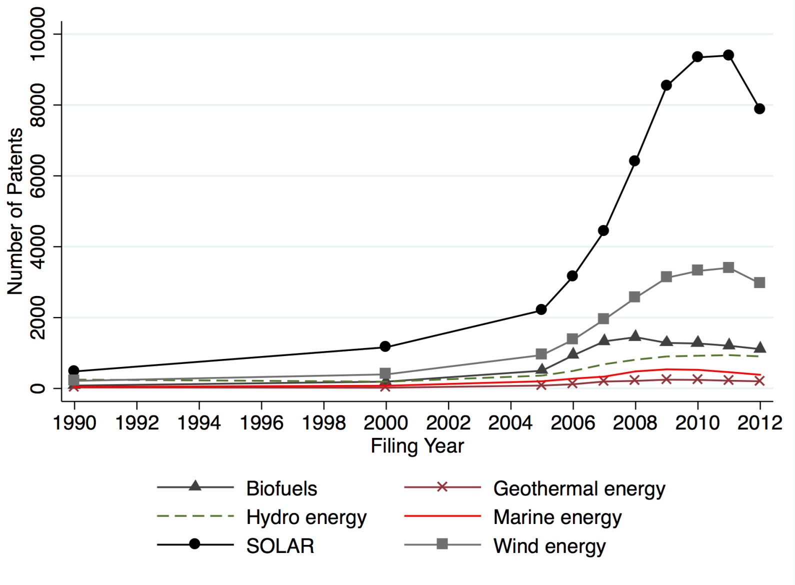
[Table 18 about here.]

[Table 19 about here.]

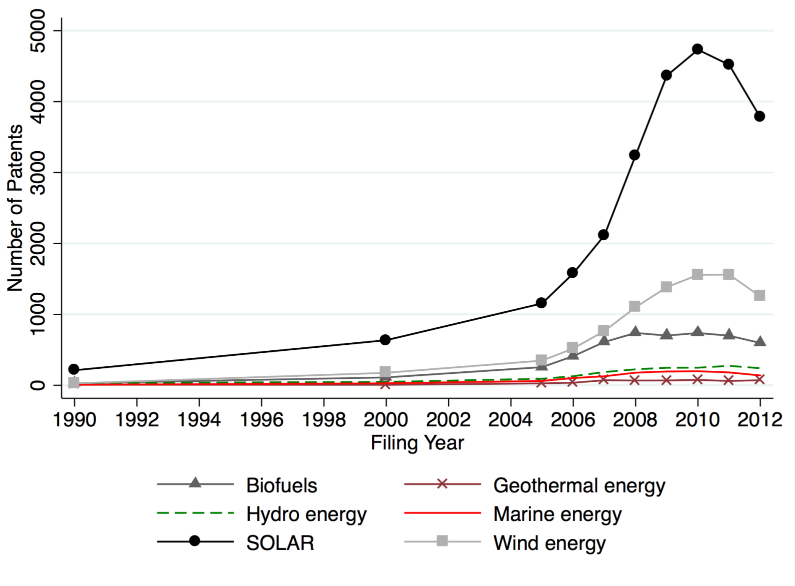
[Table 20 about here.]

Figure 1: Number of patents by family size, 1990–2012.

(a) Family size "1 and greater"



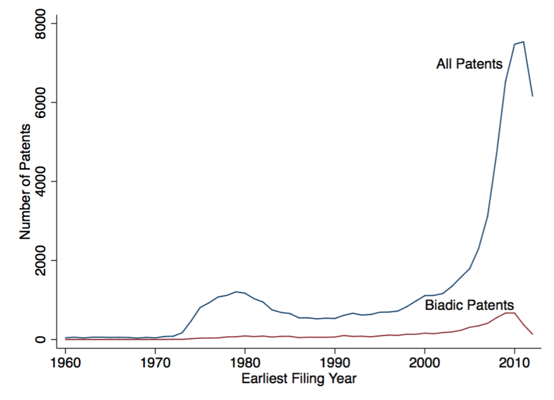
(b) Family size "2 and greater"



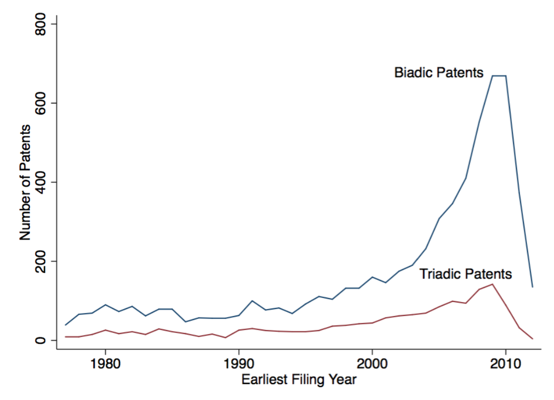
Notes: SOLAR is the summation of solar thermal energy, solar photovoltaic (PV) energy and solar thermal-PV hybrid patents. Family size "1 and greater" considers all patent priorities, including many low-value inventions. Family size "2 and greater" encompasses patents that sought protection in at least two jurisdictions, i.e. high-value inventions. *Source:* Science, Technology and Patents database, *OECD Statistics.*

Figure 2: Patent count by category-year

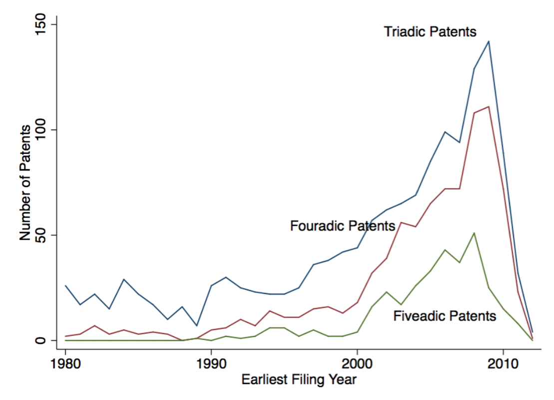
(a)



(b)



