Empirical Essays on Energy, the Environment, and Innovation

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Jürgen Kruse March 2016

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Chapter 1

Introduction

1.1 Motivation

Energy is an essential input for any economic activity and has been fundamental for human and economic development. Technological innovation in the conversion and use of energy is closely related to this development. The ability to convert ever larger quantities of energy and consume these with increasing efficiency provided greater amounts of power, heat, transport, and light and improved human societies' standard of living and economic prosperity (Fouquet, 2009). The progress from simple human power to the use of draft animals, the water wheel, and the steam engine increased power available dramatically by about 600-fold. The steam engine, in particular, revolutionized energy conversion and introduced the Industrial Age by making power plants geographically independent of the proximity to energy sources. Subsequent advances in energy technology, such as electricity, more efficient steam engines, nuclear power, renewable energy, energy distribution (such as electrical grid and pipelines), and improvements in energy efficiency have led to ever more convenient, portable, versatile, and efficient ways of energy conversion and use (Newell, 2011). This technological change can also be observed in the improvements in energy intensity that have occurred in the world's industrialized countries: The amount of energy required to produce one unit of output has been falling by approximately 1% per year over the last century. More recently, similar improvements began to occur in many transition and some developing countries (UNDP, 2000). This development allowed the world to produce ever more wealth per unit of energy.

However, today's ways of converting and consuming energy have substantial adverse effects on the environment. These include indoor and outdoor air pollution, hydrocarbon and trace metal pollution of soil and groundwater, oil pollution of the oceans, radioactive waste, and emissions of carbon dioxide (CO_2) and other anthropogenic greenhouse gases (GHG) (Gallagher et al., 2006). One of the greatest threats to the global environment is climate change caused largely by the human-induced increase in anthropogenic GHG emissions since the pre-industrial era. Climate change has already had observable negative impacts on the global environment, such as rising sea levels, expansion of deserts, and more frequent extreme weather events. Without significant reductions in GHG emissions these impacts are predicted to become severe, pervasive, and irreversible. How to provide the energy required to sustain and increase economic prosperity and, at the same time, mitigate climate change is therefore the most serious environmental policy challenge the world faces today. Averting dangerous climate change will require to limit the increase in global mean temperature to no more than two degrees Celsius above pre-industrial levels. Reaching this two degrees Celsius goal requires substantial and sustained reduction efforts to stabilize the concentration of greenhouse gases in the atmosphere. Reducing emissions from energy conversion and use is a key component to achieve this mitigation goal (IPCC, 2014).

Energy technology innovation is a crucial factor to address this challenge. Controlling and limiting climate change will require a major change in the global energy system with a transition from existing energy technologies to new green (that is, low-GHG and GHG-neutral) energy technologies (Nakicenovic and Nordhaus, 2011). These green energy technologies can reduce GHG emissions from energy conversion and use by lowering the carbon intensity of energy or the energy intensity of economic activity. Thereby, they can reduce the long-term costs of meeting a GHG reduction target to societies (IPCC, 2014). Accelerating innovation in green energy technologies is therefore essential to combat global warming. While the importance of green energy innovation is widely seen and an extensive research effort has been made to analyze these innovations, it is still not completely understood what determines and what are the economic consequences of innovation in these technologies.

This thesis aims to improve the understanding of green energy innovation. In three interrelated essays it applies empirical methods to analyze the innovation process in green energy technologies focusing on two main aspects. First, it studies the determinants of green energy innovation: on the one hand for a set of different green energy technologies, and on the other hand specifically for clean coal technologies. Second, it examines the link between innovation in green energy technologies and the economic performance of the innovating firms.

Chapter 2 empirically investigates the effect of energy prices and technological knowledge on innovation in green energy technologies using country-level European patent data. The research is motivated by the ambiguous evidence on the determinants of green energy innovation, especially with respect to the determinants of innovation in specific technologies. It aims to deepen the understanding of these determinants in order to answer the question, whether policies should foster green energy innovation by stimulating the demand for green energy technologies via increasing energy prices, or by enhancing the technological capability via improving the knowledge stock of an economy.

Chapter 3 empirically examines the determinants of clean coal innovation using firm-level worldwide patent data. Motivated by the essential role coal plays in global electricity generation and the large environmental footprint of this sector, the research seeks to shed light on the factors enhancing innovation in technologies that allow coal use in electricity generation while mitigating its impact on the environment. Understanding these factors can help policymakers to design the appropriate energy and environmental policies for encouraging more innovation in clean coal technologies.

Chapter 4 empirically analyzes and compares the impact of innovation in green and non-green energy technologies on the economic performance of firms using firm-level European patent data. The research is motivated by the insufficient evidence on the economic effects of green energy innovation, especially regarding the relationship between innovating in green energy technologies and the economic performance of the innovating firms. It aims to answer the question, whether firms gain (forgo) economic opportunities by innovating (not innovating) in green energy technologies.

1.2 Thesis Outline

After having discussed the motivation, the following section outlines the overall structure of the thesis. The main part of the thesis consists of three interrelated empirical essays dealing with two main topics of green energy innovation: its determinants and its impact on firm performance. Each of the three essays has a dedicated chapter in this thesis and can be read independently. The subsequent paragraphs briefly outline the research questions, the data used, the econometric methodology employed, and the main results of each of the three essays.

1.2.1 Energy Prices, Technological Knowledge, and Innovation in Green Energy Technologies: a Dynamic Panel Analysis of European Patent Data

The essay in Chapter 2, "Energy Prices, Technological Knowledge, and Innovation in Green Energy Technologies: a Dynamic Panel Analysis of European Patent Data", empirically investigates the effect of energy prices and technological knowledge on innovation in green energy technologies. It is forthcoming in the Journal *CESifo Economic Studies* (Kruse and Wetzel, 2015).[1] The essay was written in co-authorship with Heike Wetzel. Contributions to all aspects of the essay were made in equal parts.

In the essay, we consider both demand-pull effects, which induce innovative activity from the demand side by increasing the expected value of innovations, and technology-push effects, which drive innovative activity from the supply side by extending the technological capability of an economy. We aim to answer the question, whether demand-pull or technology-push factors are the main drivers of green energy innovation. Our analysis is conducted using patent data from the European Patent Office (EPO) on a panel of 26 Organisation for Economic Co-operation and Development (OECD) countries over a 32-year period from 1978 to 2009. We investigate the determinants of innovation separately for 11 different green energy technologies. Utilizing a dynamic count data model for panel data based on the pre-sample mean scaling estimator, we account for path dependencies in knowledge generation, endogeneity issues, and unobserved heterogeneity. The results indicate that the existing stock of knowledge is the main determinant of innovation in green energy technologies. This confirms the technology-push hypothesis stating that innovation is induced by advances in the technological capability of an economy. Furthermore, the results reveal significant differences across technologies in that energy prices have a positive impact on innovation for some but not all green energy technologies. This finding confirms the demand-pull hypothesis for some technologies suggesting energy prices as a major driver of green energy innovation and supports our approach of a technology-specific analysis. Moreover, we uncover significant differences comparing the period before and after the Kyoto protocol agreement in 1997. More precisely, the results indicate that the effect of energy prices and technological knowledge on green energy innovation becomes more pronounced after the Kyoto protocol agreement.

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

Chapter 3, "Innovation in Clean Coal Technologies: Empirical Evidence from Firm-Level Patent Data", empirically examines the determinants of clean coal innovation. This essay has been published in the *Working Paper Series of the Institute of Energy Economics at the University of Cologne* (Kruse and Wetzel, 2016). It is a joint work with Heike Wetzel, who co-authored the essay and equally contributed to all parts.

[1] This article is copyrighted by Oxford Journals and reprinted by permission. The presented article first appeared in *CESifo Economic Studies, online first October 2015, doi: 10.1093/cesifo/ifv021.*

In the essay, we analyze supply-side and demand-side factors expected to affect clean coal innovation. The factors analyzed are: 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 emissions from coal-fired electricity generation. Our analysis builds on a panel of 3,648 firms that filed 7,894 clean coal patents across 55 national and international patent offices over a 32-year period from 1978 to 2009. The study inquires into the determinants of clean coal innovation at the firm-level using almost the entire population of worldwide clean coal patents filed in the considered period. We utilize a negative binomial count panel data model based on the pre-sample mean scaling estimator that accounts for endogeneity issues, unobserved heterogeneity, and overdispersion in the count variable. Our results indicate that energy prices have a negative impact on innovation in after pollution control technologies, but do not affect innovation in efficiency improving combustion technologies. These findings suggest that increasing energy prices leads to less innovation in technologies that make the conversion of coal into electricity even more expensive. Moreover, we find evidence of a strong relationship between environmental regulation of emissions from coal-fired power plants and clean coal innovation. While regulation of CO_2 emissions has a positive impact on clean coal patenting in general, nitrogen oxide (NO_X) (and sulfur dioxide (SO_2)) regulation is found to positively affect after pollution control patenting only. A firm's history in clean coal patenting and its total patent filings are found to positively affect clean coal innovation. These results indicate that firms build on existing knowledge and innovate more in clean coal technologies the higher their overall propensity to innovate.

1.2.3 Innovation in Green Energy Technologies and the Economic Performance of Firms

The essay presented in Chapter 4, "Innovation in Green Energy Technologies and the Economic Performance of Firms", empirically analyzes and compares the impact of innovation in green and non-green energy technologies on the economic performance of firms. It was written solely by the author of this thesis and has been published in the *Working Paper Series of the Institute of Energy Economics at the University of Cologne* (Kruse, 2016).

In the essay, I seek to understand the economic effects of green energy innovation and answer the question, whether firms gain (forgo) economic opportunities by innovating (not innovating) in green energy technologies. My analysis is based on a panel of 8,619 patenting firms including 968 green energy patenters from 22 European countries over an estimation period of 8 years (2003-2010) and a patent count period of 32 years (1977-2010). To construct the panel, firm accounts data from the AMADEUS database is combined with data on firms' patent applications from the OECD REGPAT database. I measure economic firm performance in terms of productivity and use a panel data model based on an extended Cobb-Douglas production function in which productivity is a function of capital, labor, and innovative output. My results show that green energy innovation has a statistically significant negative impact on economic firm performance. In contrast, non-green energy innovation is found to have a statistically significant positive impact on economic firm performance. This suggests that private economic returns in terms of productivity are lower for green energy than for non-green energy innovation. I also find evidence that the negative effect on firm performance is more pronounced for renewable energy sources than for energy efficiency technologies. Moreover, my findings indicate that the negative relationship between green energy innovation and performance is stronger for larger firms. Furthermore, the negative impact of green energy innovation on performance is found to be stronger with a larger time lag between both. Finally, the results show that the negative impact of new green energy patents on performance is less pronounced when firms can build on an existing stock of green energy knowledge.

1.3 Literature Review and Contribution

The final section of the introduction reviews the related empirical literature on the determinants and performance effects of innovation in energy and environmental technologies and discusses the fit and contribution of the three thesis essays to this literature.

1.3.1 Determinants of Innovation in Energy and Environmental Technologies - Empirical Evidence

There is a large and growing empirical literature on the factors that affect innovation in energy and environmental technologies. The following paragraphs survey the key empirical studies in this field. Table 1.1 provides a summary of these studies.[2]

The first contributions to this literature investigate the effect of environmental regulation on energy and environmental innovation. Lanjouw and Mody (1996) examine the impact of environmental regulation stringency proxied by pollution abatement control expenditures (PACE) on innovation in environmental technologies. Innovation is measured by patent data from the United States (US), Japan, Germany, and 14 low- and middle-income countries from 1972 to 1980. On a descriptive account they find

[2] In addition to the surveyed literature this section draws on Popp et al. (2010).

strong evidence of a positive relationship between PACE and environmental innovation. Jaffe and Palmer (1997) also investigate the correlation between PACE and innovation. Their investigation is based on R&D expenditures and US patent filings across a panel of US manufacturing industries from 1974 to 1991. However, while Lanjouw and Mody (1996) focus on environmental innovation, Jaffe and Palmer (1997) look at overall (that is, environmental and non-environmental) innovation. They identify a positive impact of PACE on R&D spending, but find no effect on patenting. Brunneimer and Cohen (2003) study how environmental innovation by US manufacturing industries is affected by changes in PACE. They measure innovation by US patent filings during 1983 and 1992. In contrast to the descriptive examination in Lanjouw and Mody (1996) and Jaffe and Palmer (1997), they estimate the relationship between abatement pressures and environmental patenting using multivariate regression analysis. Their results indicate that PACE has just a small impact on environmental patenting.

Popp (2006) tests the impact of environmental regulation on innovation more directly. He investigates the effect of SO_2 and NO_X regulations on air pollution control technologies. Using patents filed in the US, Japan, and Germany during the period 1970 to 2000, he finds that patenting in pollution control significantly increased in response to higher environmental regulatory pressure. Johnstone et al. (2012) also analyze the effect of environmental regulation stringency on innovation in environmental technologies. Their study is based on worldwide patent filings by 77 countries between 2001 and 2007. Data from a World Economic Forum survey of top management business executives is used to proxy regulation stringency. They find that more stringent environmental regulations do lead to more environmental patents.

