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Innovation in Clean Coal Technologies: Empirical Evidence from Firm-Level Patent Data

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This article empirically analyzes supply-side and demand-side factors expected to affect innovation in clean coal technologies. Patent data from 93 national and international patent offices is used to construct new firm-level panel data on 3,648 clean coal innovators over the time period 1978 to 2009. The results indicate that on the supply-side a firm's history in clean coal patenting and overall propensity to patent positively affects clean coal innovation. On the demand-side we find strong evidence that environmental regulation of emissions, that is CO_2, NO_X and SO_2, induces innovation in both efficiency improving combustion and after pollution control technologies.

Key words: clean coal technologies, innovation, patents, technological change

JEL codes: C33, O31, Q40, Q55

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1 Introduction

Currently, about 40% of world electricity is produced by coal which makes it globally the first source of electricity generation. World electricity demand is predicted to increase by around two-thirds until 2035 and coal to remain the leading fuel in electricity production (IEA, 2013*b*). Reasons for this development are that coal reserves are large and geopolitically secure, coal is an affordable energy source, and coal-based power can be easily integrated into existing power systems (IEA, 2013*a*). In light of this, it is unlikely that alternative forms of energy can or will completely replace coal-based power in the near future.

However, coal burning in its current form has strong environmental impacts. On the one hand, the negative impacts of air pollutants like sulfur dioxide (SO_2) and nitrogen oxides (NO_X) on the air quality and, on the other hand, the negative impact of greenhouse gas emissions like carbon dioxide (CO_2) on the climate. The large reliance of electricity production on coal explains why this sector is, with about 41%, the largest contributor to worldwide CO_2 emissions. Coal accounts for about 70% of these emissions (IEA, 2013*b*). Therefore, it is essential to develop new and advanced technologies that allow coal use in electricity generation while mitigating its impact on the environment.

Clean coal technologies (CCT) may help achieving this goal. These technologies aim at the reduction of emissions in coal-based electricity generation: indirectly, by increasing the efficiency of the conversion of coal into electricity (efficiency improving combustion technologies), or by reducing emissions entering the atmosphere directly at the end of the pipe (after pollution control technologies).[1] Regarding CO_2, today the intensity of the most efficient coal-fired power plants lies around 700 grams of CO_2 per kilowatt-hour (gCO_2/kWh). Next generation efficiency enhancing technologies are expected to reduce CO_2 emissions from coal-based electricity generation to less than 670 gCO_2/kWh. In addition, Carbon capture and storage (CCS) technologies inherent the potential to reduce emissions to less than 100 gCO_2/kWh (IEA, 2012).

Despite the important role played by coal in electricity generation and the high mitigation potential of this sector, very little attention has been devoted to the factors determining innovation in CCT. Understanding these factors will help policymakers to design the appropriate energy and environmental policies for encouraging more innova-

[1] The term CCT is controversial as the impact of CCT innovations on the environment is ambiguous. On the one hand, CCT innovations increase the efficiency of coal conversion into electricity and therefore reduce the amount of coal use per kilowatt-hour. On the other hand, these innovations make electricity generation from coal cheaper, thereby increasing the share of coal in overall electricity generation (Aghion et al., 2016).

tion. Therefore, the goal of this article is to empirically investigate the determinants that enhance innovation in CCT. We measure innovation at the firm-level by using patent data from the Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO) (EPO, 2014). Altogether our database contains 7,894 CCT first priority patents filed worldwide by 3,648 firms over a 32-year period from 1978 to 2009. We analyze supply-side and demand-side factors expected to affect CCT innovation. These factors include scientific and technological capacity, overall propensity to patent, public R&D, coal prices, market size as well as environmental policies and regulations aiming at the reduction of SO_2, NO_X, and CO_2 emissions.

The article generally relates to the empirical literature on the determinants of innovation in clean energy technologies using patent data (see, for example, Jaffe and Palmer, 1997; Popp, 2002; Johnstone et al., 2010; Verdolini and Galeotti, 2011). In particular, we build on Voigt et al. (2008), who use EPO patent data for 22 countries from 1974 to 2005 to examine country-specific determinants of patenting activity in the field of CCT. Within their empirical analysis, the authors find a positive impact of public R&D expenditures and negative impacts of the Kyoto protocol and the share of renewables on CCT innovation.

Our study extends this analysis and contributes to the existing literature in three respects. First, we inquire into the determinants of CCT innovation using international firm-level panel data. This allows us to investigate factors that enhance CCT innovation activities directly at the innovator-level. Second, our study conducts a global analysis based on data from 93 national and international patent offices. This data includes almost the entire population of all worldwide CCT patent applications filed in the considered period. Third, we provide quantitative evidence on the temporal trends and the distribution across countries and firms of CCT innovation. This helps understanding the global patterns of CCT innovation.

The remainder of this article is structured as follows. Section 2 presents the principal hypotheses tested in our empirical analysis. Section 3 presents the data and some descriptive statistics. In section 4, we describe the empirical strategy and discuss the results. Section 5 summarizes the main findings and concludes.

2 Principal Hypotheses

The purpose of this article is to test how firm-level CCT innovation is affected by economic and political factors. The theory of induced innovation is the theoretical basis for this relationship (see, for example, Hicks, 1932; Binswanger, 1974). In general, the theory recognizes that knowledge production is a profit-motivated investment activity and posits that both changes on the supply-side and changes on the demand-side affect the rate and direction of knowledge production. Changes on the supply-side include scientific and technological advancements that affect the profitability of innovative activity at a given level of demand. Analogously, changes on the demand-side include shifts on the macro level that affect the profitability of innovative activity at a given level of scientific and technological capability (Griliches, 1990).

On the supply-side, a firm's scientific and technological capacity, that is, its existing stock of knowledge, is expected to influence its innovative activity in the future (Acemoglu et al., 2012). This stock is typically measured by innovation activities undertaken in the past, that is by historic patent filings (see, for example, Popp, 2002; Verdolini and Galeotti, 2011). Hence, we expect that firms with a broad history of CCT innovation in the past are more likely to innovate in CCT in the future. Additionally, a firm's patenting activity may be affected by its overall propensity to patent innovations. This propensity is likely to vary across firms and countries as well as across time, because different strategies are adopted by firms to capture the rents from innovation and because legal conditions differ across countries and change over time (Jaumotte and Pain, 2005). Thus, firms with an overall high propensity to seek for patent protection (typically measured by total patent filings) are expected to file more patents in CCT. Moreover, public effort in support of technological development is likely to incentivize innovation at the firm-level. Government R&D expenditures are an indicator for this effort (Popp et al., 2010). Therefore, higher CCT-related government R&D expenditures should induce technological change and hence lead to higher innovative activity in CCT.

On the demand-side, the price level (or a policy that changes the price level) can be expected to affect a firm's innovative activity. Increasing input prices change the opportunity costs associated with the use of an input and thus induce innovation in technologies that aim to reduce the use of this input (Hicks, 1932; Acemoglu et al., 2012). Thus, increasing the price of coal should lead to innovation in more efficient forms to produce electricity from coal. However, an increase in the price of coal should, in contrast, lead to less innovation in after pollution control technologies since these make electricity production from coal even more expensive. In addition, the size of the potential market is likely to affect innovation (Acemoglu et al., 2012). A large market, that is, a large demand, makes it easier for a firm to recoup its R&D investments. Hence, a potentially large market for CCT, typically proxied by electricity production, should lead to more research towards CCT (Johnstone et al., 2010). Finally, environmental policies and regulations typically affect firms' innovative activities. Restricting for example air pollutant (for example SO_2 and NO_X) and greenhouse gas (for example CO_2) emissions from coal-fired power plants increases the value of both efficiency improving combustion and after pollution control technologies. The first ones allow to produce the same output with less input and by this decrease the emissions per unit of output. The second ones reduce the emissions directly (Popp, 2006). Thus, introducing policies and regulations aiming at the restriction of emissions should incentivize CCT innovation. The hypotheses presented above are summarized in Table 1.

Table 1: Expected determinants of CCT innovation.

	CCT (EI/AP)
Supply-side determinants	
Scientific and technological capacity	+ (+/+)
(CCT knowledge stock)	
Propensity to patent	+ (+/+)
(Total patent filings)	
Public effort in support of technological development	+ (+/+)
(CCT-related government R&D)	
Demand-side determinants	
Price level	o (+/−)
(Coal price)	
Size of potential market	+ (+/+)
(Electricity production)	
Environmental policies and regulations	+ (+/+)
(Dummies indicating introduction of emission restricting policies/regulations)	

Note: + positive effect; o positive or negative effect; − negative effect. EI = Efficiency improving combustion technologies; AP = After pollution control technologies.