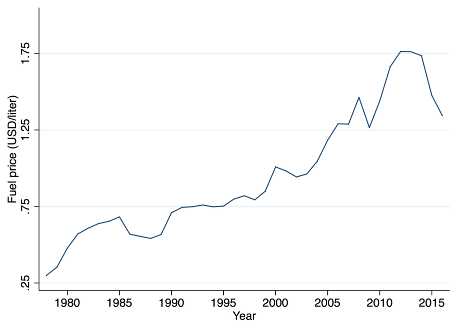
(c)



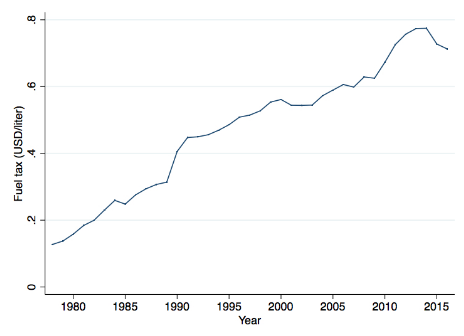
Notes: When an invention, i.e. same *docb_familiy_id*, is filed in several jurisdictions (e.g. USPTO and EPO) at different points in time it is counted as "biadic" by earliest filing year but not at all afterwards. This holds true for all patent categories. Note that the x-axis range differs between subfigures given that distinct patent offices started operating in different years (the EPO, for instance, was not in place until the late 1970s and therefore "triadic" patents cannot be operationalized until then). Source: *PATSTAT*.

Figure 3: Energy prices and taxes by energy group

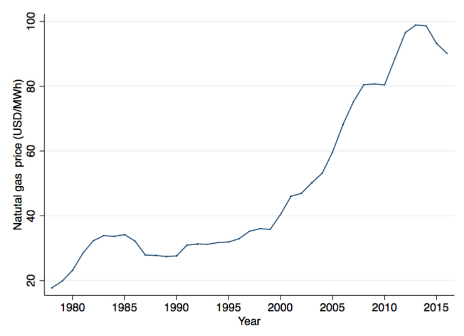
(a) Average fuel price



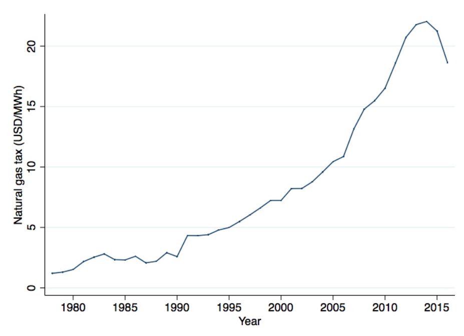
(b) Average fuel tax



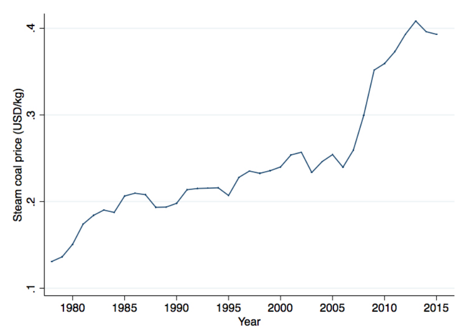
(c) Average natural gas price



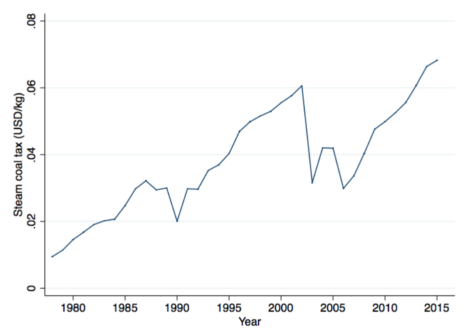
(d) Average natural gas tax



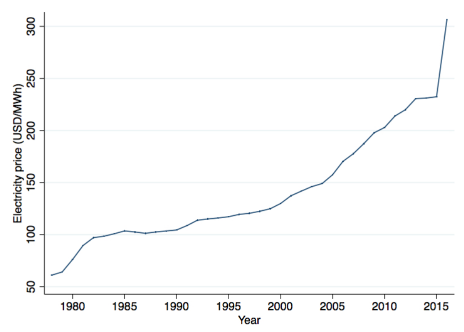
(e) Average steam coal price



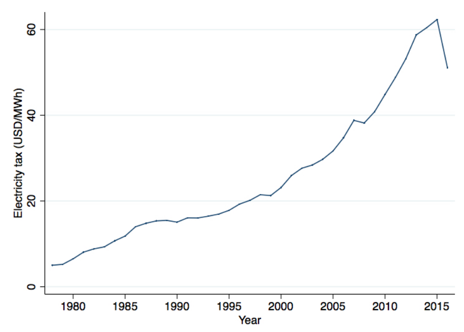
(f) Average steam coal tax



(g) Average electricity price



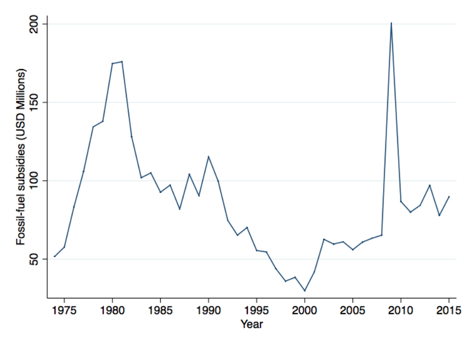
(h) Average electricity tax



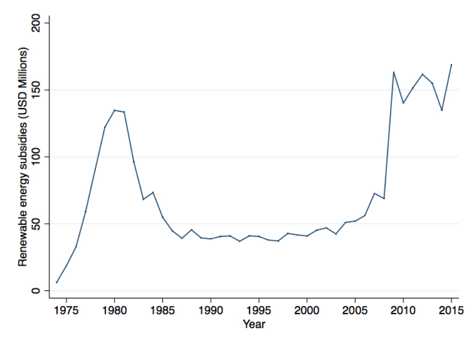
Notes: Fuel prices are calculated as the arithmetic mean of fuel oils, diesel, gasoline prices, and LPG. Source: *IEA*.