Popp (2002) contributes to the literature by considering not only the effect of demand-side factors, but also the effect of supply-side factors on technological change. He uses US patent data from 1970 to 1994 to estimate the impact of energy prices and scientific knowledge on innovation in energy and energy-efficiency technologies. Estimating a distributed-lag pooled regression model, he finds a significant positive impact of energy prices on innovation. He also shows that the existing stock of knowledge has strong positive effects on innovation. Popp (2002) concludes that both the supply of ideas and the demand for ideas shape the direction of energy and energy-efficiency innovation.

A similar analysis was carried out by Verdolini and Galeotti (2011). They study the impact of energy prices and scientific knowledge on innovation in energy technologies using panel data on US patent applications by 17 countries from 1975 to 2000. Their baseline results confirm the positive effects of both factors on innovation. Although the authors do not differentiate by individual technologies, separate estimations reveal differences between energy-supply and energy-demand technologies. While the effect of energy prices stays significant for supply technologies, it becomes insignificant for demand technologies.

This result is a first indicator that the relative importance of demand-pull and technology-push factors is specific to individual technologies. Johnstone et al. (2010) add to the literature by further investigating the technology-specific drivers of energy and environmental innovation. They use filings at the EPO from 25 OECD countries during 1978 to 2003 to investigate the determinants of technological change in five renewable energy technologies. The analysis shows that energy prices and renewable energy policies have a significant impact on patenting for some types of technologies. It is also shown that government expenditures on renewable energy R&D and growing electricity consumption are likely to increase renewable energy patenting. However, their study focuses on the policies and does not explicitly account for technology-push effects. Nesta et al. (2014) also examine the effect of renewable energy policies on innovation. They extend Johnstone et al. (2010)'s analysis by additionally looking at the interplay between these policies and competition, but do not differentiate by technologies. Based on worldwide renewable energy patent filings from 27 OECD countries over the period 1976 to 2007, they find that renewable energy policies induce innovation, but that they are more effective in countries with liberalized energy markets.

A number of papers investigate the determinants of innovation for specific energy-efficiency and renewable energy technologies. Crabb and Johnson (2010) study if higher fuel prices and stricter Corporate Average Fuel Economy (CAFE) standards lead to increased innovation in energy-efficient automobile technologies. Measuring innovation by US patent filings from 1980 to 1990 and using a dynamic model of patenting they find a positive impact of fuel prices but no impact of CAFE regulations on innovation. Peters et al. (2012) focus on the innovation effects of domestic and foreign technology-push and demand-pull policies for solar photovoltaic technologies. They analyze a panel of 15 OECD countries over the period 1978 to 2005 using worldwide patent filings. First, they find that domestic technology-push policies foster domestic but not foreign innovation. Second, they show that both domestic and foreign demand-pull policies induce domestic innovation. In a very similar setting Dechezleprêtre and Glachant (2014) analyze the effect of domestic and foreign demand-pull policies on innovation in wind power generation technologies. Worldwide wind power patent filings from 28 OECD countries are used as an indicator for innovation. In line with Peters et al. (2012), they find evidence that wind power technology innovation is positively affected by policies both from home and abroad. However, they find that the marginal effect of domestic policies is 12 times larger. Lindman and Söderholm (2015) also analyze wind energy technologies but aim at identifying the innovation impacts of different domestic policies. Using PCT patent applications from four western European countries, they show that both public R&D

and feed-in tariffs have a positive impact on wind energy innovation. In addition, they find that the impact of feed-in tariffs is more profound for mature technologies and that public R&D induces more innovation in combination with feed-in tariffs. From the latter result they conclude that innovation in wind energy technologies requires both R&D and learning-by-doing. Finally, Costantini et al. (2015) look at the differentiated impact of demand-pull and technology-push policies on biofuels innovation. Conducting an empirical analysis on EPO patents in biofuels technologies filed by 35 countries (OECD and some non-OECD), they find positive effects of technological capabilities and environmental regulation on innovation.

Our work (Kruse and Wetzel (2015); Chapter 2 of this thesis) analyzes the impact of energy prices and technological knowledge on green energy innovation based on EPO patent data from 26 OECD countries over the 1978 to 2009 period. It contributes to the literature discussed above in three respects: First, by investigating the impacts separately for 11 different green energy technologies, second, by using European patent data to assess the validity of the conclusions reached on US patent data, and third, by applying state-of-the-art count data techniques. Our findings show a positive impact of energy prices on innovation for some but not all technologies. This is, apart from differences for a small part of technologies, in line with the findings of Johnstone et al. (2010) and Verdolini and Galeotti (2011). Technological knowledge is found to have a positive effect on innovation for all technologies, which is also consistent with previous research by Popp (2002) and Verdolini and Galeotti (2011). Moreover, the results indicate that both effects are more pronounced after the Kyoto protocol agreement.

More recent studies investigate the determinants of energy and environmental innovation directly at the firm-level. Ayari et al. (2012), using data on EPO renewable energy patent counts for 154 firms from 19 European countries over the 1987 to 2007 period, find that firms' own R&D expenditures have a positive impact on renewable energy patenting, but that R&D expenses from competitors or other industries have no effect. They also find that increasing oil prices and primary energy consumption are likely to induce renewable energy innovation. Calel and Dechezleprêtre (2014) investigate the effect of the European Union Emissions Trading system (EU ETS) on innovation in low-carbon technologies. Based on EPO patent filings by 5,568 firms from 18 countries, they find that the EU ETS has increased low-carbon innovation among regulated firms, but has not affected patenting for non-regulated firms.

Barbieri (2015) and Aghion et al. (2016) focus on drivers of technological change in the automotive industry. Barbieri (2015) uses patent data on green automotive technologies filed worldwide by 355 firms between 1999 and 2010 to analyze the impact of European environmental policies on innovation. The results indicate that post-tax fuel prices, environmental vehicle taxes, CO_2 standards, and European emission standards positively affect green automotive patenting. Using a panel of 3,423 automotive industry innovators, Aghion et al. (2016) analyze which factors direct technical change from dirty (internal combustion engine) to clean (for example, electric, hybrid, and hydrogen) car technologies. They show that increasing tax-inclusive fuel prices leads to more patenting in clean and less patenting in dirty technologies. Analyzing the effect of knowledge they find path dependence for both technologies caused by firm's own patenting history and spillovers between firms.

The study by Noailly and Smeets (2015) focuses on directing technical change from fossil-fuel (FF) to renewable energy (REN) technologies in the electricity generation sector. They analyze worldwide FF and REN patents filed by 5,471 firms over the 1978 to 2006 period. Distinguishing between specialized firms, which innovate in either FF or REN technologies, and mixed firms, which innovate in both technologies, they find that FF prices positively affect innovation for both technologies. FF and REN knowledge is found to induce FF and REN innovation, respectively. FF market size only has a positive effect on FF patenting in mixed firms, while REN market size positively impacts REN innovation in specialized firms only.

Our study (Kruse and Wetzel (2016); Chapter 3 of this thesis) investigates the determinants of clean coal innovation using worldwide patent filings from 3,648 firms over the 1978 to 2009 period. It contributes to the existing literature in four respects: First, by focusing specifically on innovation in clean coal technologies, second, by inquiring into the determinants of clean coal innovation directly at the innovator-level, third, by conducting an analysis based on almost the entire population of clean coal patents, and fourth, by providing quantitative evidence on the global pattern of clean coal innovation. Our results show a negative impact of energy prices on innovation in after pollution control technologies, but no impact on innovation in efficiency increasing combustion technologies. In line with Popp (2006), we find a positive effect of NO_X/SO_2 regulation on after pollution control innovation. Moreover, we identify positive impacts of CO_2 regulation and technological knowledge on clean coal innovation in general.

Table 1.1: Empirical studies on the determinants of innovation in energy and environmental technologies.

Article	Key determinants	Data	Key results
Lanjouw and Mody (1996)	PACE	US, Japan, Germany, 14 other countries environmental patents, 1972-1980	Positive impact of PACE
Jaffe and Palmer (1997)	PACE	US overall patent filings and overall R&D expenditures by US industries, 1974-1991	Positive impact of PACE on R&D expenditures, no impact of PACE on patenting
Popp (2002)	Energy prices, knowledge	US energy and energy-efficiency patents, 1970-1994	Positive impact of energy prices and existing knowledge
Brunneimer and Cohen (2003)	PACE	US environmental patents to US industries, 1983-1992	Small positive impact of PACE
Popp (2006)	SO_2 and NO_X regulations	US, Japan, Germany SO_2 and NO_X emission reduction patents, 1970-2000	Positive impact of SO_2 and NO_X regulations
Johnstone et al. (2010)	Renewable energy policies, energy prices	EPO renewable energy patents to 25 countries, 1978-2003	Positive impact of renewable energy policies and energy prices for some technologies
Crabb and Johnson (2010)	Fuel prices, CAFE regulations	US energy-efficient automobile patents, 1980-1999	Positive impact of fuel prices, no impact of CAFE regulations
Verdolini and Galeotti (2011)	Energy prices, knowledge	US energy-supply and energy-demand patents to 17 countries, 1975-2000	Positive impact of energy prices for energy-supply technologies, no impact of energy prices for energy-demand technologies, positive impact of knowledge
Johnstone et al. (2012)	Environmental regulation stringency	Worldwide environmental patents to 77 countries, 1975-2006	Positive impact of environmental regulation stringency
Ayari et al. (2012)	R&D expenditures, oil prices	EPO renewable energy patents to 154 firms from 19 countries, 1987-2007	Positive impact of own R&D, no impact of competitors'/other industries' R&D, positive impact of oil prices
Peters et al. (2012)	Domestic and foreign demand-pull and technology-push policies	Worldwide solar photovoltaic patents to 15 countries, 1978-2005	Positive impact of domestic technology-push policies on domestic innovation but no impact on foreign innovation, positive impact of both domestic and foreign demand-pull policies on domestic innovation
Calel and Dechezleprêtre (2014)	EU ETS	EPO low-carbon patents to 5,568 firms from 18 countries, 1978-2009	Positive impact of EU ETS for regulated firms, no impact of EU ETS for non-regulated firms
Dechezleprêtre and Glachant (2014)	Demand-pull policies	Worldwide wind power generation patents to 28 countries, 1991-2008	Positive impact of domestic and foreign demand-pull policies, larger marginal effect of domestic policies

Table 1.1 (continued): Empirical studies on the determinants of innovation in energy and environmental technologies.

Article	Key determinants	Data	Key results
Nesta et al. (2014)	Renewable energy policies, product market regulation	Worldwide renewable energy patents to 27 countries, 1976-2007	Positive impact of renewable energy policies, impact stronger in countries with liberalized energy markets
Lindman and Söderholm (2015)	Public R&D, feed-in tariffs	PCT wind energy patents to 4 countries, 1977-2009	Positive impact of public R&D and feed-in tariffs, impact of feed-in tariffs more profound for mature technologies, impact of public R&D stronger in combination with feed-in tariffs
Costantini et al. (2015)	Demand-pull and technology-push policies	EPO biofuels patents to 35 countries, 1990-2010	Positive impact of technological capabilities and environmental regulation
Kruse and Wetzel (2015)	Energy prices, knowledge	EPO green energy patents to 26 countries, 1978-2009	Positive impact of energy prices for some technologies, positive impact of knowledge for all technologies, impacts more pronounced after Kyoto protocol agreement
Noailly and Smeets (2015)	Firm specialization, FF/REN prices, knowledge, market size	Worldwide FF and REN patents to 5,471 European firms, 1978-2006	Positive impact of FF prices for FF+REN technologies, positive impact of FF/REN knowledge on FF/REN technologies respectively, positive impact of FF market size for FF technologies in mixed firms, positive impact of REN market size for REN technologies in specialized firms
Barbieri (2015)	European environmental policies	Worldwide clean car patents to 355 firms, 1999-2010	Positive impact of post-tax fuel prices, environmental vehicle taxes, CO_2 standards, and European emission standards
Aghion et al. (2016)	Tax-inclusive fuel prices, knowledge	Worldwide clean and dirty car patents to 3,423 firms and individuals, 1965-2005	Positive/negative impact of tax-inclusive fuel prices for clean/dirty car technologies respectively, positive impact of own knowledge, positive impact of other firms' knowledge via spillovers
Kruse and Wetzel (2016)	Energy prices, knowledge, emission regulations	Worldwide clean coal patents to 3,648 firms, 1978-2009	Negative impact of energy prices on after pollution control technologies, no impact of energy prices on efficiency increasing combustion technologies, positive impact of knowledge, positive impact of CO_2 regulation, positive impact of NO_X/SO_2 regulation on after pollution control technologies

1.3.2 Innovation in Energy and Environmental Technologies and the Economic Performance of Firms - Empirical Evidence

The empirical literature on the relationship between innovative activity and economic performance at the firm-level is large and diverse. Table 1.2 summarizes the key empirical studies in this field. It gives an overview of the indicators used to proxy innovation and performance, the samples examined, and the central results. The majority of these studies identifies a positive impact of innovative activity on firm performance. However, since these studies analyze the impact of general innovation, the findings cannot be simply transferred to energy and environmental innovation.