3 Data

In this section, we present the data used in our empirical analysis and describe the construction of the explanatory variables. We then show descriptive statistics which provide instructive insights into the data and the global patterns of CCT innovation.

3.1 Data Sources

We use patent data as an output measure of innovative activity at the firm-level to analyze the potential determinants of innovation in CCT.[2] The data originates from PATSTAT, a statistical database on worldwide patenting activities maintained by the EPO (EPO, 2014). Patent applications related to CCT are identified by using International Patent Classification (IPC) codes taken from Voigt et al. (2008).[3] We count CCT innovations in two technology groups: efficiency improving combustion technologies (EI) and after pollution control (AP) technologies. The EI group contains technologies which improve efficiency in the conversion process of coal into electricity and thus indirectly reduce emissions. These technologies are Pulverized Coal Combustion under supercritical and ultra-supercritical steam conditions (PCC), Fluidized Bed Combustion (FBC), and Integrated Gasification Combined Cycle (IGCC). The AP group contains technologies directly reducing emissions. These are post-combustion pollution control technologies, that is end-of-pipe (EOP) technologies, and Carbon Capture and Storage (CCS) technologies. Table 2 provides an overview on the considered technologies.[4]

Table 2: Clean coal technologies.

Efficiency improving combustion technologies
Pulverized Coal Combustion
Fluidized Bed Combustion
Integrated Gasification Combined Cycle
After pollution control technologies
End-of-pipe
Carbon Capture and Storage

[2] The advantages and disadvantages of using patents as a measure of innovation have been discussed at length in the literature. See, for example, Griliches (1990), Dernis et al. (2002), and OECD (2009).

[3] To identify CCT innovations filed at the United States Patent and Trademark Office (USPTO), we follow an approach by Aghion et al. (2016). We use the same IPC codes as the ones used for non-USPTO patents and complement these with their US equivalents according to the USPC-to-IPC reverse concordance table available on the USPTO website. The reason is that the IPC system for classifying patent documents has been adopted just recently by the USPTO. Therefore some older USPTO patents have no IPC codes.

[4] A detailed list of the technologies including the IPC codes can be found in Voigt et al. (2008) and Rennings and Smidt (2010).

For our analysis, we count annual CCT first priority patent filings by firms across 93 national and international patent offices over the period 1978 to 2009.[5] [6] Counting first priority patents ensures that the same invention, which is protected by multiple patents filed in multiple patent offices, for example by one patent in Germany, one patent in the US, and two patents in Japan, is counted as one single patent.[7]

We ensure that patent applications for low-value inventions are excluded from our analysis by considering only so called claimed priorities, that is patent applications for which protection is sought in at least two of the considered offices. The patents are assigned to years based on their priority date. The priority date refers to the first filing date of the invention worldwide. It is strongly related to R&D activities and closest to the date of invention as well as to the decision to apply for a patent (see, for example, Griliches, 1990; OECD, 2009). The resulting data set contains 8,414 high-value CCT first priority patents filed by 6,302 firms across 60 offices.

A common problem with patent data is the heterogeneity of applicants' names to be found in patent documents. We use the ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT) database (ECOOM, 2014) to identify unique patent holders. This database provides a grouping of patent applicant's names achieved by harmonizing names through a comprehensive computer algorithm. In addition, we visually inspect the name match and merge associated applicants (for example, we merge Siemens with its differently named subsidiaries). This procedure enables us to reduce the number of distinct applicants of CCT patents from 6,302 to 5,028 (by using the EEE-PPAT database) and then to 4,330 (by visual inspection).

To investigate the effect of a firm's scientific and technological capacity, we construct knowledge stocks K_{it} for firm i at time t using the perpetual inventory method following Cockburn and Griliches (1988) and Peri (2005):

$$K_{it} = PAT_{it} + (1 - \delta)\, K_{it-1} \qquad (1)$$

where PAT_{it} is the number of CCT patent applications and δ is a depreciation rate accounting for the fact that knowledge becomes obsolete as time goes by. The depreciation

[5] If a single first priority patent is filed by multiple firms, we count it fractionally. That is, if a patent is filed by more than one firm, the patent count is divided by the number of firms and each firm receives equal shares of the patent. This avoids giving a higher weight to a patent filed by multiple firms compared to one filed by just one firm.

[6] As it is standard in the literature, we count USPTO patents only if they were granted. The reason is that until 2001 only granted patent applications are published by the USPTO.

[7] Multiple patents filed for the same invention are part of a patent family. To identify patents belonging to the same patent family, we use the DOCDB data set in PATSTAT.

rate is set to 10%, as is often assumed in the literature (see, for example, Verdolini and Galeotti (2011)). The initial knowledge stock K_{it_0} is given by $K_{it_0} = PAT_{it_0}/(g + \delta)$, where PAT_{ijt_0} is the number of CCT patent applications in 1978, the first year observed. The growth rate g is the pre-1978 growth in knowledge stock, assumed to be 15%, and δ again represents depreciation of 10%.[8]

As a control for a firm's overall propensity to patent innovations, we use data from PATSTAT on the firm-specific total count of annual patent filings (all patents, not only CCT) across the 93 offices. Again we only count claimed priorities, that is high-value inventions filed in at least two offices.

In order to estimate the impact of coal prices on innovation in CCT, we proxy the coal price using a country-year specific real total energy end-use price for households and industry. The price is an index with the base year 2005 and includes taxes. The data is drawn from the Energy Prices and Taxes database of the IEA (IEA, 2014*b*) and is available for 30 countries.[9] Using coal prices instead would be preferable. However, as noted by the IEA (2014*a*), coal prices for electricity generation are not necessarily comparable between countries because of a great variety of coal qualities in domestic and international trade. For example, in Germany 40% of total coal input for electricity generation is lignite. This is usually produced by mines that are located right next to the power station and owned by the utilities. Hence, for most of the lignite a market price is not available and the coal price for electricity generation published by the IEA is only based on prices for domestic and/or imported steam coal (IEA, 2014*a*). For this reason, we opted for using a more general price index that is less affected by this kind of information gap. In addition, as shown in Section 3.2, the development of the average firm-level real total energy end-use price and the average real steam coal end-use price over time is very similar.

Since the energy price index is available only at the country-year level, we make the energy price firm-year specific by constructing firm-specific weights based on the distribution of a firm's patent-portfolio across countries (Barbieri, 2015; Noailly and Smeets, 2015; Aghion et al., 2016). The underlying theory is that firms' innovation decisions are more likely to be affected by price changes in countries with high importance for their innovative activity than in countries with low importance. For example, consider

[8] Note that our empirical analysis is conducted for the time span 1983 to 2009. Thus, the influence of any inaccuracies that may be inherent in the way in which the initial knowledge stock is calculated is rather small.

[9] For the EPO we construct an energy price using the mean of GDP-weighted energy prices from EPO member states.

a firm that produces its innovations mainly for the German market. The innovative activity of such a firm is in all likelihood more influenced by the German energy price than by energy prices from other countries. Hence, we assume that firms' are differently exposed to energy prices from different countries and that this exposure depends on the geographical distribution of its patent-portfolio across countries. The energy price faced by firm i at time t is therefore computed as the weighted average of energy prices across countries:

$$P_{it} = \sum_{c} w_{ic}^{PP} \times P_{ct} \tag{2}$$

where w_{ic}^{PP} is a fixed firm-specific patent-portfolio weight for country c and P_{ct} is the energy price in country c at time t.[10] The weight proxies the relative importance of country c's market for firm i's innovation activity. The weight is calculated as $w_{ic}^{PP} = \frac{s_{ic}^{PP} \times GDP_c}{\sum_c s_{ic}^{PP} \times GDP_c}$, where s_{ic}^{PP} is the share of country c in firm i's overall (that is including all patents, not only CCT) patent-portfolio[11] over the period 1978 to 2009. Furthermore, in order to account for country c's economic size, s_{ic}^{PP} is weighted by the share of country c's GDP in world GDP over the same time period, GDP_c. Data on the countries' GDP is taken from the World Bank's World Development Indicators (The World Bank, 2015).

The firm-specific weights are time-invariant since s_{ic}^{PP} and GDP_c are computed using the patent-portfolio of each firm averaged over the whole sample period as in Barbieri (2015) and Noailly and Smeets (2015). This approach avoids endogeneity issues that could arise using time-varying weights. If changes in energy prices affect the relative importance of countries in the firms' overall patent-portfolios or the countries' shares in world GDP, there might be a feed back of the altered weights into energy prices.