Figure 4: R&D energy subsidies

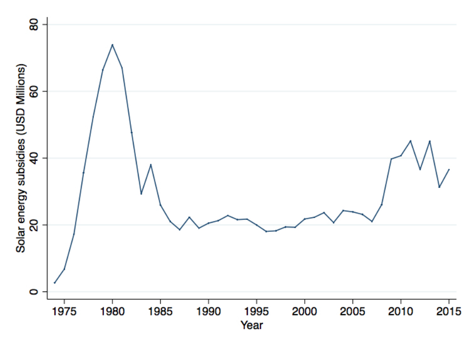
(a) Average fossil-fuels subsidy



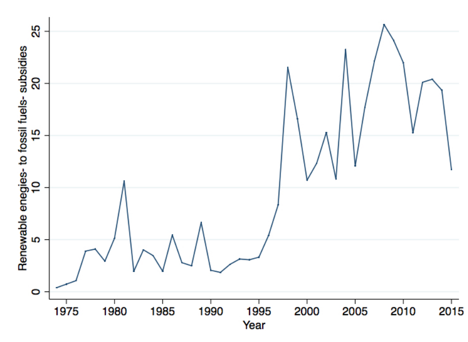
(b) Average renewable energy subsidy



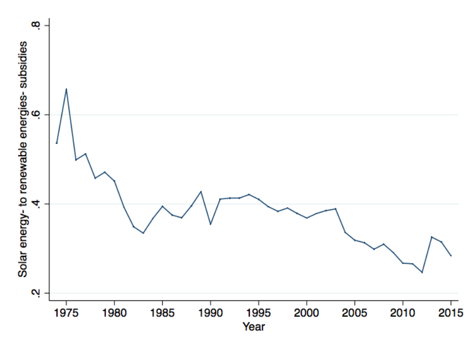
(c) Average solar energy subsidy



(d) Renewables to fossil fuels



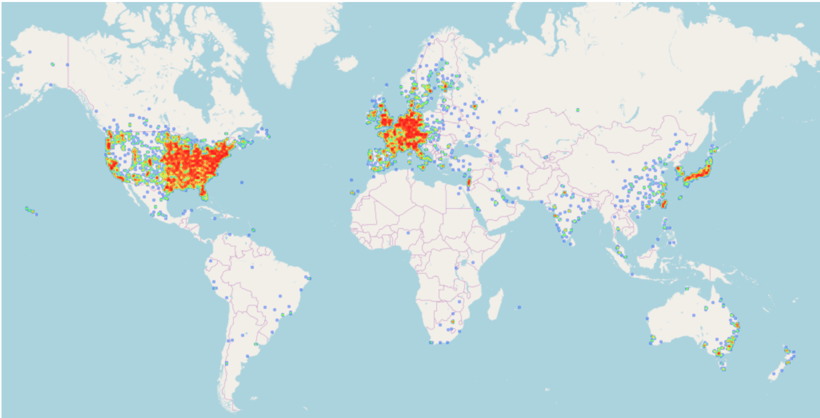
(e) Solar to renewables



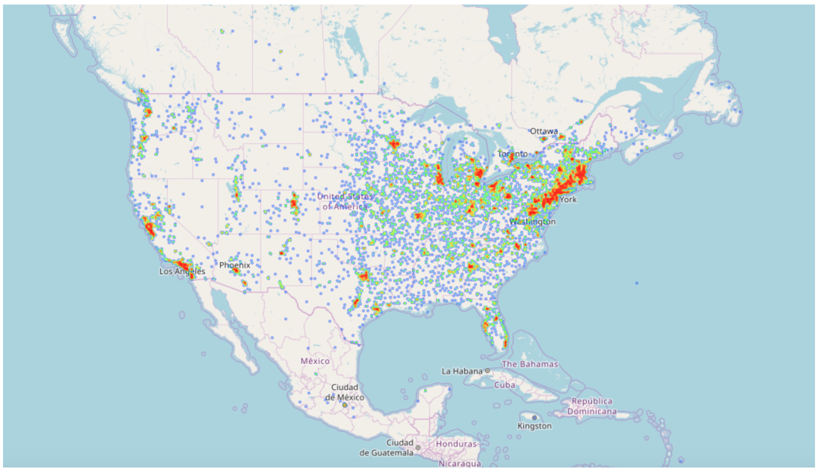
Source: IEA.

Figure 5: Geographical distribution of inventors

(a) World



(b) United States



(c) Europe

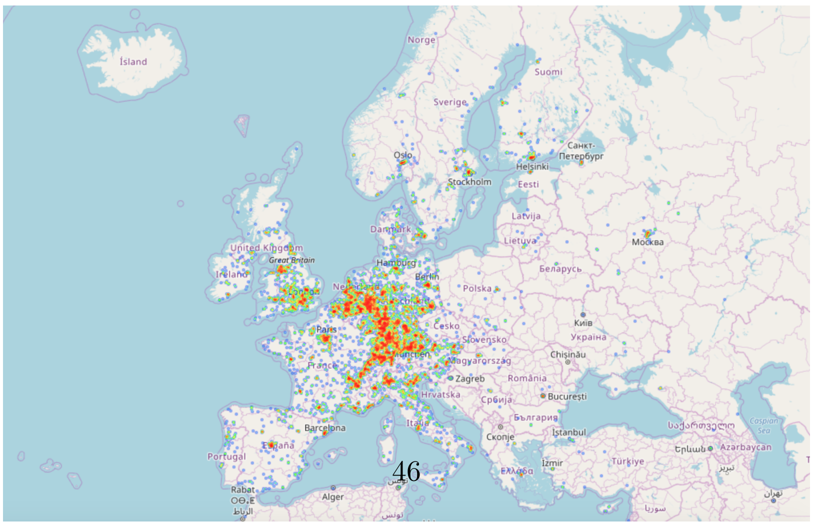
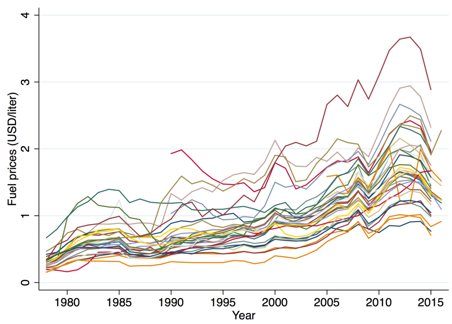
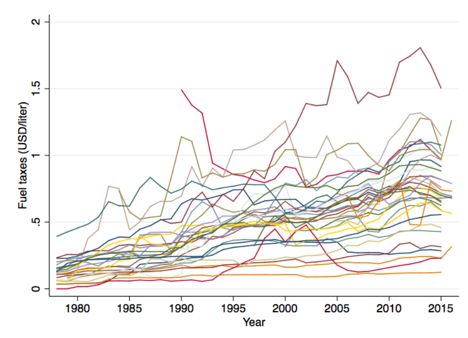