Very few empirical studies have specifically investigated the direct link between innovative activity in energy and environmental technologies and economic firm performance. Since the focus of this section is on the relationship between energy and environmental innovation and firm performance, I will confine myself at this point to referring to the studies exploring specifically this relationship. These studies are reviewed in the following paragraphs and are also summarized in Table 1.2.

To my knowledge, the study by Ayari et al. (2012) is the first attempt to investigate the direct association between innovation in energy and environmental technologies and firm performance. Ayari et al. (2012) analyze the impact of renewable energy innovation on performance based on a panel of 154 firms from 14 European countries over the 1987 to 2007 period. They use EPO renewable energy patent counts as a proxy for innovation and return on assets and stock market return as alternative measures of firm performance. They find evidence that renewable energy patenting has a significant positive impact on both measures of performance. However, since the analysis is based on a relatively small sample, the results should be read with some caution.

Marin (2014) analyzes the effect of environmental and non-environmental innovation on firm performance based on a larger but shorter panel of 5,905 Italian firms over the period 2000 to 2007. Innovation is measured by patents filed at the EPO and firm performance is proxied by value added. He finds that in most cases environmental patents have no significant impact on firm performance. For non-environmental patents, on the other hand, the effect on performance is found to be statistically significant positive. The return of environmental innovation is therefore substantially lower than that of non-environmental innovation. Since firms have innovated in environmental technologies and since resources that can be allocated to R&D activities are limited, Marin (2014) concludes that this result evidences a crowding out of environmental innovation at the expense of non-environmental innovation.

In a very similar study, Marin and Lotti (2016) assess the effect of environmental and non-environmental innovation on firm performance for a once more larger and longer panel of 11,938 Italian firms from 1995 to 2006. They use EPO and PCT-WIPO patent counts as alternative measures of innovation and value added as a proxy for performance. As in Marin (2014), they find evidence of a generally lower return for environmental compared to non-environmental innovation. This result leads them again to the conclusion, that environmental innovation crowds out more profitable non-environmental innovation.

Wörter et al. (2015) examine the link between environmental innovation and performance based on industry-level data. Their analysis is conducted on a panel of 22 manufacturing industries from 12 OECD countries over the period 1980 to 2009. They use accumulated patent counts (that is, patent stocks) from 12 different countries to measure the environmental innovation activity of the industries. Performance is, as in Marin (2014) and Marin and Lotti (2016), measured in terms of value added. The results show that the general relationship between environmental patenting and industry performance is U-shaped. But since the turning point is very high, this result is only relevant for a few industries that already have a very large environmental knowledge stock. For most industries, environmental patenting is negatively related to performance. From this finding they conclude, that environmental innovation will not proceed without further policy incentives.

Finally, my work (Kruse (2016); Chapter 4 of this thesis) analyzes the contribution of green and non-green energy innovation to economic firm performance using a panel of 8,619 firms from 22 European countries over the 2003 to 2010 period. Sales are used as a proxy for firm performance and EPO patent stocks as an indicator for innovative activity. My study contributes to the literature presented in this section in three respects: First, by providing additional evidence on the return of energy and environmental innovation, second, by comparing the return to the one of more general innovation, and third, by analyzing a comparatively large and broad sample of European firms. I find evidence that green energy patenting is negatively related to firm performance, while non-green energy patenting is positively related. The finding suggests that returns are lower for green energy than for non-green energy innovation and is in line with previous results found by Marin (2014), Marin and Lotti (2016), and Wörter et al. (2015). I conclude, that green energy innovation crowds out more rewarding non-green energy innovation, but that this crowding out can be welfare increasing if green energy technologies have higher social returns than non-green energy technologies.

Table 1.2: Empirical studies on innovation and firm performance.

Article	Innovation	Firm performance	Sample	Key results
General innovation				
Scherer (1965)	US patents	Sales growth, profits, profit ratio	365 large US firms, 1955-1960	Positive impact on sales growth and profits, no impact on profit ratio
Comanor and Scherer (1969)	US patents	Sales	57 pharmaceutical firms, 1955-1960	Positive impact
Griliches (1981)	US patents	Market value	157 large US firms, 1968-1974	Positive impact
Griliches et al. (1991)	US patents	Market value	340 US manufacturing firms, 1973-1980	No impact
Blundell et al. (1999)	UK patents	Market value	340 UK manufacturing firms, 1972-1982	Positive impact
Ernst (2001)	National and EPO patents	Sales	50 German manufacturing firms, 1984-1992	Positive impact of national and EPO patents
Bloom and Van Reenen (2002)	US patent stocks	Sales, market value	184 large UK firms, 1969-1996	Positive impact on sales and market value
Lanjouw and Schankerman (2004)	US patent stocks	Market value	1,533 large US firms, 1980-1993	Positive impact
Hall et al. (2005)	US patent stocks	Market value	4,864 large US firms, 1979-1988	Positive impact
Energy and environmental innovation				
Ayari et al. (2012)	EPO renewable energy patents	Return on assets, stock market return	154 firms from 14 countries, 1987-2007	Positive impact
Marin (2014)	EPO environmental and non-environmental patents	Value added	5,905 Italian firms, 2000-2007	No impact (environmental), positive impact (non-environmental)
Wörter et al. (2015)	12 country environmental patent stocks	Value added	22 manufacturing industries from 12 countries, 1980-2009	Negative impact
Marin and Lotti (2016)	EPO and PCT-WIPO environmental and non-environmental patents	Value added	11,938 Italian firms, 1995-2006	Positive impact, smaller for environmental than for non-environmental
Kruse (2016)	EPO green and non-green energy patent stocks	Sales	8,619 firms from 22 countries, 2003-2010	Negative impact (green), positive impact (non-green)

Chapter 2

Energy Prices, Technological Knowledge, and Innovation in Green Energy Technologies: a Dynamic Panel Analysis of European Patent Data

2.1 Introduction

In a growing field of literature, economists have empirically investigated which economic and political factors influence the rate and direction of innovation in green energy technologies. However, researchers still lack evidence on the determinants of green energy innovation, especially when it comes to the determinants of innovation in specific technologies. Understanding these determinants is crucial in order to design the appropriate policies to foster green energy innovation. Should these policies stimulate the demand for green energy technologies by increasing energy prices, or should they enhance technological capability by improving the knowledge base of an economy?

This article empirically investigates how green energy innovation in different technologies has developed in response to changes in energy prices and technological knowledge. For the purpose of this article we define green energy technologies as energy efficiency, renewable energy, fuel cell, carbon capture and storage (CCS), and energy storage technologies. We consider both demand-pull effects, which induce innovative activity from the demand side by increasing the expected value of innovations, and technology-push effects, which drive innovative activity from the supply side by extending the technological capability of an economy. We aim to shed light on the ongoing debate as to whether demand-pull or technology-push factors are the main drivers of green energy innovation. We hypothesize that both increasing demand, due to higher energy prices, and increasing technological capability induce green energy innovation.

To test these hypotheses, we analyze a panel on green energy innovation, drawing from data on patent applications at the European Patent Office (EPO). Patent counts represent an output-oriented measure of innovative activity. Compared to other measures, such as research and development (R&D) expenditures, patents are closely linked to invention, are easy to collect, and are available for a long time period at the country and technology level. The limitations are that not all inventions are patented or patentable, patents differ in their economic value, and the propensity to patent varies across technologies and countries. Some of these limitations can be addressed by counting high-value multinational patents and controlling for technology- and country-specific effects. All together, despite some problems associated with patent counts, the findings in the literature indicate that patents are a fairly good proxy for innovative activities.[3]

In line with this, we count patent applications in green energy technologies following a structure defined by the International Energy Agency (IEA) and using International Patent Classification (IPC) codes from the green inventory developed at the World Intellectual Property Organization. Our data set covers 11 distinct green energy technologies for 26 Organization for Economic Co-operation and Development (OECD) countries, spanning over a 32-year period from 1978 to 2009.

This article is related to the empirical body of literature on the determinants of green energy innovation. In particular, we build on the pioneering work of Popp (2002), who uses US patent data from 1970 to 1994 to estimate the impact of energy prices and quality-weighted knowledge on innovation in environmentally friendly technologies. Estimating a pooled regression model for all technologies, Popp finds that both factors have a significant positive impact on innovation.

More recently, a similar analysis was carried out by Verdolini and Galeotti (2011). They study the impact of energy prices and knowledge stocks on innovation in energy technologies using panel data on United States Patent and Trademark Office patent applications for 17 countries from 1975 to 2000. Their baseline results confirm the positive effects of both factors on innovation. Although the authors do not differentiate by individual technologies, separate estimations reveal differences between energy-supply and

[3] For a more detailed discussion on the advantages and disadvantages of using patents as a proxy for innovation see, for example, Griliches (1990), Dernis et al. (2002), and OECD (2009).

energy-demand technologies. While the effect of energy prices stays significant for supply technologies, it becomes insignificant for demand technologies.

This result is a first indicator that the relative importance of demand-pull and technology-push factors is specific to individual technologies. However, up to now, reliable and detailed technology-specific empirical evidence is still missing. One notable exception is Johnstone et al. (2010), who use European patent data from 1978 to 2003 to investigate the determinants of technological change in five renewable energy technologies. They find important differences across technologies. However, their study focuses on policy instruments and does not explicitly account for technology-push effects. Our study seeks to fill this void in previous research by accounting for these technology-push effects and by additionally covering a broader base of technologies.

Our work contributes to the existing literature in three respects. First, we investigate the determinants of innovation separately for 11 different green energy technologies. This may help scholars and policy makers understand the divergent effects of energy prices and technological knowledge on green energy innovation across technologies. Second, our analysis uses European patent data to assess the validity of the conclusions reached using US patent data. Third, we apply state-of-the-art count data techniques to control for unobserved heterogeneity, account for the dynamic character of knowledge generation, and address endogeneity issues.

The remainder of the article is organized as follows. Section 2.2 provides a brief outline of the baseline theory guiding our empirical analysis. Section 2.3 presents the data. Section 2.4 describes the econometric methodology employed. Section 2.5 presents and discusses the results. Section 2.6 concludes.

2.2 Theoretical Background

For green energy technologies, the process of technological change is characterized by two key market failures. First, the harmful consequences of energy conversion and energy use on the environment constitute a negative externality. In the absence of appropriate price signals, there is no economic incentive to reduce these negative consequences. Since there is no demand for reduction, the demand for reduction technologies will also be low. Consequently, there is insufficient private incentive to invest in R&D for such technologies. Even if this negative externality was internalized via, for example, a tax or a cap-and-trade system, a second market failure persists: the value accruing from private investments in R&D tends to spill over to other technology producers. These spillovers constitute a positive externality. Since the private investor incurs the full costs of its efforts but cannot capture the full value, there is insufficient private incentive to invest in R&D. This second market failure applies to private R&D activity in general and is not specific to green energy R&D. However, it has been shown that spillovers are larger for green than for the average of technologies (Dechezleprêtre et al., 2013). As a result, the two market failures together lead to a double underprovision of green energy technologies by market forces. This double underprovision can be addressed by a combination of environmental policies (addressing the negative externality) and innovation policies (addressing the positive externality) (see, for example, Jaffe et al., 2005, Newell, 2010).

The underlying concept is policy-induced innovation. This concept is the theoretical basis for the demand-pull and technology-push effects on innovation activities. First proposed by Hicks (1932), it originally states that changes in relative factor prices induce innovation, which reduces the need for the factor which has become relatively more expensive. More generally, it posits that both changes in demand and changes in technological capability determine the rate and direction of innovation. Changes in demand include shifts on the macro level that affect the profitability of innovative activity at a given level of technological capability. Analogously, changes in technological capability include scientific and technological advancements that affect the profitability of innovative activity at a given level of demand (Griliches, 1990, Verdolini and Galeotti, 2011).

Following Verdolini and Galeotti (2011), the relationship between demand, technological capability, and innovation can be formalized as

$$I_t = f(D_t, TC_t), \tag{2.1}$$

where I denotes innovative activity, D_t denotes demand, and TC_t denotes technological capability. A standard proxy for innovative activity is the number of patent applications, which measures the invention of new or the improvement of already-existing green energy technologies. This does not include the mere activation of existing green energy technologies.

Demand can be proxied by expected energy prices p_t^e, which signal the expected general scarcity of energy in an economy. Increasing energy prices increase the willingness to pay for R&D in technologies that either convert energy at a lower average cost or use energy more efficiently. More concretely, a policy-induced increase in the energy price triggers the generation of new clean or energy-saving technology patents because the value of a given patent is higher than in the scenario without the policy-induced change.