Another approach to avoid this potential endogeneity is to compute the weights using the patent-portfolio of each firm averaged over a pre-sample period and run the regressions over the residual period as in Aghion et al. (2016). However, this approach has two disadvantages. First, weights computed over a pre-sample period do not reflect changes in the patent-portfolio distribution across countries that take place after the pre-sample period. The shorter the pre-sample period, the larger this problem is. Second, a longer pre-sample period could alleviate this problem but has the drawback of a shorter estimation period which would cover neither the development in CCT patenting in the 1980s

[10] If there is no energy price available for a country or year, the other energy prices get proportionally higher weights that add up to 1. This approach is also used for the computation of the other firm-specific variables.

[11] We checked the robustness of our estimation results by using the CCT patent-portfolio instead of the overall patent-portfolio. Calculating the weights from this narrower patent pool leaves our main results unchanged.

(see Figure 1) nor the introduction of NO_X regulations (see Figure 3) in this period. Therefore, we decided to use in-sample weights.

Following Noailly and Smeets (2015), we measure the effect of the market size on CCT innovation by using country-year specific data on electricity production. The data is obtained from the IEA Energy Balances database (IEA, 2015*a*) and is measured in TWh per year. Data is available for 50 countries.[12] To make market size firm-year specific, we use the same approach as with prices. That is, we assume that firms' innovation decisions are more likely to be influenced by the market size of countries with high importance for the firms' innovative activity than of countries with low importance. Hence, market size for firm i at time t is computed as the weighted average market size across countries:

$$M_{it} = \sum_{c} w_{ic}^{PP} \times M_{ct} \tag{3}$$

where w_{ic}^{PP} is a fixed firm-specific patent-portfolio weight for country c as in (2) and M_{ct} is the market size measured by electricity production in country c at time t.

To examine the influence of emission restricting environmental policies and regulations on CCT innovation, we use country-year specific dummy variables indicating the years after the introduction of stringent NO_X regulation[13] for coal-fired power plants and the implementation of CO_2 regulation (predominantly cap-and-trade programs), respectively.[14] Data is taken from Popp (2006) (NO_X) and World Bank Group, Ecofys (2014) (CO_2). During our considered time period, 18 of the 60 countries in the data set introduced stringent NO_X regulation and 28 implemented CO_2 regulation. To make the dummy variables firm-year specific, we use the same approach as with prices and electricity production. Thus, we assume that firms' exposure to country-specific NO_X and CO_2 regulations depends on the geographical distribution of its patent-portfolio across countries. The respective dummy variable for firm i at time t is therefore computed

[12] For the EPO we construct data on electricity production by adding up production from EPO member states.

[13] In order to capture the impact of air pollution regulation on CCT innovation, one would ideally control for both NO_X and SO_2 regulation. However, comparable data for stringent SO_2 regulation is not available. Since historically there were strong linkages between the introduction of NO_X and SO_2 regulation, we decided to use stringent NO_X regulation as a proxy for both.

[14] For the EPO we construct these variables using the mean of the respective GDP-weighted dummy variables from EPO member states.

as the weighted average dummy variable across countries based on the importance of country c's market for firm i's innovation activity:

$$D_{it} = \sum_{c} w_{ic}^{PP} \times D_{ct} \tag{4}$$

where w_{ic}^{PP} is a fixed firm-specific patent-portfolio weight for country c as in (2) and (3)[15] and D_{ct} is the dummy variable in country c at time t.

Finally, to analyze the influence of government R&D on CCT innovation, we use coal country-year specific government R&D expenditures. Since no data is available for CCT-specific R&D expenditures, we use coal combustion plus CCS R&D expenditures as a proxy. The data is drawn from the IEA Energy Technology R&D database (IEA, 2015*b*) and contains the annual national government expenditures on coal combustion plus CCS research, development, and demonstration in million USD (2014 prices and PPP). Data is available for 28 countries.[16] The expenditures are made firm-year specific using a similar approach to that for prices, electricity production, and regulatory variables. However, now we incorporate information on the geographical location of patent inventors, that is, where the inventors worked at the discovery of the invention, to construct firm-specific weights (Aghion et al., 2016). The underlying theory is that patent inventors are more likely to benefit from government R&D subsidies in a country they work in than from R&D subsidies in other countries. Hence, we assume that firms' are differently exposed to government R&D subsidies from different countries and that this exposure depends on the geographical distribution of its various patent inventors across countries. Thus, government R&D expenditures faced by firm i at time t are:

$$RD_{it} = \sum_{c} w_{ic}^{I} \times RD_{ct} \tag{5}$$

where w_{ic}^{I} is a fixed firm-specific inventor weight for country c and RD_{ct} is the R&D expenditure in country c at time t. The weight proxies the relative importance of country c in firm i's pool of inventors. The weight is calculated as $w_{ic}^{I} = \frac{s_{ic}^{I} \times GDP_c}{\sum_c s_{ic}^{I} \times GDP_c}$, where s_{ic}^{I}

[15] Using the same patent-portfolio weights to compute the firm-year specific energy price, electricity production, and regulatory variables could of course create multicollinearity problems among these explanatories. However, since we have a large number of observations and since the correlation among these variables is fairly low (see Table A5 (Appendix)), this should not be a problem.

[16] For the EPO we construct coal R&D expenditures by adding up expenditures from EPO member states.

is the share of all firm i's inventors in country c over the period 1978 to 2009.[17] In order to account for country c's economic size, s^I_{ic} is weighted by the share of country c's GDP in world GDP over the same time period, GDP_c.[18]

After matching the patent data with energy prices, electricity production, regulatory variables, and government R&D, our final panel data set contains 7,894 high-value CCT first priority patents filed by 3,648 firms across 55 patent offices over the period 1978 to 2009. In total (all patents, not only CCT), these firms have filed 832,621 first priority patents over the same period. Table 3 reports summary statistics for the sample.

Table 3: Summary statistics for all 3,648 firms from 1978 to 2009.

	Mean	Std. dev.	Min.	Max.
CCT patents	0.07	0.57	0.00	36
CCT knowledge stock	0.51	3.34	0.00	139
Total patents	7.36	89.24	0.00	8163
CCT-related government R&D	151.88	418.36	0.00	3511
Energy price	91.12	12.74	51.35	149
Electricity production	2559.84	668.67	16.40	4343
NO_X dummy	0.53	0.31	0.00	1
CO_2 dummy	0.07	0.18	0.00	1
Observations	113035			

Note: Energy prices are an index with the base 2005 including taxes. Electricity production is in TWh/year. CCT-related government R&D is in 2014 million USD (PPP).
Source: Authors' calculations, based on PATSTAT, IEA Energy Technology R&D, IEA Energy Prices and Taxes, IEA Energy Balances, Popp (2006) and World Bank Group, Ecofys (2014).

3.2 Descriptive Statistics

Figure 1 shows the trends in annual priority patent counts of the considered CCT. Consistent with Voigt et al. (2008), we observe that the different CCT peak at different points in time. PCC peaks in the early-1980s and FBC in the early- and almost again in the late-1980s. IGCC shows a positive trend since the beginning of the early-1990s and peaks at the end of the sample period. The developments allow to identify three generations of the EI technologies. From the AP technologies EOP peaks in the mid-1980s and almost again in the mid-1990s and late-2000s but never drops under a level of

[17] If a patent is filed by multiple inventors, we count inventor countries fractionally. This avoids giving a higher weight to a patent filed by multiple inventors compared to one filed by just one inventor.

[18] Note that the inventor weight w^I_{ic} in equation (5), which is based on the distribution of a firm's various inventors across countries, is very distinct from the patent-portfolio weight w^{PP}_{ic} in equation (2), (3), and (4), which is based on the distribution of a firm's patent-portfolio across countries. Figure A1 (Appendix) shows for the USA, that these distributions vary considerably across firms.