Figure 6: Country-level energy prices and taxes by energy group

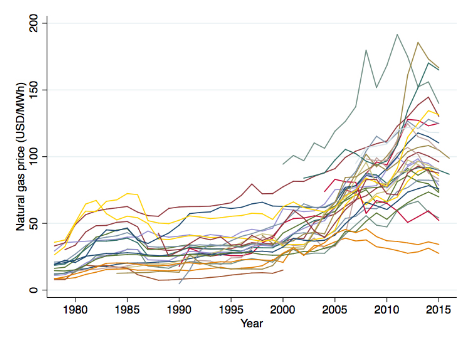
(a) Fuel prices



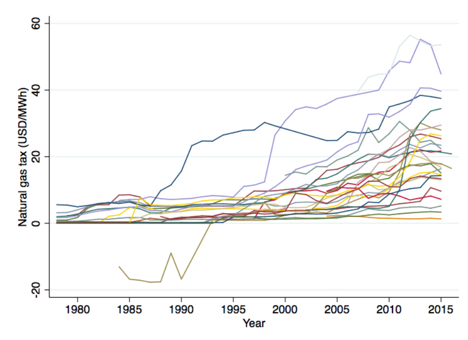
(b) Fuel taxes



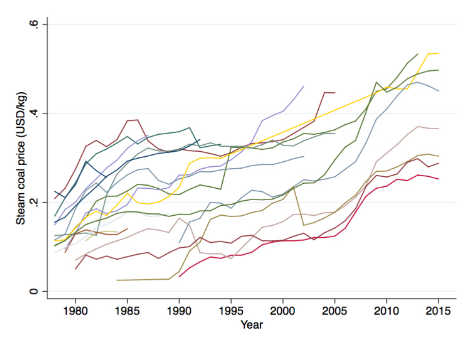
(c) Natural gas prices



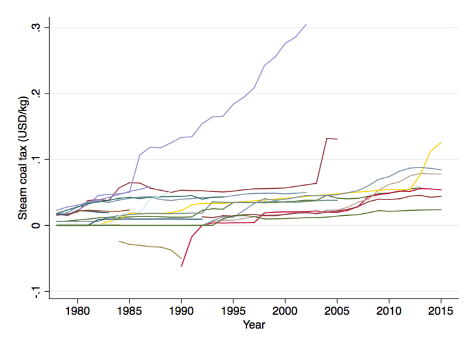
(d) Natural gas taxes



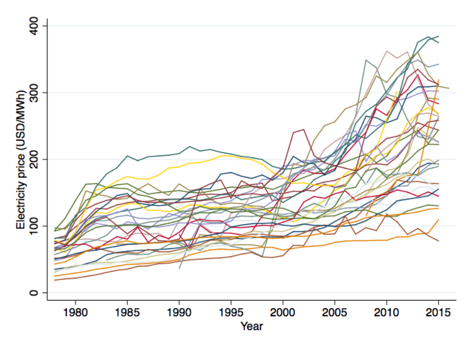
(e) Steam coal prices



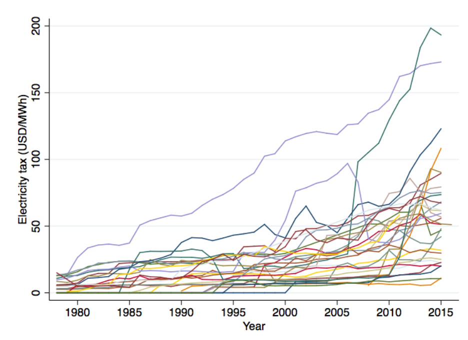
(f) Steam coal taxes



(g) Electricity prices



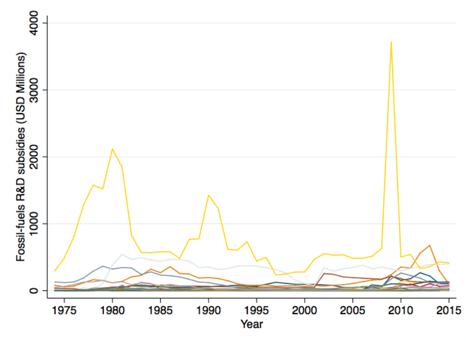
(h) Electricity taxes



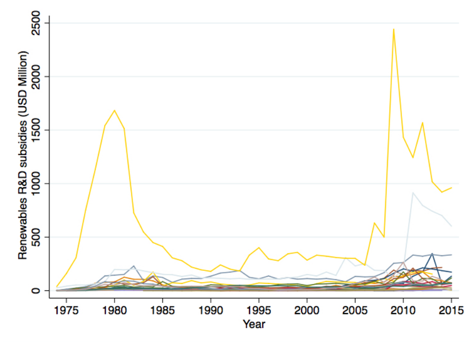
Notes: Fuel prices are calculated as the arithmetic mean of fuel oils, diesel, gasoline prices, and LPG. Source: *IEA*.