Technological capability can be proxied by technological knowledge, a concept which is typically measured by innovation activities undertaken in the past. Innovation activities in the past are expected to induce innovation activities today or, as expressed by Baumol (2002), 'innovation breeds innovation'. Due to the cumulative nature of research, earlier innovations facilitate later ones, as these can build on existing technological knowledge. The positive effect of earlier innovations consists of making later innovations possible, reducing costs, or accelerating development and, as such, creating private benefits for later innovators (Scotchmer, 1991). Acemoglu et al. (2012) show that this path dependence exists in green technological change. Firms in economies with a history of innovation in green technologies in the past are more likely to innovate in green technologies in the future. Using the end-of-period stock of past patents, K_{t-1}, as a measure for innovation activities in the past, Equation 2.1 becomes

$$I_t = g(p_t^e, K_{t-1}), \tag{2.2}$$

where both factors are expected to have a positive impact on innovation activity.

Following these expectations, governments can foster green energy innovation in two ways: implement policies that increase energy prices and thus increase the private payoff to successful innovation, that is demand-pull, and implement policies that increase the stock of knowledge and thus decrease the private cost of producing innovation, that is technology-push. Examples of policies that increase energy prices are emission taxes and emission trading systems. Examples of policies that increase the knowledge stock are government support for the private generation and patenting of scientific and technological knowledge, the provision of high quality education and training systems, promotion of business networks and technology transfer as well as government-sponsored R&D and tax incentives to invest in private R&D. Researchers have come to a consensus that in order to stimulate innovation in green energy technologies, both types of instruments are necessary (Nemet, 2009).

2.3 Data

Our analysis is conducted using patent data from the OECD REGPAT database (OECD, 2013). The database combines information on patent activities from two complementary sources: the EPO's Worldwide Patent Statistical Database (PATSTAT) and the OECD patent database. It contains patent applications filed at the EPO based on the priority date, that is, the first filing date of the invention worldwide. Several studies have shown that this date is strongly related to R&D activities and is closest to the date of discovery of an invention (see, for example, Griliches, 1990, OECD, 2009). Furthermore, in contrast to patent applications filed at national institutions, multinational patent applications such as those filed at the EPO often constitute innovations of high value that are expected to be commercially profitable and thus justify the relatively high application costs (Johnstone et al., 2010). Hence, utilizing EPO patent applications ensures that applications for low-value inventions are excluded from our analysis.

All patents are classified according to the IPC system, which assigns each patent to a specific area of technology (WIPO, 2013a). In particular, the 'IPC Green Inventory' provides the IPC codes for patents relating to so-called Environmentally Sound Technologies (WIPO, 2013b). Combining the IPC codes with the energy technology structure developed at the IEA (IEA, 2011), we count the technology-specific annual green energy patent applications at the EPO between 1978 and 2009 on the country level.[4] The patent applications are assigned by country of origin (based on the country of the inventor) using fractional counts. That is, each patent application is counted as a fraction for the respective country, depending on the inventor's share in the patent.

As a result of the availability of appropriate IPC codes and missing values for some of the utilized variables, our analysis covers 11 green energy technologies and 26 OECD countries. The technologies are: energy efficiency in residential and commercial buildings, appliances, and equipment (EEBAE), energy efficiency in transport (EET), other energy efficiency (EEO),[5] solar energy, wind energy, ocean energy, biofuels, geothermal energy, fuel cells, CCS, and energy storage.

Table 2.1 provides an overview of the development of the total number of EPO patent applications in these technologies for the 26 countries. As shown, in the whole sample period, the highest number of green energy patent applications is observed for the USA, followed by Japan and Germany. The lowest number of green energy patent applications belongs to Slovakia. Furthermore, all countries significantly increase their patent activities in green energy technologies over time. Across all countries, we observe an increase in green energy patenting of more than 130% from the 1978-1984 period to the 2005-2009 period. In total, our database contains more than 175,000 green energy patent applications.

As patent activities in green energy technologies may be affected by a country's overall propensity to patent innovations, we include a control variable covering the country-specific total number of annual EPO patent applications. In doing so, we control for variations in the propensity to patent both across countries and across time. Figure 2.1

[4] Patents with multiple IPC codes belonging to multiple green energy technologies are counted for each of these technologies. The total number of green energy patents corresponds to the sum of patents from all green energy technologies.

[5] Following the IEA energy technology structure, the other energy efficiency group includes waste heat recovery and utilization, heat pumps, and measurement of electricity consumption.

Table 2.1: Number of green energy EPO patent applications by country and time period.

Country	1978-1984	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	Total
AT	213	226	316	328	543	752	2,379
AU	157	173	204	340	487	413	1,774
BE	171	148	202	378	442	422	1,763
CA	170	259	266	671	966	993	3,325
CH	654	609	563	766	780	896	4,269
CZ	1	1	5	11	32	70	120
DE	4,544	3,829	3,555	5,303	7,421	8,394	33,046
DK	69	130	238	448	546	939	2,371
ES	30	32	91	170	278	651	1,252
FI	45	92	185	224	274	348	1,168
FR	1,630	1,619	1,512	1,900	2,101	2,670	11,433
GB	1,323	1,260	1,046	1,592	1,788	1,572	8,581
GR	5	9	26	23	26	51	140
HU	64	40	27	32	27	42	232
IE	7	14	6	36	60	121	244
IT	341	515	471	612	1,080	1,364	4,383
JP	1,647	2,628	3,195	5,934	10,043	10,082	33,528
LU	10	3	7	18	15	32	84
NL	615	634	656	1,008	1,439	1,542	5,894
NO	35	45	68	130	206	327	810
NZ	9	18	20	48	72	68	236
PT	1	7	7	9	16	49	88
SE	415	255	373	481	505	633	2,663
SK	0	0	1	8	19	18	45
TR	2	2	1	5	14	39	63
US	5,849	6,628	7,362	12,324	13,341	9,824	55,328
Total	18,004	19,177	20,405	32,798	42,521	42,314	175,220

Note: The country codes represent Austria (AT), Australia (AU), Belgium (BE), Canada (CA), Switzerland (CH), Czech Republic (CZ), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), United Kingdom (GB), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Japan (JP), Luxembourg (LU), Netherlands (NL), Norway (NO), New Zealand (NZ), Portugal (PT), Sweden (SE), Slovakia (SK), Turkey (TR), and United States (US).

shows the annual trends in green energy and total patenting for the six leading (in terms of green energy) innovative countries in our database. Green energy patent applications are shown on the left axis and total patent applications on the right axis. In all countries, we see a steady and similar growth in green energy and total patent applications.

Figure 2.2 illustrates the annual trends in patenting for the 11 technologies. First of all, it can be seen that the number of patent applications differs significantly among the technologies. A huge number of patent applications is related to biofuels, EET, and EEO. In contrast, the number of patent applications in ocean energy is rather low. Furthermore, for all technologies, we observe an increase in patent activities over time. However, the growth paths differ substantially. For example, for biofuels and fuel cells, we see a significant increase during the 1990s. After that, patent activities begin to decrease. A completely different picture emerges for wind and solar energy. Here, we observe an above-average growth starting from the mid-1990s, with exceptionally high growth from the mid-2000s. This result emphasizes the increasing prominence of

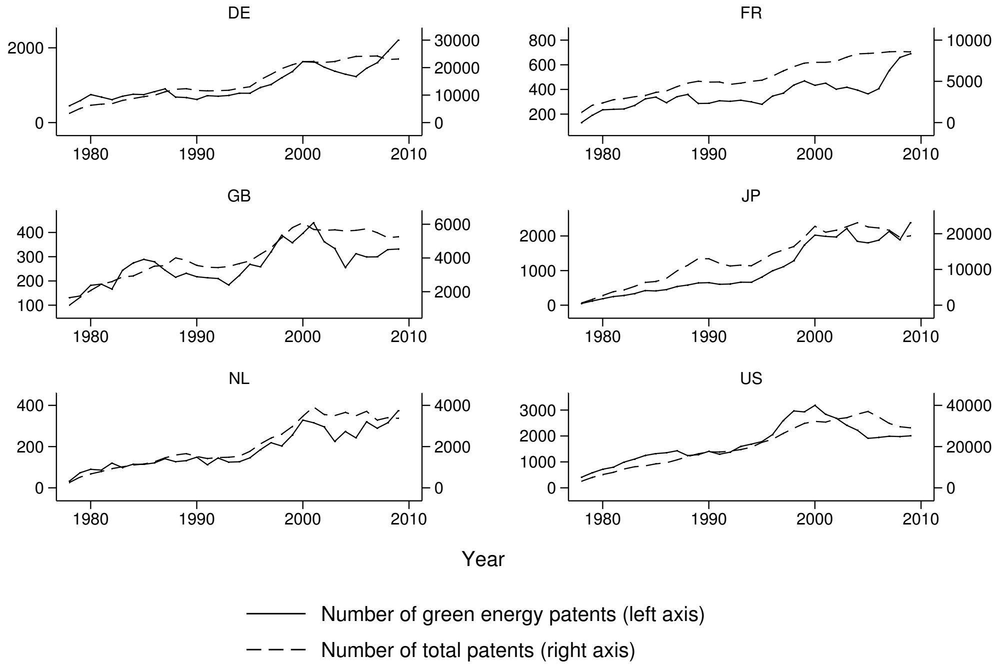

Figure 2.1: Annual number of green energy EPO patent applications and annual number of total EPO patent applications by six leading innovative countries and by time period, 1978-2009. *Note*: The country codes are the same as in Table 2.1.

electricity generation from wind and solar energy resources over the last two decades. Especially in the case of solar photovoltaics, the technological development is reflected by a tremendous reduction in panel costs, peaking at a 75% cost decrease between 2008 and 2011 (IEA, 2012b).

Energy storage, CCS, and geothermal energy have experienced relatively steady growth but on rather low levels. Apart from different growth paths, there is also a significant difference in the level of patent activity between the categories considered. In particular, patent activity has grown from about 0 to above 1,000 for solar energy and the three energy efficiency technologies, while other technologies grew on rather low levels. An exception is biofuels, which had a high level of patent activity already in 1980.

As the main focus of our analysis is to investigate the impact of energy prices and technological knowledge on green energy innovation, we include a price index and a knowledge stock in our model. The price index is drawn from the Energy Prices and Taxes Database of the IEA (IEA, 2012a). It depicts the country-specific real total energy end-use price (including taxes) for households and industry with the base year 2005. As described in Section 2.2, expected energy prices signal the expected scarcity of energy in an economy and thus affect the demand for innovation in green energy technologies. Our energy index is used as a proxy for these expected energy prices.

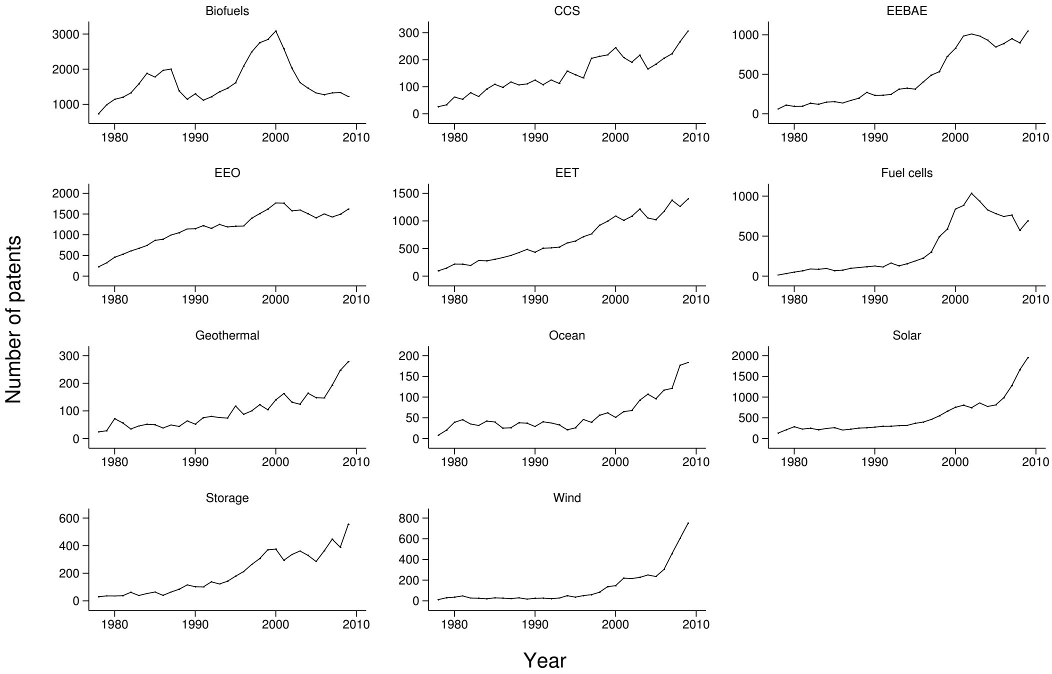

Figure 2.2: Total annual number of EPO patent applications of 26 OECD countries by green energy technology and by time period, 1978-2009.