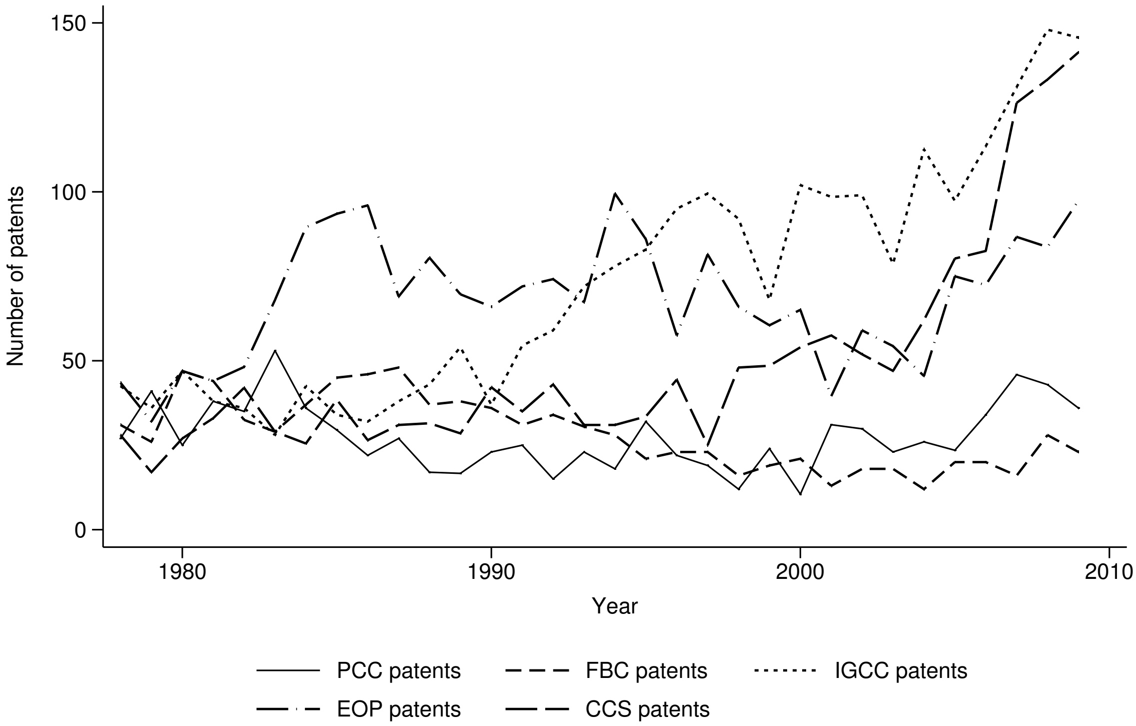

Figure 1: Total number of PCC, FBC, IGCC, EOP, and CCS priority patent applications (claimed priorities) filed worldwide of all firms, 1978-2009. *Source:* Authors' calculations, based on PATSTAT.

about 50 patents per year. CCS stays nearly constant until the late-1990s and increases significantly afterwards.

Table 4 shows the top ten inventor firms in CCT, which together account for one quarter of worldwide CCT inventions during the sample period. The firms are listed in declining order of their rank. In addition, the total number of patents is reported so that the relative share of CCT patents in total inventions can be computed. Looking at the results, a great heterogeneity between the firms can be observed. The firms differ greatly with respect to their overall innovative activity ranging from 375 (Foster Wheeler) to 43,229 (Siemens) patents. The relative share of CCT inventions ranges from at most 52.93% to 0.54%, again attributable to Foster Wheeler and Siemens respectively. This reflects the fact that the top ten is composed of firms focusing on CCT innovation on the one hand and others having an overall high propensity to patent innovations on the other hand. Both factors are expected to influence patent filings in CCT. The market leader in CCT is Mitsubishi with 377 patents, followed by Alstom and Babcock & Wilcox with more than 250 patents in this field. Regarding total patents, Hitachi, Mitsubishi,

Table 4: Top ten inventor firms in CCT.

Firm	Rank	CCT patents	Other patents	Total patents	Relative share of CCT in total inventions	Relative share in world CCT inventions
Mitsubishi	1	377	26,680	27,057	1.39	4.78
Alstom	2	252	1,689	1,941	12.99	3.19
Babcock & Wilcox	3	252	926	1,178	21.36	3.19
Siemens	4	233	42,996	43,229	0.54	2.95
Asea Brown Boveri (ABB)	5	218	4,056	4,274	5.09	2.76
Foster Wheeler	6	199	177	375	52.93	2.52
General Electric (GE)	7	132	17,481	17,613	0.75	1.67
Hitachi	8	125	33,731	33,856	0.37	1.58
Royal Dutch Shell	9	95	5,619	5,713	1.66	1.20
Combustion Engineering	10	91	482	573	15.88	1.15
Total	—	1,974	133,837	135,809	1.45	24.99

Note: The table reports the top ten CCT patent holders based on total number of CCT priority patent applications (claimed priorities) filed worldwide by all firms from 1978 to 2009. It also reports the total number of total priority patent applications (including CCT and other patents; claimed priorities) filed worldwide by these firms from 1978 to 2009.
Source: Authors' calculations, based on PATSTAT.

and General Electric have the highest innovative activity after Siemens, all exhibiting five-figure patent numbers. The other listed firms patent significantly less.

As described in the section on data sources, we know for every CCT first priority patent in our data set whether the invention subsequently has also been protected in any of the other considered 93 patent offices. Accordingly, Table 5 summarizes the geographical coverage of CCT patent protection across the main countries from 1978 to 2009. More than 80% of CCT inventions are filed, amongst other countries, in the USA. EPO is the second most important patent office covering nearly 70% of CCT patents of the sample. Other countries holding high shares include Japan (57%), Germany (44%), and Canada (42%). While about one third of the patents is filed in China and Australia, all other countries are characterized by lower coverage of patenting activity.

Turning to the demand-side effects, Figure 2 displays the average firm-level development of the weighted average real steam coal end-use price as well as the real total energy end-use price for all firms in the sample from 1978 to 2009. The coal price increases sharply until the early-1980s before entering a long period of decline which was mainly caused by technological progress and excess capacities (Ellermann, 1995). During the

Table 5: Geographical coverage of CCT patent protection across top twenty countries respectively patent offices for all firms from 1978 to 2009.

Country	Share	Country	Share
USA	81%	Denmark	10%
EPO	69%	United Kingdom	9%
Japan	57%	Russia	9%
Germany	44%	Brazil	9%
Canada	42%	South Africa	8%
China	35%	Mexico	8%
Australia	31%	France	8%
South Korea	16%	Norway	7%
Spain	15%	Finland	6%
Austria	13%	Poland	6%

Note: The patents in our data set are claimed priorities, that is patents filed in at least two offices. The table reports the share of these patents that are filed in the top 20 countries respectively patent offices.
Source: Authors' calculations, based on PATSTAT.

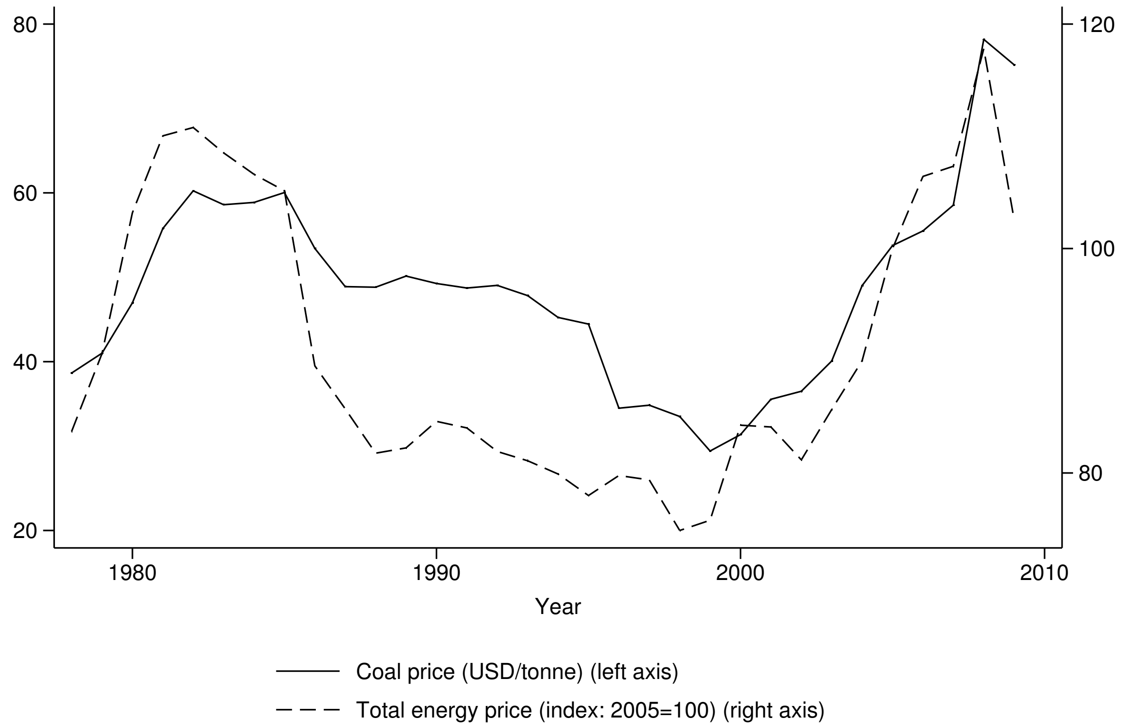

Figure 2: Average firm-level development of the weighted average real total energy end-use price (index with base year 2005) and real steam coal end-use price for all firms (USD per tonne, 1996 prices and PPP), 1978-2009. *Source:* Authors' calculations, based on PATSTAT, and IEA Energy Prices and Taxes.