Figure 7: Country-level R&D energy subsidies

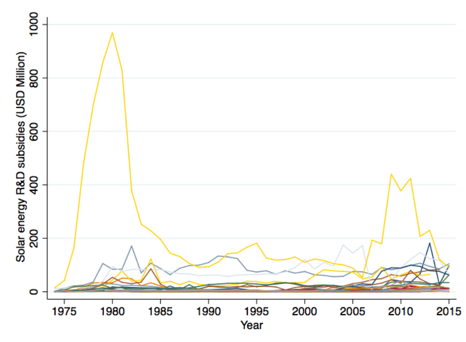
(a) Fossil-fuels



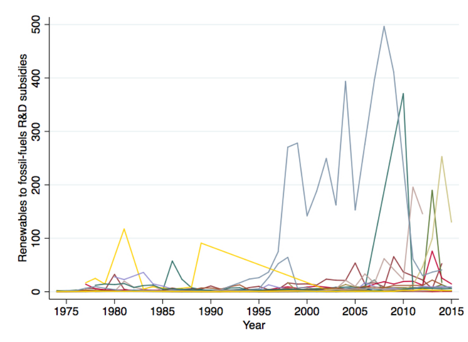
(b) Renewable energies



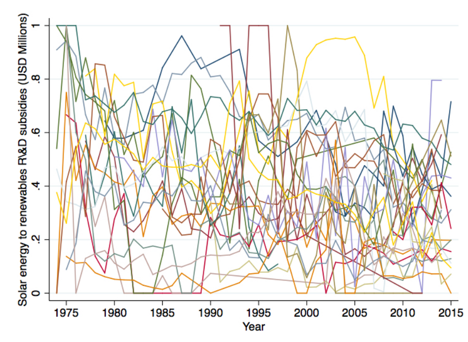
(c) Solar energy



(d) Renewables to fossil fuels



(e) Solar to renewables



Source: IEA.

Table 1: Gross electricity production from renewable sources (GWh)

	1990	**2000**	**2010**	**2013**	**2015**	**Avg. annual % change 2000-2015**
Total Electricity	**1335269**	**1545370**	**1937524**	**2315785**	**2469884**	**3.2**
Hydro	1185210	1348969	1343279	1410026	1364237	0.1
Geothermal	23190	25752	32377	34735	38885	2.8
Solar PV	18	718	30738	115342	172165	44.1
Solar thermal	663	526	1644	5787	8502	20.4
Tide, wave, ocean	529	539	506	919	1033	4.4
Wind	3844	28505	267096	442050	556090	21.9
Solid biofuels	94192	81990	148329	164120	173187	5.1
Biogases	3562	13093	44843	71296	78414	12.7

Source: .

Table 2: Units of analysis before and after harmonization

	Applicants	Inventors
Non harmonizing	32,139	34,460
Harmonizing	23,541	25,962
Sample size reduction	26.75%	24.66%

Table 3: Applicants' distribution across sectors, all patents

Sector	Number of applicants	Percentage
Individual	18,042	76.64
Company	2,849	12.10
None	2,098	8.91
University	327	1.39
Gov Non-Profit	147	0.62
Unknown	58	0.25
Company Gov Non-Profit	18	0.08
Gov Non-Profit University	2	0.01
Total	23,541	100

Table 4: Applicants' distribution by quality of inventions

Patent Category	**Biadic**	**Triadic**	**Fouradic**	**Fivadic**
SECTOR				
Individual	83.07%	78.66%	78.47%	60%
Company	13.88%	17.63%	18.05%	30%
University	1.82%	2.35%	2.35%	10%
Gov Non-Profit	0.75%	0.76%	0.79%	–
Unknown	0.28%	0.38%	0.35%	–
None	0.11%	0.08%	–	–
Company Gov Non-Profit	0.07%	0.14%	–	–
Gov Non-Profit University	0.02%	–	–	–
APPLICANTS	8,581	2,638	1,147	10

Table 5: Weighting schemes: Dynamic vs. Static

	DYNAMIC Our approach			vs.	STATIC Aghion et al. (2016)		
	US	JP	KR		US	JP	KR
MURATA MANUFACTURING							
1989 ($t = 0$)	0.97	0	0		0.97	0	0
2000	0.71	0.01	0.09		0.97	0	0
2010	0.38	0.39	0.11		0.97	0	0
SAMSUNG ELECTRONICS							
1989 ($t = 0$)	0.03	0	0.94		0.03	0	0.94
2000	0.06	0	0.85		0.03	0	0.94
2010	0.07	0	0.91		0.03	0	0.94
SANYO ELECTRIC							
1989 ($t = 0$)	0.34	0.03	0.32		0.34	0.03	0.32
2000	0.14	0.13	0.85		0.34	0.03	0.32
2010	0.09	0.24	0.32		0.34	0.03	0.32
SEIKO INSTRUMENTS							
1989 ($t = 0$)	0.76	0	0.07		0.76	0	0.07
2000	0.85	0.10	0.03		0.76	0	0.07
2010	0.65	0.15	0.13		0.76	0	0.07
VELCRO INDUSTRIES							
1989 ($t = 0$)	0.2	0	0.1		0.2	0	0.1
2000	0.8	0	0.03		0.2	0	0.1
2010	0.84	0	0.03		0.2	0	0.1

Notes: $t = 0$ denotes the last year of the presample regression period, i.e. 1989. Since not all markets were listed, weights do not necessarily add up to one. The three markets and five companies listed in this table were arbitrarily selected.

Table 6: Summary statistics, biadic sample

VARIABLE	OBS.	MEAN	SD.	MIN	MAX
Solar patents ($\text{PAT}_{SE,it}$)	28,380	0.371	2.070	0.000	67.000
Electricity price ($\ln \text{ElecP}_{it}$)	13,046	4.544	0.156	3.911	5.549
Fuel price ($\ln \text{FP}_{it}$)	13,083	-0.748	0.402	-1.268	0.569
Natural gas price ($\ln \text{NGP}_{it}$)	12,749	3.36	0.313	2.707	4.698
Steam coal price ($\ln \text{SC}_{it}$)	85,000	5.689	0.195	5.151	5.909
Own stock solar innovation ($\ln \text{K20se}_{it}$)	28,380	0.330	0.636	0	5.135
Own stock non-solar innovation ($\ln \text{K20ns}_{it}$)	28,303	1.512	2.175	-3.223	10.840
Solar energy subsidies ($\ln \text{SEsubs}_{it}$)	12,738	4.842	0.591	-0.434	6.211
Fossil-fuels subsidies ($\ln \text{FFsubs}_{it}$)	12,745	6.271	0.886	-1.234	8.221
Financial System ($\ln \text{FD}_{it}$)	14,093	-0.232	0.171	-1.137	-0.076

Notes: Descriptive statistics correspond to the 1,419 organizations in the biadic sample for the regression period 1990-2009.