Using different energy prices for different technologies would be preferable.[6] However, technology-specific price series often show a high amount of missing values. Furthermore, as we have technology groups covering several sub-technologies, it is not always possible to identify the appropriate price. Overall, as the index used in this study is a composite of industry and household prices for oil products, coal, natural gas, and electricity, it is expected to be a reliable proxy for the average development of energy prices.[7] Comparable indices have been used in a number of other studies (see, for example, Popp, 2002, Verdolini and Galeotti, 2011).

Figure 2.3 displays the average real total energy end-use price index for households and industry among the 26 OECD countries in the database from 1978 to 2009. After a peak in the early 1980s (following the oil crises of the 1970s), a rough decrease in the energy price index is seen until the late 1990s. From then on, the index almost continuously increases. In 2008, it indicates an increase in the total energy end-use price of approximately 15%, relative to the base year 2005. A similar pattern can be observed for the vast majority of the country-specific indices.[8]

[6] For instance, we would prefer to use electricity prices for electricity generation technologies and oil prices for transport technologies.

[7] In fact, the development of the individual energy price time series for the years and countries where detailed data are available is very similar to the development of the utilized composite index.

[8] The country-specific price indices are provided in the appendix (Figure A.5).

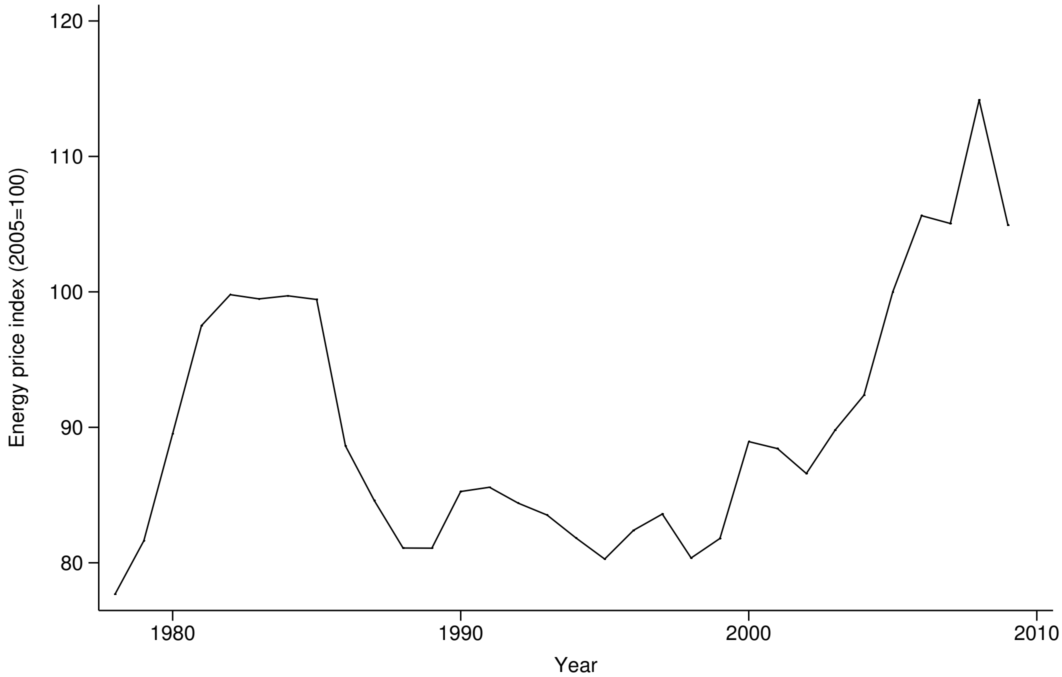

Figure 2.3: Average real total energy end-use price for households and industry among 26 OECD countries (index: 2005=100), 1978-2009.

The knowledge stock is constructed using the perpetual inventory method following Cockburn and Griliches (1988) and Peri (2005). Basically, the technology-specific knowledge stock is obtained by counting all patents which have accumulated for the respective technology in a country up to a certain year. The technology-specific knowledge available to researchers and inventors in each country and year is then represented by the end-of-period stock, which covers all patents accumulated up to the previous year.

The end-of-period knowledge stock K_{ijt-1} for technology $j = 1, ..., M$ in country $i = 1, ..., N$ and year $t = 1, ..., T$ is calculated as

$$K_{ijt-1} = PAT_{ijt-1} + (1 - \delta)\, K_{it-2}, \tag{2.3}$$

where PAT_{ijt-1} is the number of patent applications, and δ is a depreciation rate that accounts for the fact that knowledge becomes obsolete as time goes by. The rate of depreciation is set to 10%, which is consistent with other applications in the patent and R&D literature (see, for example, Verdolini and Galeotti (2011)). The initial knowledge stock K_{ijt_0} is given by $K_{ijt_0} = PAT_{ijt_0}/(\delta + g)$, where PAT_{ijt_0} is the number of 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%.[9]

Figure 2.4 depicts the development of the accumulated technology-specific knowledge stocks over time. Except for biofuels and EEO, all technologies start at a very low level of patents (close to zero) in 1978. Thereafter, the majority of technologies exhibit a distinct development: the accumulated stock rises linearly until it begins to increase sharply at the end of the 1990s. The increase of CCS, EEO, and geothermal patents at the end of the 1990s remains moderate. The development of ocean patents stands still throughout the 1990s before it also starts to sharply increase. In 2009, the highest accumulated stocks are observed for biofuels and EEO, whereas the lowest stocks are for geothermal and ocean.

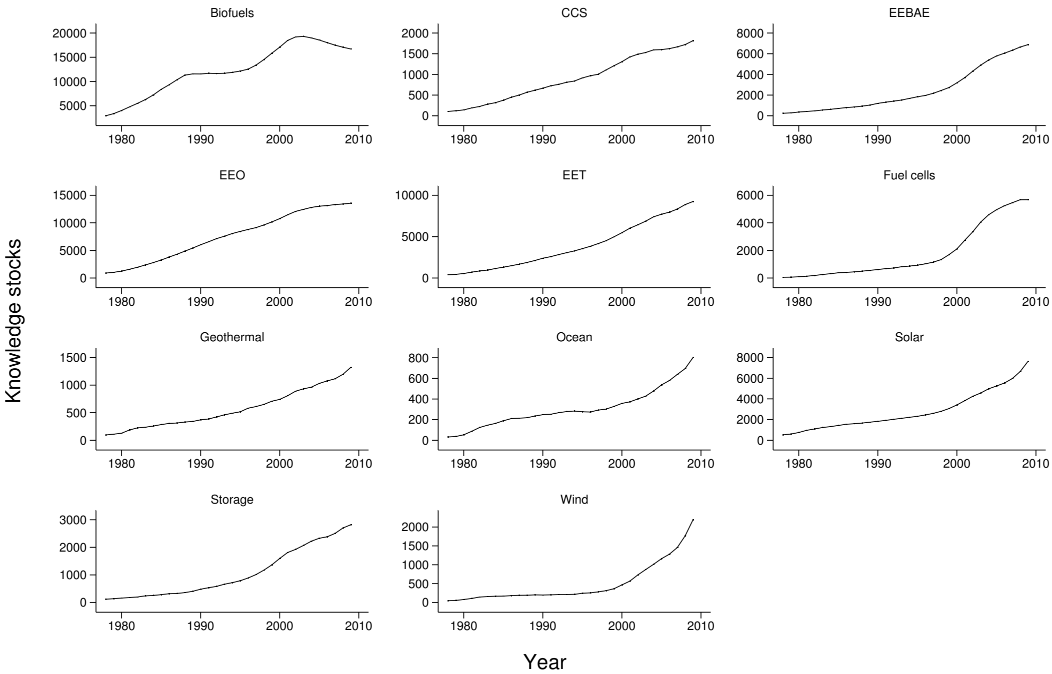

Figure 2.4: Accumulated knowledge stocks of 26 OECD countries by green energy technology and by time period, 1978-2009.

In addition to the price, knowledge stock, and total patents variables, we also include a variable reflecting publicly funded research, development, and demonstration expenditures. The data are drawn from the Energy Technology Research and Development Database of the IEA (IEA, 2012c) and contains the annual national government expenditures on energy research, development, and demonstration disaggregated by technology in million constant US dollars at 2011 prices.

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

2.4 Model Specification

As we measure green energy innovation by patent counts, we use count data techniques in our econometric approach. A standard Poisson regression model for panel data takes the following exponential form:

$$y_{it} = exp(x'_{it}\beta + \eta_i) + u_{it}, \tag{2.4}$$

where y_{it} is a nonnegative integer count variable, x'_{it} is a vector of explanatory variables, η_i is a unit-specific fixed effect, and u_{it} is a standard error term. The subscripts $i = 1, ..., N$ and $t = 1, ..., T$ denote the observation unit and time, respectively.

It should be noted that the values of our dependent variable, the fractional counts of patent applications, are not necessarily integers. That is, strictly speaking, our dependent variable is not count data. However, as noted by Silva and Tenreyro (2006) and Wooldridge (2002), the dependent variable does not have to be an integer for the Poisson estimator to be consistent. An alternative approach used in a number of empirical studies is the estimation of a log-linear model by ordinary least squares. However, this approach cannot handle zero values in the data and hence would be unnecessarily restrictive. For this reason, Silva and Tenreyro (2006) strongly recommend a Poisson specification for a nonnegative continuous dependent variable with zero values.

Following this recommendation, our baseline model can be defined as

$$\begin{aligned} PAT_{ijt} = exp(&\beta_0 + \beta_p \, ln\, P_{it-1} + \beta_K \, ln\, K_{ijt-1} + \beta_{R\&D} \, ln\, R\&D_{ijt-1} \\ &+ \beta_{TPAT} \, ln\, TPAT_{it-1} + \beta_t \, T_t + \eta_i) + u_{ijt}, \end{aligned} \tag{2.5}$$

where PAT_{ijt} is the fractional patent count for technology j in country i and time t, P is a price index, K represents the end-of-period knowledge stock as defined in Equation 2.3, $R\&D$ denotes publicly funded expenditures on research, development, and demonstration, $TPAT$ is the fractional patent count of all patent applications, T represents a time trend, η_i is a unit-specific fixed effect, and u_{ijt} is a standard error term. The independent variables P_{it}, $R\&D_{ijt}$, and $TPAT_{it}$ are lagged by 1 year in order to mitigate any reverse causality problems.

Another econometric issue that needs to be addressed is the dynamic character of our model. As defined in Section 2.3, our knowledge stock variable is a function of the lagged dependent variable. This path dependence violates the assumption of strict exogeneity of all regressors required by the traditional fixed effect count data estimator developed by Hausman et al. (1984).

To account for this problem of predetermined (that is, weakly exogenous) regressors in dynamic count data models, Blundell et al. (1995, 2002) propose an alternative estimator: the pre-sample mean (PSM) scaling estimator. This estimator relaxes the strict exogeneity assumption by modeling the unit-specific fixed effects via pre-sample information on the dependent variable. Following this approach, the unit-specific fixed effects in Equation 2.5 are defined as

$$\eta_i = \theta \; ln \, P\bar{A}T_{ij}, \tag{2.6}$$

where $P\bar{A}T_{ij} = (1/N)\sum_{n=1}^{N} PAT_{ijn}$ is the PSM of patent applications by country i in technology j and year n. N is the number of pre-sample observations and θ is an unknown parameter to be estimated.

Another alternative to estimate dynamic count data models with predetermined regressors is the quasi-differenced generalized method of moments (GMM) estimator developed by Chamberlain (1992) and Wooldridge (1997). However, as noted by Blundell et al. (2002), a well-known problem of this estimator is that it can be severely biased. In particular, when the sample is small and the regressors are highly persistent over time, the lagged values of the predetermined regressors can be weak predictors of the future.

Conducting Monte Carlo simulations, Blundell et al. (2002) show that the PSM scaling estimator outperforms the quasi-differenced GMM estimator in almost all settings. Furthermore, while formally shown to be consistent for a large number of pre-sample periods only, it outperforms the quasi-differenced GMM estimator even in the case of only four pre-sample observations. We therefore follow Blundell et al. (1995, 2002) and build our empirical model on the PSM scaling estimator as defined in Equations 2.5 and 2.6.