2000s, the coal price again increases substantially starting from 30 USD per tonne in 1999 and peaking at nearly 80 USD per tonne in 2009. The reason for the increasing price trend can be found in the low level of investments in the period with depressed prices and a subsequent rapid increase in coal demand, especially from newly industrializing countries (Wårell, 2006). The data thus provides a great amount of variation which will be useful in determining the effect of changes in the coal price on innovation. However, as discussed before, the coal price would be preferable but because of the mentioned information gaps the total energy price will be used in the empirical analysis instead. Since both variables follow a very similar trend, we consider the total energy price to be a good proxy for the coal price.

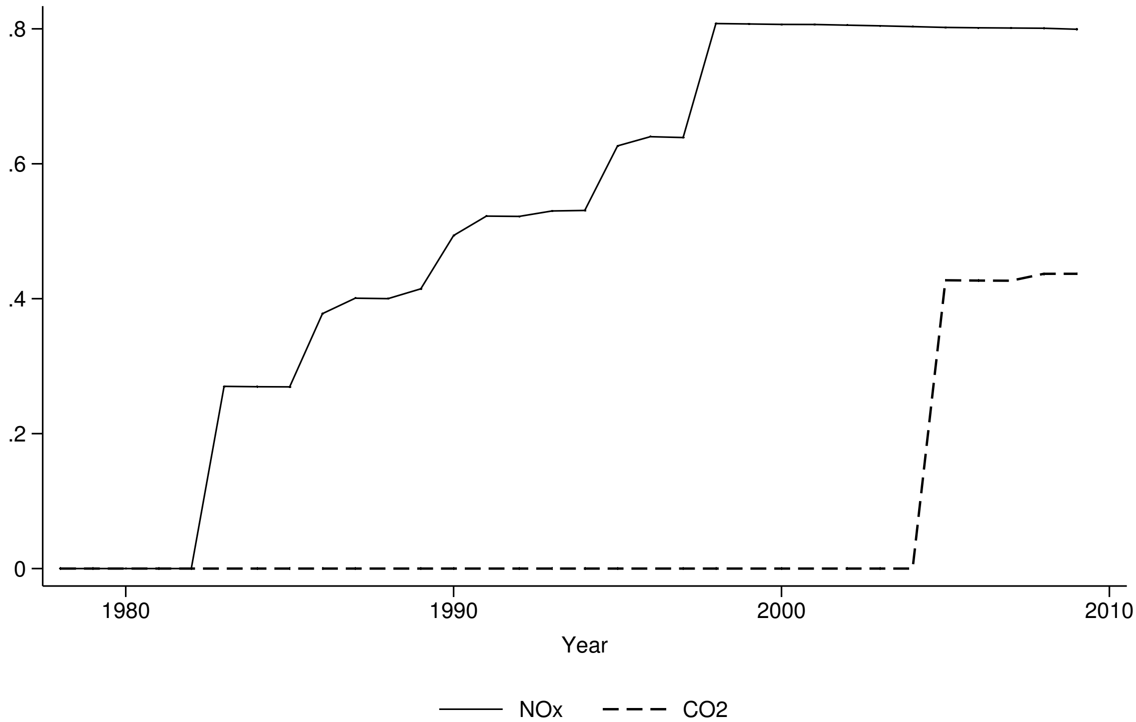

Figure 3: Average firm-level development of the weighted average NO_X and CO_2 dummy variables for all firms, 1978-2009. *Source:* Authors' calculations, based on PATSTAT, Popp (2006) and World Bank Group, Ecofys (2014).

Figure 3 depicts further demand-side determinants, namely the average firm-level development of the weighted average NO_X and CO_2 dummy variables for all firms in the sample from 1978 to 2009. The firm-specific dummies depend on the introduction of NO_X and CO_2 regulations in all countries with importance for the firms' overall innovations. Therefore, the developments in countries with a larger coverage of patents have a larger effect on the average firm-level dummies. Chronologically, NO_X regulation kicks in first in 1983 (Germany and Switzerland). Other countries follow among which Japan (1996) and the USA (1998) can be found. As the three individually most important countries have implemented NO_X regulations, the dummy variable jumps to the value 0.8 in 1998. Regulation on CO_2 was almost exclusively implemented in the European Union with the introduction of the cap-and-trade system in 2005. This is reflected in a dummy variable of about 0.4 from 2005 onwards.

4 Empirical Strategy and Results

In this section we specify the empirical model and discuss the estimation method. Then we present the estimation results of our baseline specifications and conduct a number of robustness tests.

4.1 Empirical Model

Given the hypotheses stated in Section 2 and the variables described in Section 3.1, our empirical model can be specified as follows:

$$\begin{aligned} PAT_{ijt} = exp(&\beta_0 + \beta_1\, ln\, P_{it-1} + \beta_2\, ln\, K_{ijt-1} + \beta_3\, ln\, RD_{it-1} + \beta_4\, ln\, TPAT_{it-1} \\ &+ \beta_5\, ln\, M_{it-1} + \beta_6\, CO2_{it} + \beta_7\, NOx_{it} + \tau_t + \eta_i) + u_{ijt} \end{aligned} \tag{6}$$

where i, j, and t index the firm, technology, and time, respectively. PAT is the annual firm-level patent count for technology j and $TPAT$ is the annual firm-level patent count for all patents. K represents the end-of-period knowledge stock as defined in Equation 1. P, RD, and M denote the weighted firm-year energy price, the weighted firm-year government R&D expenditures, and the weighted firm-year market size as defined in Equations 2-4. $CO2$ and NOx are dummy variables indicating the implementation of CO_2 regulations (mainly cap-and-trade programs) and (stringent) NO_X regulations, respectively. Like the the energy price and the market size the dummy variables are weighted by the share of firm i's patent filings in country c and country c's economic importance (that is, share in world GDP). τ and η capture unobserved firm- and time-specific heterogeneity and u_{ijt} is a standard error term. The variables P, K, RD, $TPAT$, and M are lagged by one year in order to mitigate any reverse causality problems.

Given the count data nature of our dependent variable we use count data techniques to estimate Equation 6. A standard approach for panel data is the Poisson fixed effect count data estimator developed by Hausman et al. (1984). However, this estimator requires strict exogeneity of all regressors to be consistent. In our model, the regulatory variables ($CO2$ and NOx) and the market size variable M are unlikely to be strictly exogenous. In addition, as the knowledge stock variable K is a function of the lagged dependent variable, it is predetermined.

To account for this problem, Blundell et al. (1995, 2002) proposed an alternative estimator: the pre-sample mean scaling estimator. This estimator relaxes the strict exogeneity assumption by modeling firm heterogeneity via pre-sample information on the firm's patenting activities. Following this approach, the firm-specific effects in Equation 6 are defined as:

$$\eta_i = \theta_1 \, ln \, P\bar{A}T_{ij} + \theta_2 \, D(P\bar{A}T_{ij} > 0) \tag{7}$$

where $P\bar{A}T_{ij} = (1/N) \sum_{n=1}^{N} PAT_{ijn}$ is the pre-sample mean of patent applications by firm i, technology j, and year n. N is the number of pre-sample observations and D is a dummy variable equal to one if the firm ever patented in the pre-sample period.

Another econometric issue that needs to be addressed is possible overdispersion in the data. A standard Poisson regression model assumes equidispersion, that is, the mean and the variance of the counts are equal. However, in many real data applications the variance is greater than the mean, which is named overdispersion. In this case the standard Poisson regression model yields inefficient estimates with downwardly biased standard errors.

A model that relaxes the equidispersion assumption of the standard Poisson regression model is the negative binomial regression model. The model includes a so called dispersion parameter α, that allows the variance and the mean of the counts to differ from each other. If α is equal to zero, the negative binomial model reduces to the Poisson model (see, for example, Long and Freese (2014)).

4.2 Empirical Results

The estimation results of our empirical model are presented in Table 6. We estimate the model defined in Equation 6 separately for EI-CCT and AP-CCT as well as for all CCT together. Pre-estimation analyses of the data reveal that for CCT and EI-CCT the variance of the patents counts is about five times higher than the mean. For AP-CCT it is about 2.5 times higher. For this reason, we start our empirical analysis with a comparison of the PSM Poisson and negative binomial regression results. Several standard tests for model selection, the Akaike Information Critieria (AIC), the Baysian Information Criteria (BIC), and the likelihood-ratio (LR) test of including the overdispersion parameter α in the model are reported in Table 6. For all technology groups the null hypothesis of α equal to zero is strongly rejected. Furthermore, the AIC and BIC statistics are always lower for the negative binomial than for the Poisson regression model. These results consistently indicate that the negative binomial regression model is preferred over the Poisson regression model.