Table 7: Correlation matrix, biadic sample

	$\mathrm{PAT}_{SE,it}$	$\ln \mathrm{ElecP}_{it}$	$\ln \mathrm{FP}_{it}$	$\ln \mathrm{NGP}_{it}$	$\ln \mathrm{K20se}_{it}$	$\ln \mathrm{K20ns}_{it}$	$\ln \mathrm{SEsubs}_{it}$	$\ln \mathrm{FFsubs}_{it}$	$\ln \mathrm{FD}_{it}$
$\mathrm{PAT}_{SE,it}$	1								
$\ln \mathrm{ElecP}_{it}$	0.0744	1							
$\ln \mathrm{FP}_{it}$	0.0758	0.8841	1						
$\ln \mathrm{NGP}_{it}$	0.0669	0.8064	0.9517	1					
$\ln \mathrm{K20se}_{it}$	0.6146	0.0992	0.1148	0.1131	1				
$\ln \mathrm{K20ns}_{it}$	0.2073	-0.1598	-0.1467	-0.1389	0.3832	1			
$\ln \mathrm{SEsubs}_{it}$	0.0789	0.1543	0.0785	0.0362	0.1238	0.0195	1		
$\ln \mathrm{FFsubs}_{it}$	0.0735	0.1022	0.1355	0.1414	0.1154	0.0236	0.7219	1	
$\ln \mathrm{FD}_{it}$	0.0360	0.2798	0.4267	0.5747	0.0905	-0.0701	0.1530	-0.0321	1

Table 8: Baseline results, biadic sample

Regressand: PATse	(1)	(2)	(3)	(4)
$\ln \text{ElectP}_{t-1}$	3.293***	1.716**	1.977***	1.994***
	(0.695)	(0.738)	(0..672)	(0.677)
$\ln \text{K20se}_{t-1}$		0.436***	0.401**	0.403**
		(0.156)	(0.164)	(0.164)
$\ln \text{K20ns}_{t-1}$		0.365***	0.384***	0.385***
		(0.102)	(0.109)	(0.109)
$\ln \text{SEsubs}_{t-1}$			0.133**	0.154**
			(0.067)	(0.068)
$\ln \text{FFsubs}_{t-1}$			-0.114	-0.174**
			(0.079)	(0.079)
$\ln \text{FD}_{t-1}$				-0.777**
				(0.381)
Time dummies	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes
Observations	9,109	9,045	8,879	8,879
Organizations	761	759	747	747
AIC	12,075	11,127	10,830	10,827
BIC	12,131	11,199	10,915	10,919

Notes: All regressions include controls for population size, a measure of market size for the renewable sector and GDP per capita. Standard errors are cluster-robust at the organization level and are expressed in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Lagged electricity prices, biadic sample

Regressand: PATse	(1)	(2)	(3)	(4)	(5)
$\ln \text{ElectP}_t$	4.293***				
	(0.655)				
$\ln \text{ElectP}_{t-1}$		3.293***			
		(0.695)			
$\ln \text{ElectP}_{t-2}$			2.824***		
			(0.581)		
$\ln \text{ElectP}_{t-3}$				2.571***	
				(0.776)	
$\ln \text{ElectP}_{t-4}$					2.320*
					(1.312)
Time dummies	Yes	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	9,036	9,109	8,019	7,109	6,184
Organizations	749	761	691	625	565
AIC	11,991	12,075	10,792	9,831	9,001
BIC	12,048	12,131	10,848	9,886	9,055

Notes: Estimation is by the Poisson panel estimator. All regressions include controls for population size, a measure of market size for the renewable sector and GDP per capita. Standard errors are cluster-robust at the organization level and are expressed in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Estimates for different energy prices, biadic sample

Regressand: PATse	(1)	(2)	(3)	(4)	(5)	(6)
$\ln \text{ElectP}_{t-1}$	3.293***					
	(0.695)					
$\ln \text{ElectP}_{t-2}$		2.824***				
		(0.581)				
$\ln$ Natural gas price$_{t-1}$			1.839***			
			(.381)			
$\ln$ Natural gas price$_{t-2}$				1.529***		
				(.290)		
$\ln$ Fuel price$_{t-1}$					1.619***	
					(0.211)	
$\ln$ Fuel price$_{t-2}$						1.255***
						(0.214)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,109	8,019	8,919	7,862	9,153	8,060
Organizations	761	691	749	681	762	692
AIC	12,075	10,792	12,102	10,911	11,923	10,666
BIC	12,132	10,848	12,159	10,967	11,980	10,722

Notes: All regressions include controls for population size, a measure of market size for the renewable sector and GDP per capita. Standard errors are cluster-robust at the organization level and are expressed in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Reestimated results for $\delta = 0.15$, biadic sample

Regressand: PATse	(1)	(2)	(3)	(4)
$\ln \mathrm{ElectP}_{t-1}$	3.293***	1.779**	2.031***	2.048***
	(0.695)	(0.769)	(0.700)	(0.701)
$\ln \mathrm{K15se}_{t-1}$		0.369**	0.332**	0.334**
		(0.162)	(0.171)	(0.171)
$\ln \mathrm{K15ns}_{t-1}$		0.397***	0.418***	0.420***
		(0.109)	(0.116)	(0.116)
$\ln \mathrm{SEsubs}_{t-1}$			0.142**	0.162**
			(0.067)	(0.067)
$\ln \mathrm{FFsubs}_{t-1}$			-0.119	-0.180**
			(0.081)	(0.080)
$\ln \mathrm{FD}_{t-1}$				-0.789**
				(0.516)
Time dummies	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes
Observations	9,109	9,045	8,879	8,879
Organizations	761	759	747	747
AIC	12,075	11,223	10,918	10,915
BIC	12,132	11,294	11,003	11,007

Notes: All regressions include controls for population size, a measure of market size for the renewable sector and GDP per capita. Standard errors are cluster-robust at the organization level and are expressed in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Assessment of results by alternative estimation techniques