2.5 Results

2.5.1 Baseline Results

Our baseline results are presented in Table 2.2. As the explanatory variables enter the estimations in log form, the estimated coefficients can be interpreted as elasticities. We estimate our model for each technology separately as well as for all technologies together. As shown, the results differ significantly between the technologies, which strongly supports our approach of a technology-specific analysis. The observed differences can be explained by the different application areas, cost structures as well as maturity levels of the technologies. Nevertheless, one common result for all technologies is the positive impact of the knowledge stock on patent applications. The corresponding coefficients are positive and statistically significant at the 1% level in all models. The estimated elasticities between 0.534 and 1.020 suggest that, depending on the technology, a 10% increase in knowledge stock is associated with a 5.3-10.2% increase in patent activities. This finding is consistent with previous research (see, for example, Popp, 2002, Verdolini and Galeotti, 2011) and in line with the technology-push hypothesis stating that innovation is induced by advances in the technological capability of an economy.

Table 2.2: Estimated coefficients of the PSM Poisson model. Estimation time span: 1983-2009. Dependent variable: Number of patent applications at the EPO.

Variable	EEBAE	EET	EEO	Solar	Wind	Ocean
Energy price$_{t-1}$ (log)	-0.559	0.205	0.059	1.115^{***}	-0.180	0.612^{*}
	(0.350)	(0.179)	(0.166)	(0.150)	(0.496)	(0.348)
Knowledge stock$_{t-1}$ (log)	0.930^{***}	1.011^{***}	0.534^{***}	0.640^{***}	0.884^{***}	0.743^{***}
	(0.095)	(0.067)	(0.079)	(0.080)	(0.069)	(0.128)
Public R&D$_{t-1}$ (log)	-0.002	-0.004	-0.001	0.036	0.187^{***}	0.072
	(0.011)	(0.011)	(0.008)	(0.051)	(0.042)	(0.063)
Total patents$_{t-1}$ (log)	0.316^{**}	0.185^{***}	0.558^{***}	0.497^{***}	-0.049	-0.002
	(0.145)	(0.058)	(0.075)	(0.133)	(0.060)	(0.098)
Time trend	-0.026^{**}	-0.036^{***}	-0.039^{***}	0.013^{**}	0.059^{***}	0.030^{***}
	(0.012)	(0.007)	(0.006)	(0.006)	(0.007)	(0.010)
Constant	0.029	-2.706^{***}	-2.642^{***}	-1.917^{***}	-1.228^{*}	-4.349
	(2.170)	(0.950)	(0.727)	(1.137)	(2.244)	(1.595)
Observations	518	517	517	534	518	462
	Biofuels	Geothermal	Fuel cells	CCS	Storage	All
Energy price$_{t-1}$ (log)	-0.638^{*}	0.370^{**}	1.730	0.563^{***}	0.026	0.086
	(0.380)	(0.145)	(1.847)	(0.215)	(0.250)	(0.165)
Knowledge stock$_{t-1}$ (log)	0.749^{***}	0.793^{***}	0.948^{***}	1.020^{***}	0.732^{***}	1.013^{***}
	(0.130)	(0.117)	(0.207)	(0.068)	(0.081)	(0.032)
Public R&D$_{t-1}$ (log)	0.100^{***}	0.050	0.024	-0.057^{**}	0.048	0.017^{*}
	(0.024)	(0.043)	(0.068)	(0.023)	(0.035)	(0.010)
Total patents$_{t-1}$ (log)	0.371^{***}	0.215^{***}	0.017	-0.015	0.510^{***}	0.138^{***}
	(0.107)	(0.069)	(0.212)	(0.047)	(0.137)	(0.022)
Time trend	-0.058^{***}	0.006	-0.218^{**}	-0.024^{***}	-0.018^{*}	-0.036^{***}
	(0.007)	(0.009)	(0.088)	(0.005)	(0.010)	(0.006)
Constant	1.232	-4.351^{***}	-3.011	-3.436^{***}	-4.062^{***}	-1.856^{**}
	(1.673)	(0.735)	(5.785)	(1.052)	(1.523)	(0.848)
Observations	523	503	114	485	519	5210

Notes: All models control for unit-specific fixed effects by using PSM information on the first 5 years available (1978-1982). Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1, 5, and 10% level.

A completely different picture emerges for our second focus of interest, the impact of energy prices or demand-pull effects on innovation activities. Here, our results reveal significant differences among the technologies. The coefficient for the energy price is positive and statistically significant for solar, ocean, geothermal energy, and CCS only.

The strongest impact is observed for solar energy, indicating a price elasticity higher than 1. This finding is in accordance with Johnstone et al. (2010), who also find a significant positive effect of the energy price on patent activities in solar energy. Furthermore, also in common with Johnstone et al. (2010), we do not find any effect of the energy price on patent activities in wind energy. For the other two technologies, however, our results differ from those of Johnstone et al. (2010). While Johnstone et al. (2010) do not find any effect of the energy price on patent activities in geothermal or ocean energy, our results indicate a positive effect. However, the estimated coefficient for ocean energy is only significant at the 10% level. Interestingly enough, for biofuels, we observe a statistically significant negative coefficient for the energy price, however, again only at the 10% level.

Finally, for the three energy efficiency technologies, we do not find any significant impact of the energy price on patent activities. This is in line with the concept of the energy efficiency gap. While the demand-pull hypothesis assumes that increasing energy prices increase the market value of innovations that convert energy at a lower average cost or use energy more efficiently, market success of energy-saving technologies is not always assured. Due to the uncertainty about future energy prices and the irreversible nature of the investment, consumers heavily discount and thus undervalue future savings from energy efficiency improvements (Greene et al., 2013). Other explanations for failing market diffusion include imperfect information, costs of adoption, and consumer heterogeneity (Jaffe and Stavins, 1994). When innovators predict non-adoption by consumers despite cost-effectiveness at current prices, they are not reacting to price signals. Empirical evidence of the energy efficiency gap in particular stems from energy demand technologies, which confirms our empirical findings (see, for example, Alberini et al., 2013, Greene et al., 2013).[10]

Our result of insignificant price coefficients for the three considered energy efficiency technologies is also in line with the findings of Verdolini and Galeotti (2011) for a pooled group of energy demand technologies. Regarding energy supply technologies, however, we observe a more heterogeneous picture. While the pooled approach of Verdolini and Galeotti (2011) suggests a significant positive impact of the energy price on patent activities in a group of energy supply technologies, our technology-specific approach with a separated regression for each technology reveals divergent effects. We find a significant positive impact of the energy price on patent activities in four supply technologies (solar, ocean, geothermal energy, and CCS), a negative impact in one supply technology (biofuels), and no significant impact in three supply technologies (wind, fuel cells, and storage).

[10] For a discussion of theoretical explanations and the controversial empirical evidence see, for example, Gillingham and Palmer (2014).

Referring to public R&D expenditures, the estimated coefficients indicate either no or just a minor impact of public R&D expenditures on patent activities. A statistically significant impact of public R&D expenditures is shown for wind energy, biofuels, and CCS only. Among these, the highest elasticity can be observed for wind energy. The estimated elasticity of 0.187 suggests that a 10% increase in public R&D expenditures results in an approximate 1.9% increase in patent activities. This result is consistent with Klaassen et al. (2005), who find that public R&D plays a key role in inducing cost-reducing wind energy innovations in Europe. In contrast, the estimated negative elasticity of public R&D expenditures for CCS indicates a decrease in patent activities when public R&D expenditures increase. As noted by Popp (2002), such a result may be driven by a crowding-out effect of public R&D expenditures on private R&D expenditures.[11]

The estimation results for our control variable total patents are generally as expected. For 7 of the 11 technologies, we find a statistically significant and positive coefficient, suggesting that for the majority of green energy technologies, patent activities are affected by the overall propensity to patent. This is also confirmed by the highly statistically significant and positive coefficient for total patents in the model including all technologies. Only for wind energy, ocean energy, fuel cells, and CCS do overall patent activities seem to have no impact on the technology-specific patent activities.

In order to account for the development of green energy innovation activities over time, we also add a time trend to our estimations. Here, we observe a statistically significant negative time trend for 7, a statistically significant positive time trend for 3, and a statistically insignificant time trend for 1 of the 11 technologies. A negative time trend suggests diminishing returns to R&D activities or, in other words, more difficulties in developing new innovations. As new innovations are more difficult for relatively mature technologies, the different signs of the time coefficients point to different maturity levels of the technologies.

2.5.2 Robustness Tests

In order to test the sensitivity of our baseline results, we conduct a number of robustness tests. First, we repeat the estimations in Table 2.2 with different dynamic specifications for the energy price. More specifically, we reestimate our baseline model with the energy price lagged 2 years, 3 years, and with a moving average of past energy prices over 5

[11] As noted before, we lag the R&D variable by 1 year in order to mitigate any reverse causality problems. This approach also accounts for the fact that R&D efforts do not immediately lead to innovative output (Hall et al., 1986). In order to test the sensitivity of the R&D results to other lag structures, we reestimate the baseline model from Table 2.2 with public R&D expenditures lagging 2, 3, and 4 years. Overall, the results are robust to these alternative specifications.

years. The estimated coefficients for the alternative energy prices as well as for the 1-year lagged energy price used in our baseline model are depicted in Table 2.3.

Table 2.3: Different dynamic specifications for the energy price. Estimation time span: 1983-2009. Dependent variable: Number of patent applications at the EPO.

Variable	EEBAE	EET	EEO	Solar	Wind	Ocean
Energy price$_{t-1}$ (log)	-0.559	0.205	0.059	1.115***	-0.180	0.612*
	(0.350)	(0.179)	(0.166)	(0.150)	(0.496)	(0.348)
Energy price$_{t-2}$ (log)	-0.481	0.340**	0.085	1.198***	-0.015	0.577
	(0.346)	(0.148)	(0.144)	(0.165)	(0.526)	(0.365)
Energy price$_{t-3}$ (log)	-0.366	0.353**	0.138	1.209***	0.007	0.610***
	(0.311)	(0.164)	(0.130)	(0.182)	(0.535)	(0.227)
Energy price$_{MA}$ (log)	-0.411	0.344*	0.119	1.275***	0.006	0.526*
	(0.363)	(0.182)	(0.154)	(0.169)	(0.617)	(0.295)
	Biofuels	Geothermal	Fuel cells	CCS	Storage	All
Energy price$_{t-1}$ (log)	-0.638^{*}	0.370**	1.730	0.563***	0.026	0.086
	(0.380)	(0.145)	(1.847)	(0.215)	(0.250)	(0.165)
Energy price$_{t-2}$ (log)	-0.552	0.382***	0.600	0.703***	0.148	0.159
	(0.368)	(0.128)	(1.186)	(0.127)	(0.224)	(0.146)
Energy price$_{t-3}$ (log)	-0.528^{*}	0.322**	1.413	0.818***	0.253	0.211*
	(0.307)	(0.145)	(0.991)	(0.105)	(0.231)	(0.118)
Energy price$_{MA}$ (log)	-0.714^{*}	0.375**	3.369**	0.805***	0.216	0.179
	(0.405)	(0.152)	(0.145)	(0.145)	(0.259)	(0.144)

Notes: Estimations are based on the same specification as in Table 2.2. To conserve space, only the coefficients for the different energy prices are presented. The complete tables are available from the authors upon request. Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1, 5, and 10% level. Energy price$_{MA}$: Moving average of the energy prices of the previous 5 years.

Overall, the estimated coefficients are very similar for all specifications. Only for EET, ocean energy, and fuel cells do we see some notable changes in statistical significance or magnitude. With an increasing time lag between energy prices and patent activities, the price coefficients for EET become statistically significant. Thus, it seems that energy prices from 2 or more years prior have a positive impact on patent activities in transport energy efficiency. A similar effect can be observed for fuel cells, with the moving average of past energy prices being statistically significant at the 1% level. For ocean energy, however, the results remain ambiguous. While the highly statistically significant coefficient for the 3-year lagged price indicates a positive price effect, the other price coefficients are either insignificant or only significant at the 10% level.

The second robustness test we conduct is the utilization of different depreciation rates in the calculation of the end-of-period knowledge stock. Table 2.4 reports the estimated knowledge stock coefficients for depreciation rates of 5%, 10% (as used in the baseline model depicted in Table 2.2), 15%, and 20%. For all specifications, the coefficients are positive and highly statistically significant at the 1% level. Furthermore, the magnitude of the coefficients is very similar within each technology. Thus, our baseline result saying that the knowledge stock is a significant driver of patent activities in all technologies is robust to different assumptions on the depreciation rate.

Table 2.4: Different depreciation rates for the knowledge stock. Estimation time span: 1983-2009. Dependent variable: Number of patent applications at the EPO.