Column (3) in Table 6 reports the negative binomial estimation results for all CCT together. As the explanatory variables enter the estimations in log form, the estimated coefficients can be interpreted as elasticities. Interestingly, the energy price has a negative and statistically significant impact on CCT patent activities. While this seems counterintuitive at first glance, the estimated price coefficients for the EI-CCT and AP-CCT models in Column (5) and (7) reveal that this result is driven by the price reaction of patent activities in AP technologies. The energy price has no significant impact in the EI-CCT model but a relatively high negative and strongly significant impact in the AP-CCT model. The estimated elasticity of -2.155 suggests that a 1% increase in energy prices results in an approximately 2% decrease in AP patent activities. This result is in line with our hypothesis that higher energy prices lead to less innovation in AP technologies, since these make electricity production from coal even more expensive. Nevertheless, the insignificance of the energy price in the EI-CCT model is unexpected. In general, we would expect a positive impact of higher energy prices on patent activities, since innovation in EI-CCT aims at producing electricity from coal more efficiently, that is with less energy (coal) input.

For the knowledge stock and total patents we observe a common result for both technology groups. The corresponding coefficients are positive and statistically significant at the 1% level in all models. In the preferred negative binomial regression models the estimated elasticities for the knowledge stock between 0.954 and 0.996 suggest that a 1% increase in knowledge stock is associated with an approximately 1% increase in patent activities. The corresponding elasticities for total patents vary between 0.341 in the AP-CCT model and 0.390 in the CCT model. These findings are consistent with previous research (see, for example, Popp, 2002; Verdolini and Galeotti, 2011) and confirm our hypotheses that innovation in CCT is positively affected by both the scientific and technology capacity and the overall propensity to patent of the firms.

A different picture emerges for public R&D expenditures. A negative and statistically significant impact is shown in the CCT, EI-CCT, and AP-CCT model. Although we did

Table 6: Baseline results for CCT, EI-CCT, and AP-CCT.

	CCT		EI-CCT		AP-CCT	
	Poisson	NegBin	Poisson	NegBin	Poisson	NegBin
Energy price$_{t-1}$	-1.094	-1.839^{***}	-0.513	-1.250	-1.514	-2.155^{**}
(log)	(1.145)	(0.684)	(1.759)	(1.095)	(1.056)	(0.845)
Knowledge stock$_{t-1}$	0.844^{***}	0.954^{***}	0.883^{***}	0.996^{***}	0.892^{***}	0.964^{***}
(log)	(0.049)	(0.038)	(0.066)	(0.053)	(0.051)	(0.049)
Public R&D$_{t-1}$	-0.039^{***}	-0.066^{***}	-0.059^{***}	-0.088^{***}	-0.033^{**}	-0.048^{***}
(log)	(0.013)	(0.009)	(0.016)	(0.013)	(0.015)	(0.012)
Total patents$_{t-1}$	0.319^{***}	0.390^{***}	0.325^{***}	0.371^{***}	0.310^{***}	0.341^{***}
(log)	(0.024)	(0.018)	(0.025)	(0.022)	(0.018)	(0.017)
Electricity prod.$_{t-1}$	-0.020	-0.059	0.017	-0.011	-0.062	-0.091^{*}
(log)	(0.049)	(0.037)	(0.083)	(0.067)	(0.054)	(0.048)
CO_2 regulation	0.808^{**}	0.519^{***}	1.138^{***}	0.777^{***}	0.761^{***}	0.502^{**}
	(0.335)	(0.171)	(0.416)	(0.254)	(0.281)	(0.208)
NO_X regulation	0.457^{***}	0.518^{***}	0.239	0.311	0.621^{***}	0.631^{***}
	(0.158)	(0.135)	(0.217)	(0.201)	(0.203)	(0.182)
Pre-sample mean	-0.256	-0.924^{**}	0.235	-0.657	-0.963^{***}	-1.171^{***}
	(0.408)	(0.363)	(0.461)	(0.487)	(0.331)	(0.334)
Pre-sample dummy	0.219^{*}	0.150	-0.092	0.069	0.163	0.057
	(0.128)	(0.101)	(0.209)	(0.138)	(0.112)	(0.097)
Constant	2.083	6.370^{*}	-1.102	3.147	4.483	8.029^{**}
	(5.637)	(3.266)	(8.735)	(5.392)	(5.173)	(3.970)
Log-likelihood	-16735	-15924	-8415	-7888	-9577	-9384
Overdispersion parameter α		0.943		1.115		0.772
LR-test of $\alpha = 0$		1622^{***}		1055^{***}		387^{***}
		(0.000)		(0.000)		(0.000)
AIC	33540	31920	16900	15847	19224	18839
BIC	33870	32259	17206	16162	19535	19159
Observations	91219	91219	46043	46043	53375	53375
Firms	3638	3638	1820	1820	2138	2138

Notes: Estimation time span: 1983-2009. All models control for unit-specific fixed effects by using PSM information on the first 5 years available (1978-1982). All models include a full set of time dummies (not reported). Robust standard errors clustered at the firm-level are in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. For likelihood-ratio test of $\alpha = 0$, $Prob \geq \chi^2$ in parentheses. AIC: Akaike Information Criterion, BIC: Bayesian Information Criterion.

not expect such a result, it may indicate that public R&D expenditures have a crowding-out effect on private R&D expenditures (Popp, 2002). Nevertheless, the magnitude of the coefficients is rather small suggesting that from an economic point of view public R&D expenditures do not really affect firm-level patent activities in CCT. A similar result is observed for the potential market size. In contrast to our hypothesis, the negative coefficients for electricity production indicate a negative impact of the potential market size on innovation activities in CCT. However, the coefficients are small in magnitude and only statistically significant at the 10% level in the AP-CCT model.

Referring to our regulatory variables, implementation of CO_2 regulation and implementation of NO_X regulation, the estimated coefficients for the different technologies provide some interesting results. The estimated coefficients for CO_2 regulation are positive and statistically significant in all models, as expected. For NO_X regulation a positive impact is shown in the CCT and AP-CCT model only. This outcome can be explained by the specific focus of AP technologies on SO_2 and NO_X abatement processes.

In our baseline models firm-specific fixed effects are captured by two pre-sample variables: the firm's average patent count in CCT in the pre-sample period and a dummy variable equal to one if the firm ever patented in CCT in the pre-sample period. We find statistically significant coefficients for the pre-sample mean in the CCT and the AP-CCT model indicating that the applied pre-sample mean estimator is able to capture at least some of the unobserved firm heterogeneity in our sample.

As a robustness check of this approach, we re-estimate the preferred negative binomial regression models with a different specification of the pre-sample variables. Instead of using pre-sample information on CCT patent activities, we now use pre-sample information on patent activities in general. The results are presented in Columns (2)-(4) in Table 7. As shown, the magnitude as well as the sign of the statistically significant coefficients are robust to this alternative specification. Only for electricity consumption a change in significance is observed. The coefficient is not statistically significant any more in the AP-CCT model. Furthermore, the pre-sample variables are statistically significant in all models. This suggests that the pre-sample information on patent activities in general is an even better indicator for unobserved firm heterogeneity than the pre-sample information on patent activities in CCT only.

The second robustness test we conduct is the exclusion of the top ten innovative firms in CCT. These firms are responsible for approximately 25% of all CCT patents in the sample and thus may bias some of our baseline results. As seen in Columns (5)-(7) in Table 7, our main results carry over. In addition, the weak statistical significance of

Table 7: Robustness results for different pre-sample specification and exclusion of top innovative firms.