Regressand: PATse	(1) Main Results Poisson FE	(2) Negative Binomial FE	(3) Negative Binomial Exch. correlations	(4) Poisson RE
$\ln \text{ElectP}_{t-1}$	1.994^{***}	1.953^{***}	1.542^{***}	1.468^{***}
	(0.677)	(0.371)	(0.333)	(0.598)
$\ln \text{K20se}_{t-1}$	0.403^{**}	0.314^{***}	1.058^{***}	0.676^{***}
	(0.164)	(0.039)	(0.043)	(0.146)
$\ln \text{K20ns}_{t-1}$	0.385^{***}	0.197^{***}	0.081^{***}	0.206^{***}
	(0.109)	(0.018)	(0.023)	(0.0378)
$\ln \text{SEsubs}_{t-1}$	0.154^{**}	0.111^{*}	0.130^{*}	0.124^{*}
	(0.068)	(0.066)	(0.073)	(0.0785)
$\ln \text{FFsubs}_{t-1}$	-0.174^{**}	-0.131^{*}	-0.038	-0.105^{*}
	(0.079)	(0.078)	(0.066)	(0.0846)
$\ln \text{FD}_{t-1}$	-0.777^{**}	-0.048	0.281	-0.273
	(0.381)	(0.669)	(0.577)	(0.470)
Observations	8,879	8,879	11,505	11,505
Organizations	747	747	1,169	1,169
AIC	10,827	10,827	–	15,599
BIC	10,919	9,793	–	15,709

Notes: All regressions include controls for population size, a measure of market size for the renewable sector and GDP per capita. Standard errors are cluster-robust at the organization level and are expressed in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Comparison of results across samples

Regressand: PATse	(1) All patents	(2) Biadic	(3) Triadic	(4) Fouradic
$\ln \text{ElectP}_{t-1}$	1.825***	1.994***	1.788**	1.827*
	(0.491)	(0.677)	(0.772)	(1.027)
$\ln \text{K20se}_{t-1}$	-0.082	0.403**	0.663***	0.725***
	(0.142)	(0.164)	(0.157)	(0.197)
$\ln \text{K20ns}_{t-1}$	0.425***	0.385***	0.278***	0.209*
	(0.104)	(0.109)	(0.091)	(0.108)
$\ln \text{SEsubs}_{t-1}$	0.198***	0.153**	0.184**	0.177*
	(0.041)	(0.068)	(0.077)	(0.097)
$\ln \text{FFsubs}_{t-1}$	-0.005	-0.174**	-0.266***	-0.326***
	(0.091)	(0.079)	(0.081)	(0.096)
$\ln \text{FD}_{t-1}$	-0.789**	-0.777**	-0.662*	-0.476
	(0.403)	(0.381)	(0.400)	(0.470)
Time dummies	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes
Observations	22,664	8,879	4,545	1,957
Panel units	3,249	747	345	156

Notes: All regressions are estimated by Poisson fixed-effects and include controls for population size, a measure of market size for the renewable sector and GDP per capita. Standard errors are cluster-robust at the organization level and are expressed in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Main results, different weighting schemes

Regressand: PATse	(1) Dynamic	(2) Static	(3) Semi-static	(4) Placebo
$\ln \text{ElectP}_{t-1}$	1.994***	1.560**	1.358*	1.873***
	(0.677)	(0.621)	(0.732)	(0.421)
$\ln \text{K20se}_{t-1}$	0.403**	0.714***	0.495***	0.386***
	(0.164)	(0.126)	(0.164)	(0.097)
$\ln \text{K20ns}_{t-1}$	0.385***	0.336***	0.371***	0.471***
	(0.109)	(0.088)	(0.103)	(0.065)
$\ln \text{SEsubs}_{t-1}$	0.153**	0.190**	0.334***	-0.176**
	(0.068)	(0.085)	(0.081)	(0.086)
$\ln \text{FFsubs}_{t-1}$	-0.174**	-0.197**	-0.153*	0.228***
	(0.079)	(0.092)	(0.083)	(0.088)
$\ln \text{FD}_{t-1}$	-0.777**	-1.327**	-0.605	0.333
	(0.381)	(0.658)	(0.468)	(0.484)
Time dummies	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes
Observations	8,879	5,884	7,644	23,610
Organizations	747	317	659	1,246

Notes: All regressions include controls for population size, a measure of market size for the renewable sector and GDP per capita. Standard errors are cluster-robust at the organization level and are expressed in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Organizations vs. firms

Regressand: PATse	(1) Orgs. $\delta = 0.20$	(2) Orgs. $\delta = 0.15$	(3) Firms δ=0.20	(4) Firms δ=0.15
$\ln \text{ElectP}_{t-1}$	1.994***	2.048***	2.101***	2.152***
	(0.677)	(0.706)	(0.739)	(0.771)
$\ln \text{Kse}_{t-1}$	0.403**	0.333**	0.456***	0.394**
	(0.164)	(0.171)	(0.170)	(0.178)
$\ln \text{Kns}_{t-1}$	0.385***	0.420***	0.378***	0.406***
	(0.109)	(0.116)	(0.116)	(0.121)
$\ln \text{SEsubs}_{t-1}$	0.154**	0.163**	0.135*	0.141*
	(0.068)	(0.067)	(0.079)	(0.077)
$\ln \text{FFsubs}_{t-1}$	-0.174**	-0.180**	-0.183**	-0.188**
	(0.079)	(0.081)	(0.093)	(0.096)
$\ln \text{FD}_{t-1}$	-0.777**	-0.789**	-0.968**	-0.962**
	(0.381)	(0.380)	(0.433)	(0.427)
Time dummies	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes
Observations	8,879	8,879	7,237	7,237
Organizations	747	747	613	613

Notes: All regressions include controls for population size, a measure of market size for the renewable sector and GDP per capita. Standard errors are cluster-robust at the organization level and are expressed in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Regional patent offices and number of member states

Regional Patent Office	Code	Member States
International Bureau of WIPO	IB	188
European Patent Office	EP	38
African Regional IP Organization	AP	19
USSR Gospatent	SU	15
Eurasian Patent Organization	EA	11
Coop. Council for the Arab States of the Gulf	GC	6
Yugoslavian Patent Office	YU	6
Czechoslovak Patent Office	CS	2

Source: World Intellectual Property Organization (WIPO).