Variable	EEBAE	EET	EEO	Solar	Wind	Ocean
Knowledge stock$_{t-1}$,	0.952^{***}	1.055^{***}	0.522^{***}	0.641^{***}	0.941^{***}	0.741^{***}
$\delta = 0.05$ (log)	(0.107)	(0.079)	(0.083)	(0.091)	(0.071)	(0.156)
Knowledge stock$_{t-1}$,	0.930^{***}	1.011^{***}	0.534^{***}	0.640^{***}	0.884^{***}	0.743^{***}
$\delta = 0.10$ (log)	(0.095)	(0.067)	(0.079)	(0.080)	(0.069)	(0.128)
Knowledge stock$_{t-1}$,	0.915^{***}	0.980^{***}	0.547^{***}	0.638^{***}	0.844^{***}	0.718^{***}
$\delta = 0.15$ (log)	(0.086)	(0.060)	(0.075)	(0.070)	(0.070)	(0.113)
Knowledge stock$_{t-1}$,	0.904^{***}	0.958^{***}	0.560^{***}	0.635^{***}	0.814^{***}	0.684^{***}
$\delta = 0.20$ (log)	(0.079)	(0.055)	(0.072)	(0.063)	(0.071)	(0.105)
	Biofuels	Geothermal	Fuel cells	CCS	Storage	All
Knowledge stock$_{t-1}$,	0.804^{***}	0.836^{***}	0.948^{***}	1.063^{***}	0.738^{***}	1.069^{***}
$\delta = 0.05$ (log)	(0.138)	(0.133)	(0.229)	(0.087)	(0.094)	(0.039)
Knowledge stock$_{t-1}$,	0.749^{***}	0.793^{***}	0.948^{***}	1.020^{***}	0.732^{***}	1.029^{***}
$\delta = 0.10$ (log)	(0.130)	(0.117)	(0.207)	(0.068)	(0.081)	(0.034)
Knowledge stock$_{t-1}$,	0.723^{***}	0.746^{***}	0.949^{***}	0.977^{**}	0.720^{***}	0.980^{***}
$\delta = 0.15$ (log)	(0.124)	(0.107)	(0.191)	(0.063)	(0.072)	(0.028)
Knowledge stock$_{t-1}$,	0.716^{***}	0.702^{***}	0.950^{***}	0.938^{***}	0.704^{***}	0.960^{***}
$\delta = 0.20$ (log)	(0.118)	(0.101)	(0.179)	(0.065)	(0.067)	(0.025)

Notes: Estimations are based on the same specification as in Table 2.2. To conserve space, only the coefficients for the different knowledge stocks are reported. The complete tables are available from the authors upon request. Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1, 5, and 10% level.

Another robustness test is conducted by limiting our sample to the time span 1998-2009. The reasoning for this is 2-fold: First, we observe a significant growth in green energy patent applications within the latter periods of our sample. Hence, our results may be influenced, in particular, by developments in these periods. Second, a shorter sample period implies a longer pre-sample period that can be used to calculate the PSM information. By choosing the cut-off year 1998, we increase the number of pre-sample periods from 5 to 20 years.

Furthermore, 1998 is the first year after the Kyoto protocol was signed. The Kyoto protocol was the first international agreement among the world's industrialized countries that aimed to reduce greenhouse gas emissions via a legally binding commitment. Even though the protocol did not come into force until 2005, it can be interpreted as a first indicator toward a more green energy-oriented policy. This change of future policy expectations may have affected the development of green energy innovations in the years following (Johnstone et al., 2010).[12] [13]

Table 2.5 reports the results of our short-term model with the estimation time span 1998-2009. Still, for all technologies, the knowledge stock seems to be a major driver of green energy innovation. Moreover, for most technologies, the magnitude of the corresponding coefficient is much higher than in our baseline estimations. Assuming diminishing marginal productivity of the stocks in generating patents, this result indicates that the stocks significantly increased in the period after the Kyoto protocol was signed. As depicted in Figure 2.4 in the data section, such a development can be observed for the majority of the technologies.

The most pronounced impact of the knowledge stock in the short-term model is shown for fuel cells, with an estimated elasticity of 1.378. This value indicates that a 10% increase in knowledge stock is associated with an approximately 14% increase in patent activities.

For the energy price, a more diversified picture is shown. In fact, we observe a number of significant changes compared to the results of our baseline model depicted in Table 2.3. While the formerly statistically significant price coefficients for ocean energy, biofuels, and CCS are now insignificant, the respective coefficients for EET and energy storage become significant. Furthermore, the magnitude of the still positive and statistically significant price coefficients for solar and geothermal energy is much higher than before.

Referring to the other variables, public R&D, total patents, and the time trend the results of the short-term model are in general in line to those obtained from the baseline model. Still, public R&D expenditures seem to have only a minor impact on patent activities. However, compared to our baseline model indicating a statistically significant and positive impact of public R&D on patent activities for wind energy and biofuels only, we now observe a statistically significant and positive impact of public R&D for two more technologies, namely EEBAE and energy storage. Furthermore, in spite of some changes in significance, the estimated coefficients for total patents and the time trend again suggest a positive impact of the overall propensity to patent and diminishing returns to R&D activities over time on green energy patent activities for most technologies.

[12] The signature of the Kyoto protocol may not be the only factor that changed the development of green energy innovation in these years. Other political and economic reasons might be, for instance, the rise of China and India or the liberalization of the European energy markets. Nevertheless, since the Kyoto protocol marks a substantial break in international environmental policy, the Kyoto argumentation seems to be the most plausible one in this context.

[13] In the European Union, the Kyoto obligations were fulfilled via the implementation of an Emissions Trading System, which sets a price on emissions from power generators and specific industries from 2005 onward. Its effect on energy prices is captured in the energy price index.

Table 2.5: Estimated coefficients of the PSM Poisson model. Estimation time span: 1998-2009. Dependent variable: Number of patent applications at the EPO.

Variable	EEBAE	EET	EEO	Solar	Wind	Ocean
Energy price$_{t-1}$ (log)	0.376	0.766*	0.163	1.735***	0.721	−1.158
	(0.750)	(0.429)	(0.389)	(0.480)	(0.592)	(0.795)
Knowledge stock$_{t-1}$ (log)	1.362***	1.260***	0.816***	1.005***	0.955***	1.015***
	(0.092)	(0.111)	(0.200)	(0.085)	(0.071)	(0.154)
Public R&D$_{t-1}$ (log)	0.054***	0.008	−0.020**	−0.010	0.194***	0.069
	(0.016)	(0.008)	(0.010)	(0.040)	(0.053)	(0.072)
Total patents$_{t-1}$ (log)	−0.067	0.040	0.496***	0.485***	−0.132**	−0.048
	(0.198)	(0.074)	(0.154)	(0.127)	(0.054)	(0.095)
Time trend	−0.134***	−0.084***	−0.054***	−0.053**	−0.016	0.072**
	(0.029)	(0.022)	(0.018)	(0.022)	(0.020)	(0.036)
Constant	0.467	−3.104	−2.102	−9.407***	−2.805	2.564
	(3.638)	(1.906)	(1.744)	(2.109)	(2.502)	(3.183)
Observations	241	240	241	248	243	225
	Biofuels	Geothermal	Fuel cells	CCS	Storage	All
Energy price$_{t-1}$ (log)	0.251	1.536***	1.398	0.093	1.080***	0.529**
	(0.158)	(0.239)	(1.907)	(0.499)	(0.317)	(0.234)
Knowledge stock$_{t-1}$ (log)	0.824***	0.817***	1.378***	0.916***	0.369**	1.235***
	(0.269)	(0.184)	(0.139)	(0.189)	(0.165)	(0.083)
Public R&D$_{t-1}$ (log)	0.129**	0.066	0.029	−0.033	0.089***	0.012
	(0.059)	(0.040)	(0.050)	(0.023)	(0.029)	(0.012)
Total patents$_{t-1}$ (log)	0.277***	0.277***	0.281*	−0.104**	0.011	0.139***
	(0.073)	(0.101)	(0.160)	(0.046)	(0.097)	(0.026)
Time trend	−0.154***	−0.037	−0.218**	−0.014	−0.035**	−0.096***
	(0.022)	(0.024)	(0.087)	(0.023)	(0.014)	(0.015)
Constant	0.648	−8.598***	−2.850	−0.728	−5.727***	−1.649
	(0.709)	(1.355)	(6.244)	(2.114)	(1.761)	(1.208)
Observations	247	229	114	236	242	2506

Notes: All models control for unit-specific fixed effects by using PSM information on the first 20 years available (1978-1997). Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1, 5, and 10% level.

Our last robustness test deals with the observed differences between the estimated price coefficients in our short-term and baseline models (see Tables 2.2 and 2.5). In order to obtain a more comprehensive picture and to check whether these differences are only related to the usage of a 1-year lagged energy price specification, we reestimate our short-term model with different dynamic specifications for the energy price (as done before for the baseline model, see Table 2.3). The results are shown in Table 2.6.

First of all, it can be seen that all estimated price coefficients in the model including all technologies are positive and statistically significant at least at the 5% level. In our baseline model, we observe a positive impact of the energy price on patent activities

Table 2.6: Different dynamic specifications for the energy price. Estimation time span: 1998-2009. Dependent variable: Number of patent applications at the EPO.

Variable	EEBAE	EET	EEO	Solar	Wind	Ocean
Energy price$_{t-1}$ (log)	0.376	0.766*	0.163	1.735***	0.721	−1.158
	(0.750)	(0.429)	(0.389)	(0.480)	(0.592)	(0.791)
Energy price$_{t-2}$ (log)	0.379	1.125***	0.151	1.728***	1.002*	−1.273
	(0.690)	(0.266)	(0.339)	(0.458)	(0.553)	(0.916)
Energy price$_{t-3}$ (log)	0.597	1.095***	0.331	1.662***	0.891*	−0.742
	(0.493)	(0.319)	(0.292)	(0.468)	(0.486)	(0.661)
Energy price$_{MA}$ (log)	0.766	1.155***	0.342	1.879***	1.227**	−1.394
	(0.554)	(0.333)	(0.328)	(0.429)	(0.607)	(0.916)
	Biofuels	Geothermal	Fuel cells	CCS	Storage	All
Energy price$_{t-1}$ (log)	0.251	1.536***	1.398	0.093	1.080***	0.529**
	(0.158)	(0.239)	(1.907)	(0.499)	(0.317)	(0.234)
Energy price$_{t-2}$ (log)	0.320**	1.479***	−0.366	0.624*	1.166***	0.650***
	(0.133)	(0.238)	(1.057)	(0.334)	(0.277)	(0.196)
Energy price$_{t-3}$ (log)	0.832***	1.457***	0.453	1.094***	1.151***	0.848***
	(0.190)	(0.252)	(0.958)	(0.283)	(0.326)	(0.169)
Energy price$_{MA}$ (log)	0.979***	1.757***	1.858	0.941**	1.181***	0.886***
	(0.361)	(0.297)	(1.562)	(0.420)	(0.353)	(0.194)

Notes: Estimations are based on the same specification as in Table 2.5. To conserve space, only the coefficients for the different knowledge stocks are reported. The complete tables are available from the authors upon request. Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1, 5, and 10% level.

in green energy technologies only for the 3-year lagged price and just at a 10% level of significance. This finding, together with the other observed differences in the estimates of our baseline and short-term models, points to the fact that, at least for some green energy technologies, the development of patent activities changed significantly after the signing of the Kyoto protocol. With the number of green energy patents rapidly increasing within this period, our results for the knowledge stock and for the energy price suggest that both technology-push effects and demand-pull effects gain a more pronounced impact on patent activities in this period.

Nevertheless, while this observation holds for all technologies in the case of technology-push effects, demand-pull effects seem to affect only some technologies. With at least three of the four energy price specifications tested being statistically significant, the results in Table 2.6 clearly indicate a positive impact of the energy price on patent activities in 7 of the 11 technologies, namely EET, solar energy, wind energy, biofuels, geothermal energy, CCS, and energy storage. In our baseline model, this is only the case for four technologies: EET, solar energy, geothermal energy, and CCS.

Referring to the magnitude of the estimated price coefficients, some other interesting results are obtained from our short-term model estimations. For EET, solar, and geothermal energy, the magnitude of the price coefficients is much higher in the short-term model than in the baseline model. Moreover, for solar and geothermal energy, the price coefficients are much higher than the knowledge stock coefficients, indicating that the energy price for these technologies is the main driver of patent activities after the Kyoto protocol was signed.

A similar result can be observed for energy storage. While the estimated price coefficients are insignificant for all energy price specifications tested in our baseline model, they are highly statistically significant and positive in our short-term model. Moreover, the magnitude of the price coefficients is much higher than the magnitude of the knowledge stock coefficient.

Overall, these results point to a shift in expectations after the Kyoto protocol agreement. In particular, they suggest that market participants expected green energy-oriented policies to be pushed forward and energy prices to persistently increase in the future. Arguing on the basis of a classical demand curve for fossil energy, such a development induces both an upward movement along and an inward shift of the curve. The demand for fossil energy decreases, and already-available clean substitutes or energy-saving technologies come into use earlier than without green energy-oriented policies and increased prices. In addition, the market conditions of green energy technologies become more profitable and, hence, new patents are generated in this area.