	Pre-sample information: total patents			Without top ten CCT firms		
	CTT	EI-CCT	AP-CCT	CTT	EI-CCT	AP-CCT
Energy price$_{t-1}$	-1.706^{**}	-1.011	-2.107^{**}	-1.785^{***}	-1.455	-1.976^{**}
(log)	(0.690)	(1.099)	(0.864)	(0.671)	(1.018)	(0.826)
Knowledge stock$_{t-1}$	0.925^{***}	0.966^{***}	0.915^{***}	0.953^{***}	0.997^{***}	0.956^{***}
(log)	(0.034)	(0.043)	(0.044)	(0.039)	(0.050)	(0.052)
Public R&D$_{t-1}$	-0.066^{***}	-0.087^{***}	-0.049^{***}	-0.072^{***}	-0.097^{***}	-0.052^{***}
(log)	(0.009)	(0.013)	(0.012)	(0.009)	(0.013)	(0.012)
Total patents$_{t-1}$	0.417^{***}	0.402^{***}	0.359^{***}	0.401^{***}	0.369^{***}	0.337^{***}
(log)	(0.020)	(0.027)	(0.022)	(0.017)	(0.022)	(0.017)
Electricity prod.$_{t-1}$	-0.046	0.012	-0.080	-0.065^{*}	-0.035	-0.092^{**}
(log)	(0.039)	(0.070)	(0.050)	(0.037)	(0.066)	(0.047)
CO_2 regulation	0.528^{***}	0.792^{***}	0.505^{**}	0.521^{***}	0.723^{***}	0.500^{**}
	(0.176)	(0.261)	(0.212)	(0.165)	(0.233)	(0.200)
NO_X regulation	0.422^{***}	0.254	0.519^{***}	0.555^{***}	0.391^{*}	0.660^{***}
	(0.136)	(0.202)	(0.183)	(0.137)	(0.207)	(0.185)
Pre-sample mean	-0.593^{***}	-0.518^{***}	-0.487^{***}	-1.246^{***}	-1.419^{**}	-0.965^{*}
	(0.110)	(0.146)	(0.117)	(0.342)	(0.562)	(0.526)
Pre-sample dummy	0.464^{***}	0.397^{***}	0.422^{***}	0.130	0.171	-0.049
	(0.075)	(0.111)	(0.080)	(0.087)	(0.123)	(0.098)
Constant	5.642^{*}	1.787	7.746^{*}	6.170^{*}	4.353	7.229^{*}
	(3.302)	(5.418)	(4.068)	(3.211)	(5.006)	(3.869)
Log-likelihood	-15894	-7873	-9371	-15094	-7128	-8875
Observations	91219	46043	53375	90959	45783	53115
Firms	3638	1820	2138	3628	1810	2128

Notes: Estimation time span: 1983-2009. All models control for unit-specific fixed effects by using PSM information on the first 5 years available (1978-1982). All models include a full set of time dummies (not reported). Robust standard errors clustered at the firm-level are in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level.

electricity production in the AP-CCT model is back and NO_X regulation is shown to be statistically significant in all models.

Table 8: Robustness results for different lagged and forward values of the energy price, public R&D expenditures, and electricity production.

	CTT	EI-CCT	AP-CCT
Energy price$_{t-1}$ (log)	-1.839^{***}	-1.250	-2.155^{***}
	(0.684)	(1.095)	(0.845)
Energy price$_{t-2}$ (log)	-1.955^{***}	-1.641	-2.140^{***}
	(0.653)	(1.012)	(0.825)
Energy price$_{t-3}$ (log)	-2.392^{***}	-2.510^{**}	-2.263^{***}
	(0.660)	(0.998)	(0.844)
Energy price$_{t+1}$ (log)	-1.314^{*}	-0.511	-1.704^{*}
	(0.743)	(1.198)	(0.894)
Public R&D$_{t-1}$ (log)	-0.066^{***}	-0.088^{***}	-0.048^{***}
	(0.009)	(0.013)	(0.012)
Public R&D$_{t-2}$ (log)	-0.056^{***}	-0.077^{***}	-0.038^{***}
	(0.010)	(0.014)	(0.013)
Public R&D$_{t-3}$ (log)	-0.048^{***}	-0.066^{***}	-0.033^{**}
	(0.010)	(0.015)	(0.014)
Electricity prod.$_{t-1}$ (log)	-0.059	-0.011	-0.091^{*}
	(0.037)	(0.067)	(0.048)
Electricity prod.$_{t-2}$ (log)	-0.052	-0.007	-0.092^{*}
	(0.037)	(0.064)	(0.048)
Electricity prod.$_{t-3}$ (log)	-0.048	-0.012	-0.088^{*}
	(0.039)	(0.065)	(0.049)
Electricity prod.$_{t+1}$ (log)	-0.083^{**}	-0.046	-0.109^{**}
	(0.040)	(0.069)	(0.052)

Notes: Estimations are based on the same specification as in Table 6. To conserve space only the coefficients for the different lagged and forward values of the energy price, public R&D expenditures, and electricity production are presented. The complete tables are available from the authors upon request. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level.

Given the somehow unexpected results for the energy price, public R&D, and market size in some of our baseline models, we complete our robustness analysis with alternative specifications on the lag structure of these variables. More specifically, we re-estimate our baseline negative binomial specification with a two-year and three-year lagged energy price, public R&D, and market size (electricity production) variable. Furthermore, as firms rather consider the future than the past for their innovation decisions, we also estimate model specifications with forward values, that is, values in $t + 1$, for the energy price and the market size. Of course, the utilization of forward values as a proxy for the firm's expectations assumes that the expected value in the future is equal to the realized value in the future.

The estimated coefficients for the different lag and forward structures of the energy price, public R&D, and electricity production variable are depicted in Table 8. As shown, our baseline results are left intact. The estimated coefficients for all lagged and forward values of the energy price indicate a negative impact of higher energy prices on patent activities in the AP-CCT model. Except for the third lag, the coefficients for EI-CCT are not statistically significant. In the case of public R&D expenditures the magnitude of the coefficients gets smaller with increasing lags. Finally, the coefficients for all lagged and forward values of electricity production indicate a statistically significant negative impact of market size on patent activities in the AP-CCT model at the 10% level.

5 Conclusions

In this article, we empirically analyzed the determinants of innovation in clean coal technologies. We conducted our analysis on a panel of 3,648 firms which filed 7,894 CCT patents across 55 patent offices over the period 1978 to 2009. We examined supply-side and demand-side factors expected to affect innovation in CCT. Our contribution to the literature is 3-fold. First, we investigate the determinants of CCT innovation directly at the firm-level. Second, our analysis builds on an almost entire population of all CCT patents filed worldwide in the considered period. Third, we provide interesting descriptive evidence on firms' global CCT patenting behavior.

Overall, our results show that a number of supply- and demand-side factors influence firm-level patenting activities in CCT. On the supply-side we find evidence that firms with a higher technology capacity, that is a longer history of patent activities in CCT and a higher overall propensity to patent, are more active in CCT innovation than others. This finding confirms previous results for other technologies and is in line with the technology-push hypothesis stating that innovation activities are path dependent and built on existing knowledge. Public policies should keep this in mind and create a research friendly economic environment that fosters the private generation of scientific and technological knowledge and enables firms to exploit their existing knowledge base.

Another supply-side policy that is usually assumed to push private innovation activities is public R&D spending. However, for CCT we do not find such an impact. On the contrary, our findings suggest that public R&D spending reduces or 'crowds-out' private R&D investments and thus reduces private innovation activities. Nevertheless, this potential crowding-out effect seems to be very small and, hence, is economically negligible.

Referring to the demand-side, we find a strong relationship between emission restricting regulations and CCT innovation. Regulation of CO_2 emissions has a positive impact on CCT patenting activities in general and NO_X regulation has a positive impact on AP-CCT innovation. Given the ongoing high dependence of worldwide electricity production on coal-fired power plants, this finding emphasizes the importance of strict environmental regulations on the way towards a cleaner electricity system.

For energy prices a diversified picture emerges. Our hypothesis was that higher energy prices have a positive impact on input-saving EI-CCT innovation and a negative impact on post-combustion AP-CCT innovation. However, the findings only support the latter. As AP technologies make electricity production from coal even more expensive, an increase in energy prices leads to less innovation in these technologies.

The outcome that we do not find a positive impact of increasing energy prices on EI-CCT innovation may be due to two effects. On the on hand, we would expect that increasing energy prices induce innovation in input-saving EI-CCT, as stated in our initial hypothesis. On the other hand, increasing energy prices may indicate a stronger support of public authorities for other less polluting types of electricity-generation technologies, in particular electricity generation from renewables and natural gas. In this case, increasing energy prices would have a negative impact on coal-burning patenting activities in general. The two effects are opposed to each other and, hence, may cancel each other out.

Finally, referring to market size, our results contradict the hypothesis that a potentially larger market size leads to more innovation in CCT. We either find no statistically significant impact or a slightly significant negative impact. We do not have an explanation for this result. However, as both the statistical significance and the economic significance are very low, this unexpected result should not be taken too seriously.

Further research in this field should examine the impact of environmental regulations on the diffusion of CCT. In this study we analyzed one stage of technological progress, that is, innovation. The following stage is diffusion. It would be interesting to analyze how environmental regulations influence the adoption of new technologies in electricity production processes. Another promising path for additional research is the analysis of spillover effects among the firms.