Table 17: CPC codes for identifying solar energy technologies

Code	Description
Y02E10/40	**Solar thermal energy**
Y02E10/41	Tower concentrators
Y02E10/42	Dish collectors
Y02E10/43	Fresnel lenses
Y02E10/44	Heat exchange systems
Y02E10/45	Trough concentrators
Y02E10/46	Conversion of thermal power into mechanical power
Y02E10/465	Thermal updraft
Y02E10/47	Mountings or tracking
Y02E10/50	**Photovoltaic [PV] energy**
Y02E10/52	PV systems with concentrators
Y02E10/54	Material technologies
Y02E10/541	CuInSe2 material PV cells
Y02E10/542	Dye sensitized solar cells
Y02E10/543	Solar cells from Group II-VI materials
Y02E10/544	Solar cells from Group III-V materials
Y02E10/545	Microcrystalline silicon PV cells
Y02E10/546	Polycrystalline silicon PV cells
Y02E10/547	Monocrystalline silicon PV cells
Y02E10/548	Amorphous silicon PV cells
Y02E10/549	Organic PV cells
Y02E10/56	Power conversion electric or electronic aspects
Y02E10/563	For grid-connected applications
Y02E10/566	Concerning power management inside the plant
Y02E10/58	Maximum power point tracking [MPPT] systems
Y02E10/60	**Solar thermal-PV hybrids**

Table 18: Non-harmonized vs. harmonized applicants in 2010

(a) Non-harmonized applicants

Ranking	Country	Name	Sector	Solar patents	Non-solar patents	Total patents	Solar/total
1	JP	Canon Kabushiki Kaisha	Company	524	47546	48070	0.011
2	JP	Sharp Kabushiki Kaisha	Company	361	11148	11509	0.040
3	KR	Samsung Electronics Co.	Company	321	125795	126116	0.003
4	JP	Sanyo Electrics Co.	Company	277	6936	7213	0.038
5	–	–not available –	–	272	24668	24940	0.011
6	DE	Merck Patent GmbH	Company	264	4609	4873	0.054
9	KR	Samsung SDI Co.	Company	212	18407	18619	0.011
11	US	Applied Materials, Inc.	Company	178	2948	3126	0.057
13	US	Applied Materials, Inc.	Company	173	4205	4378	0.031
14	DE	Merck Patent GmbH	Company	164	1109	1273	0.129

(b) Harmonized applicants

Ranking	Name	Sector	Solar patents	Non-solar patents	Total patents	Solar/Total
1	Canon	Company	524	47546	48070	0.011
2	Sharp Corporation	Company	361	15076	15437	0.023
3	Samsung Electronics Co.	Company	321	125795	126116	0.003
4	Sanyo Electric Co.	Company	277	6936	7213	0.038
5	–not available –	–	272	24668	24940	0.011
6	Merck Patent	Company	264	4609	4873	0.054
7	Fraunhofer	Gov Non-Profit	215	6602	6817	0.032
8	Samsung SDI Co.	Company	212	18407	18619	0.011
9	Industrial Technology Research Institute	Gov Non-Profit	201	9683	9884	0.02
10	Applied Materials	Company	178	4200	4378	0.041

Notes: Applicants in tables 19a and 19b were identified by the variables *psn_id* and *hrm_l2_id*, from PATSTAT and EEE-PPAT tables, respectively. Numeric entries represent the cumulative count of unique inventions.

Table 17: Top 15 inventors in solar energy

(a) Year: 2010

Name	Solar patents	Non-solar patents	Total patents
Shunpei Yamazaki	84	1115	1199
Stephen R. Forrest	63	52	115
Philipp Stoessel	56	18	74
Bulent M. Basol	45	27	72
Benyamin Buller	44	4	48
Roland Winston	42	20	62
Stanford R. Ovshinsky	41	195	236
Masahiro Kanai	40	58	98
Christoph Brabec	37	17	54
Arne Buesing	37	10	47
Holger Heil	36	10	46
Mehrad M. Moslehi	35	21	56
Seung-Yeop Myong	35	1	36
Subhendu Guha	35	12	47
Susanne Heun	34	10	44

(b) Year: 2005

Name	Solar patents	Non-solar patents	Total patents
Shunpei Yamazaki	61	785	846
Masahiro Kanai	40	57	96
Stephen R. Forrest	35	44	79
Kimitoshi Fukae	34	6	40
Stanford R. Ovshinsky	33	183	216
Katsumi Nakagawa	32	13	45
Prem Nath	31	15	46
Roland Winston	30	16	46
Isamu Shimizu	29	17	74
Ichiro Kataoka	28	45	28
Akiharu Takabayashi	28	0	30
Nobuyoshi Takehara	27	2	42
Shigenori Itoyama	27	15	29
Hidenori Shiotsuka	27	2	28
Satoru Yamada	26	1	26

Notes: Inventors were identified by *hrm_l2_id* from the EEE-PPAT table. Numeric entries represent the cumulative count of unique inventions.

Table 18: Top 20 applicants in solar energy, 2010

Ranking	Name	Sector	Solar patents	Non-solar patents	Total patents	Solar/Total
1	Canon	Company	524	47546	48070	0.011
2	Sharp Corporation	Company	361	15076	15437	0.023
3	Samsung Electronics Co.	Company	321	125795	126116	0.003
4	Sanyo Electric Co.	Company	277	6936	7213	0.038
5	–not available –	–	272	24668	24940	0.011
6	Merck Patent	Company	264	4609	4873	0.054
7	Fraunhofer	Gov Non-Profit	215	6602	6817	0.032
8	Samsung SDI Co.	Company	212	18407	18619	0.011
9	Industrial Technology Research Institute	Gov Non-Profit	201	9683	9884	0.02
10	Applied Materials	Company	178	4200	4378	0.041
11	DuPont	Company	174	9405	9579	0.018
12	Siemens	Company	158	38614	38772	0.004
13	Sumitomo Chemical Co.	Company	152	4947	5099	0.030
14	Hyundai Heavy Industries Co.	Company	142	2615	2757	0.052
15	GE (General Electric Co.)	Company	138	47958	48096	0.003
16	Fujifilm Corporation	Company	131	11019	11150	0.012
17	Sony Corporation	Company	128	32525	32653	0.004
18	Jusung Engineering Co.	Company	122	610	732	0.167
19	Robert Bosch	Company	119	50177	50296	0.002
20	IBM	Company	110	43900	44010	0.003

Notes: Numeric entries represent the cumulative count of unique inventions.