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Appendix

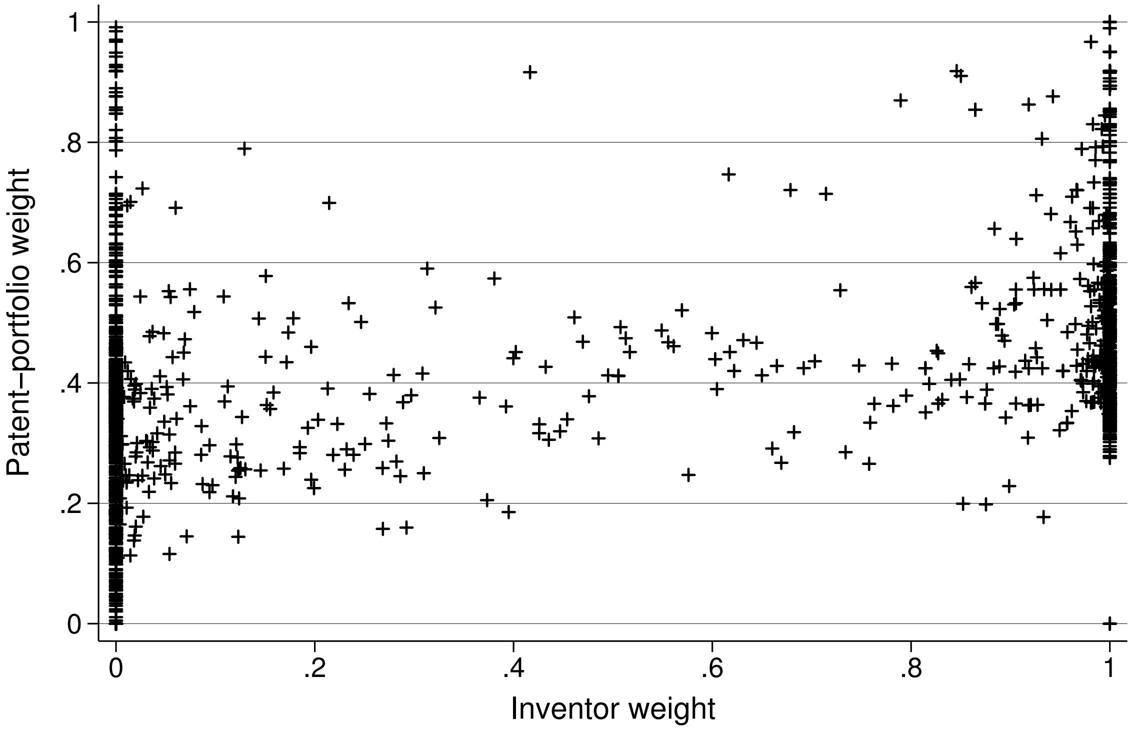

Figure A1: Patent-portfolio weights versus inventor weights for the USA. *Source:* Authors' calculations, based on PATSTAT. *Note:* The figure shows combinations of patent-portfolio weights (y-axis) and inventor weights (x-axis) for the USA for all 3,684 firms.

Table A1: Total number of CCT, EI, AP, PCC, FBC, IGCC, EOP, and CCS patents.

Year	CCT	EI	AP	PCC	FBC	IGCC	EOP	CCS
1978	172	101	72	27	31	43	44	28
1979	152	103	49	41	26	36	32	17
1980	193	119	74	25	47	47	47	27
1981	197	120	77	38	44	38	44	33
1982	194	104	90	35	33	36	48	42
1983	207	110	97	53	29	28	68	29
1984	231	116	115	36	37	43	90	26
1985	241	109	132	30	45	34	94	39
1986	223	100	123	22	46	32	96	27
1987	213	113	100	27	48	38	69	31
1988	209	97	112	17	37	43	81	32
1989	207	109	98	17	38	54	70	29
1990	204	96	108	23	36	37	66	42
1991	218	111	107	25	31	55	72	35
1992	225	108	117	15	34	59	74	43
1993	224	126	98	23	31	72	67	31
1994	254	124	130	18	28	78	99	31
1995	255	136	120	32	21	83	86	34
1996	242	140	102	22	23	95	58	44
1997	248	142	107	19	23	100	82	25
1998	234	120	114	12	16	92	66	48
1999	220	111	109	24	19	68	60	49
2000	253	134	119	11	21	102	65	54
2001	240	143	97	31	13	99	40	58
2002	258	147	111	30	18	99	59	52
2003	221	120	101	23	18	79	54	47
2004	258	151	108	26	12	113	45	62
2005	296	141	155	23	20	97	75	80
2006	322	168	155	34	20	113	72	83
2007	406	193	213	46	16	131	87	126
2008	436	219	217	43	28	148	84	133
2009	443	205	239	36	23	146	97	141
Total	7,894	4,129	3,765	883	911	2,335	2,190	1,575

Note: The table reports the total number of CCT, EI, AP, PCC, FBC, IGCC, EOP, and CCS priority patent applications (claimed priorities) filed worldwide per year of all firms.
Source: Authors' calculations, based on PATSTAT.

Table A2: Distribution of patent-portfolio weights across top four countries respectively patent offices for the top ten CCT inventor firms from 1978 to 2009.

Firm and countries/patent offices	Weight	Firm and countries/patent offices	Weight
(1) Mitsubishi		**(6) Foster Wheeler**	
Japan	0.324	USA	0.155
USA	0.273	Japan	0.133
Germany	0.106	Canada	0.126
EPO	0.065	EPO	0.099
(2) Alstom		**(7) General Electric (GE)**	
EPO	0.212	USA	0.235
USA	0.200	Japan	0.183
Germany	0.158	EPO	0.151
Japan	0.072	Germany	0.100
(3) Babcock & Wilcox		**(8) Hitachi**	
USA	0.182	Japan	0.342
Canada	0.124	USA	0.322
EPO	0.114	EPO	0.083
Japan	0.112	Germany	0.072
(4) Siemens		**(9) Royal Dutch Shell**	
Germany	0.270	USA	0.133
EPO	0.239	EPO	0.133
USA	0.175	Japan	0.093
Japan	0.095	Canada	0.093
(5) Asea Brown Boveri (ABB)		**(10) Combustion Engineering**	
EPO	0.230	USA	0.274
Germany	0.205	Japan	0.126
USA	0.142	Canada	0.119
Japan	0.074	EPO	0.089

Note: Patent-portfolio weights are constructed based on the distribution of firms' patent portfolios across countries over the period 1978 to 2009.
Source: Authors' calculations, based on PATSTAT.

Table A3: Distribution of patent-portfolio weights across top twenty countries respectively patent offices averaged over all firms from 1978 to 2009.

Country/patent office	Weight	Country/patent office	Weight
USA	0.233	France	0.015
Japan	0.189	Austria	0.014
EPO	0.130	Spain	0.012
Germany	0.110	Brazil	0.009
China	0.070	South Africa	0.005
South Korea	0.065	Norway	0.005
Canada	0.032	Mexico	0.005
Australia	0.023	Russia	0.004
Taiwan	0.017	Denmark	0.004
United Kingdom	0.017	Italy	0.004

Note: Patent-portfolio weights are constructed based on the distribution of firms' patent portfolios across countries over the period 1978 to 2009.
Source: Authors' calculations, based on PATSTAT.

Table A4: Distribution of inventor weights across top twenty countries averaged over all firms from 1978 to 2009.

Country	Weight	Country	Weight
Germany	0.295	Belgium	0.006
USA	0.285	Sweden	0.006
South Korea	0.149	Finland	0.006
Japan	0.099	Canada	0.005
France	0.056	Italy	0.005
Switzerland	0.020	Norway	0.003
Netherlands	0.015	Denmark	0.003
United Kingdom	0.012	Singapore	0.003
Taiwan	0.009	Australia	0.002
Austria	0.009	China	0.002

Note: Inventor weights are constructed based on the distribution of firms' inventors across countries over the period 1978 to 2009.
Source: Authors' calculations, based on PATSTAT.

Table A5: Correlation matrix.

	CCT patents	CCT knowledge stock	Total patents	CCT-related government R&D	Energy price	Electricity production	NO_X dummy	CO_2 dummy
CCT patents	1							
CCT knowledge stock	0.701	1						
Total patents	0.271	0.265	1					
CCT-related government R&D	0.004	0.005	-0.002	1				
Energy price	0.016	0.001	0.008	0.135	1			
Electricity production	0.010	0.009	0.030	0.198	-0.119	1		
NO_X dummy	0.029	0.051	0.049	0.102	-0.212	0.619	1	
CO_2 dummy	0.026	0.022	0.011	0.175	0.471	0.324	0.294	1

Source: Authors' calculations, based on PATSTAT, IEA Energy Technology R&D, IEA Energy Prices and Taxes, IEA Energy Balances, Popp (2006) and World Bank Group, Ecofys (2014).