2.6 Conclusions

In this article, we analyzed the effect of energy prices and technological knowledge on innovation in green energy technologies. We based our analysis on green energy patent counts from 26 OECD countries and 11 technologies over the period 1978-2009. Our contribution to the induced innovation literature is 3-fold. We investigated demand and supply determinants of green energy innovation separately for different technologies. We used European patent data to consolidate previous results reached on US patent data. Finally, we estimated a dynamic count data model for panel data using the PSM scaling estimator proposed by Blundell et al. (1995, 2002). This approach allowed us to account for path dependencies in knowledge production, endogeneity issues, and unobserved heterogeneity.

Our analysis yields several interesting findings. First of all, our results indicate that the main determinant of innovation in green energy technologies is the availability of technological knowledge. This confirms the technology-push hypothesis, stating that innovation is induced by advances in the technological capability of an economy. It also confirms previous results suggesting that inventors build on existing knowledge and 'see further by standing on the shoulders of giants'. Moreover, concerning the demand-pull hypothesis suggesting energy prices as a major driver of green energy innovation, our results reveal significant differences across technologies. We find that increasing energy prices induce innovation in some but not all green energy technologies. This result supports our approach of a technology-specific analysis. However, even more important is that we uncovered significant differences comparing the period before and after the Kyoto protocol adoption. More precisely, our results indicate that the effect of both energy prices and technological knowledge on green energy innovation is stronger after the Kyoto protocol agreement. This suggests that the general awareness for clean energy generation increased. Finally, evidence is presented that government R&D plays either no or just a minor role in inducing green energy innovation.

From our results, several policy implications can be drawn. First, the strong evidence for the technology-push hypothesis suggests that policies should enhance technological capability to foster green energy innovation. That is, policies should support the private generation and patenting of scientific and technological knowledge as well as enable economies to exploit their existing knowledge base. As existing patents spur further innovative activity, research conditions for companies should be designed accordingly. Furthermore, depending on the technology, subsidizing energy R&D can encourage innovation and thus increase the economy's stock of knowledge. Second, concerning demand-pull, our results show that policies increasing the energy price to internalize the negative externality have very different inducement effects on different technologies. Policy makers should be aware of these differences but, once the negative externality is internalized, let the market decide on innovation activity and the evolution of the energy technology mix. All together, it may be concluded that distinct technologies have distinct innovation characteristics and, thus, the same set of policies may have different consequences for different green energy technologies.

Further research could extend our analysis in several aspects. First, the observed differences across technologies appear to merit further examination in more detail. In particular, as our analysis does not include any spillover effects among technologies or countries, further research could help clarify as to what extent knowledge spillovers are of particular relevance for green energy innovations. Second, a closer analysis of the period after the Kyoto protocol agreement seems promising. A deeper understanding of how this agreement and the related country-specific green energy policies have changed the innovators' patent behavior could lead to more targeted policy recommendations toward a green energy economy.

Chapter 3

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

3.1 Introduction

Currently, about 40% of world electricity is produced from 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, 2013b). 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, 2013a). 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 oxide (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, 2013b). 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).[14] 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, 2012b).

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 innovation. 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, Johnstone et al., 2010, Popp, 2002, 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

[14] 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).

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 3.2 presents the principal hypotheses tested in our empirical analysis. Section 3.3 presents the data and some descriptive statistics. In section 3.4, we describe the empirical strategy and discuss the results. Section 3.5 summarizes the main findings and concludes.

3.2 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, Binswanger, 1974, Hicks, 1932). 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 (Acemoglu et al., 2012, Hicks, 1932). 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 3.1.

Table 3.1: 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 (Coal price)	*o* (+/−)
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.

3.3 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.

3.3.1 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.[15] 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).[16] 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 3.2 provides an overview on the considered technologies.[17]

Table 3.2: 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

[15] 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).

[16] 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.

[17] 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.[18] [19] 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.[20]

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):

$$K_{it} = PAT_{it} + (1 - \delta)\, K_{it-1} \tag{3.1}$$

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 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 $K_{it_0} = PAT_{it_0}/(g + \delta)$,

[18] 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.

[19] 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.

[20] 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.

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%.[21]

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, 2014b) and is available for 30 countries.[22] Using coal prices instead would be preferable. However, as noted by the IEA (2014a), 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, 2014a). 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 3.3.2, 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.[23]

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 (Aghion et al., 2016, Barbieri, 2015, Noailly and Smeets, 2015). 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 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

[21] 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.

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

[23] In order to capture not only the effect of changing absolute prices, but also the effect of changing relative prices on CCT innovation, one could use spreads between different energy prices. However, to construct price spreads one needs data on fuel-specific price series. These series often show a high amount of missing values. Therefore, we chose to use absolute energy prices in our empirical analysis.

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:

$$P_{it} = \sum_{c} w_{ic}^{PP} \times P_{ct} \tag{3.2}$$

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.[24] 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[25] 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 (see Figure 3.1) nor the introduction of NO_X regulations (see Figure 3.3) 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

[24] 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.

[25] 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.

obtained from the IEA Energy Balances database (IEA, 2015a) and is measured in TWh per year. Data is available for 50 countries.[26][27] 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:

$$M_{it} = \sum_c w_{ic}^{PP} \times M_{ct} \tag{3.3}$$

where w_{ic}^{PP} is a fixed firm-specific patent-portfolio weight for country c as in (3.2) 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[28] for coal-fired power plants and the implementation of CO_2 regulation (predominantly cap-and-trade programs), respectively.[29] 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 as the weighted average dummy variable across countries based on the importance of country c's market for firm i's innovation activity:

$$D_{it} = \sum_c w_{ic}^{PP} \times D_{ct} \tag{3.4}$$

where w_{ic}^{PP} is a fixed firm-specific patent-portfolio weight for country c as in (3.2) and (3.3)[30] and D_{ct} is the dummy variable in country c at time t.

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

[27] Using the share of coal in electricity production as a proxy for the size of the potential market for CCT innovations would be preferable. However, since data on electricity production from coal is available only for a fraction of countries and years, we decided to use total electricity production.

[28] 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.

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

[30] We use the same patent-portfolio weights to compute the firm-year specific energy price, electricity production, and regulatory variables because we think that firms' exposure to these determinants has the same driver, that is the geographical distribution of patenting across countries. Since we have no

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, 2015b) 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.[31] 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:

$$RD_{it} = \sum_c w_{ic}^I \times RD_{ct} \tag{3.5}$$

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 is the share of all firm i's inventors in country c over the period 1978 to 2009.[32] In order to account for country c's economic size, s_{ic}^I is weighted by the share of country c's GDP in world GDP over the same time period, GDP_c.[33]

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

good theory why the exposure would have different drivers, we decided not to use different weights for a robustness test. Using the same weights could of course create multicollinearity problems among these explanatories. However, as multicollinearity problems only arise if the number of observations is low or if the correlation between explanatory variables is high and since we have a large number of observations and since the correlation among our explanatories is fairly low (see Table B.5 (Appendix)), multicollinearity is very unlikely to pose a problem for our estimations (see, for example, Wooldridge, 2016).

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

[32] 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.

[33] Note that the inventor weight w_{ic}^I in equation (3.5), which is based on the distribution of a firm's various inventors across countries, is very distinct from the patent-portfolio weight w_{ic}^{PP} in equation (3.2), (3.3), and (3.4), which is based on the distribution of a firm's patent-portfolio across countries. Figure B.1 (Appendix) shows for the USA, that these distributions vary considerably across firms.

2009. In total (all patents, not only CCT), these firms have filed 832,621 first priority patents over the same period. Table 3.3 reports summary statistics for the sample.

Table 3.3: 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).

3.3.2 Descriptive Statistics

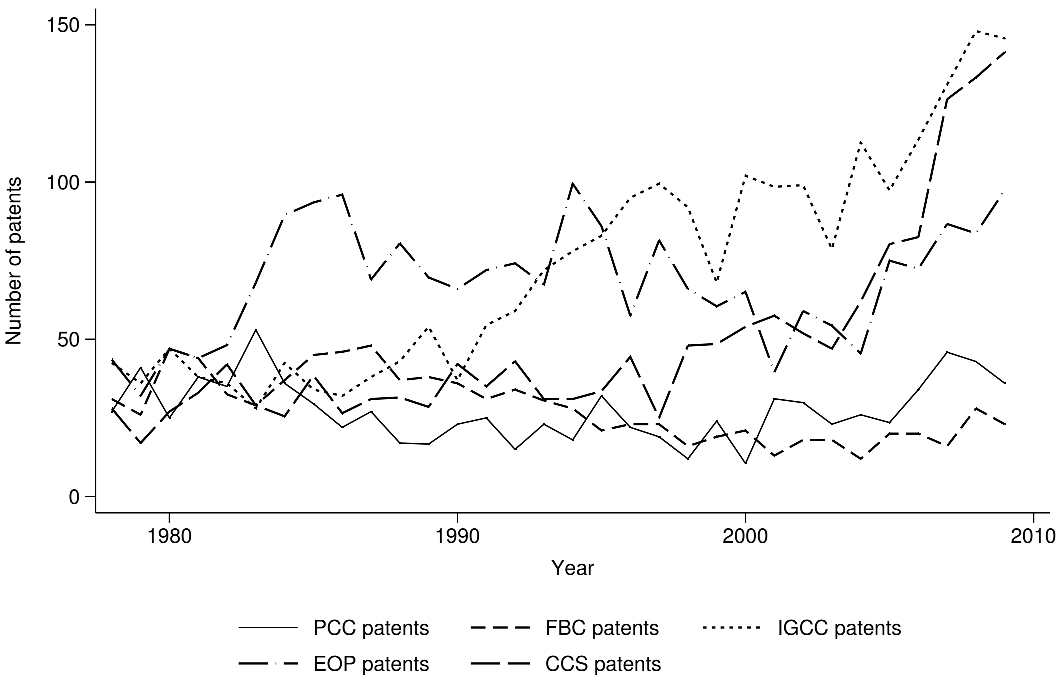

Figure 3.1: Total number of PCC, FBC, IGCC, EOP, and CCS priority patent applications (claimed priorities) filed worldwide of all firms, 1978-2009. *Source:* Authors' calculations, based on PATSTAT.

Figure 3.1 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 about 50 patents per year. CCS stays nearly constant until the late-1990s and increases significantly afterwards.

Table 3.4: 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.

Table 3.4 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, and General Electric have the highest innovative activity after Siemens, all exhibiting five-figure patent numbers. The other listed firms patent significantly less.

Table 3.5: 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.

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 3.5 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 3.2 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 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

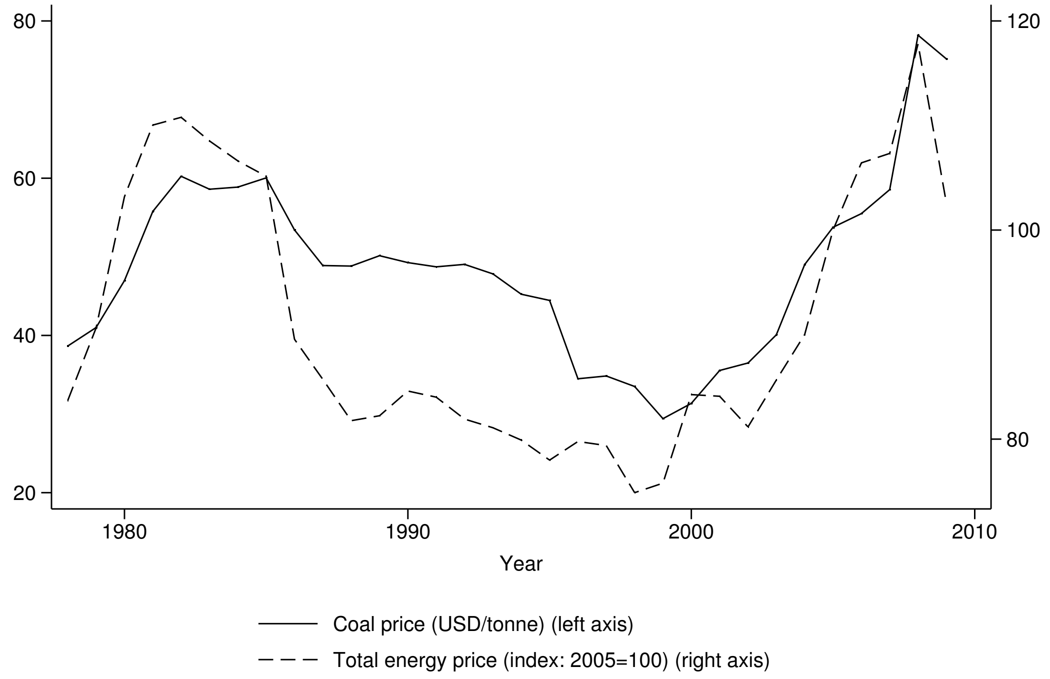

Figure 3.2: Average firm-level development of the weighted average real total energy end-use price (index with base year 2005) and real steam coal end-use price for all firms (USD per tonne, 1996 prices and PPP), 1978-2009. *Source:* Authors' calculations, based on PATSTAT and IEA Energy Prices and Taxes.

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 3.3 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.

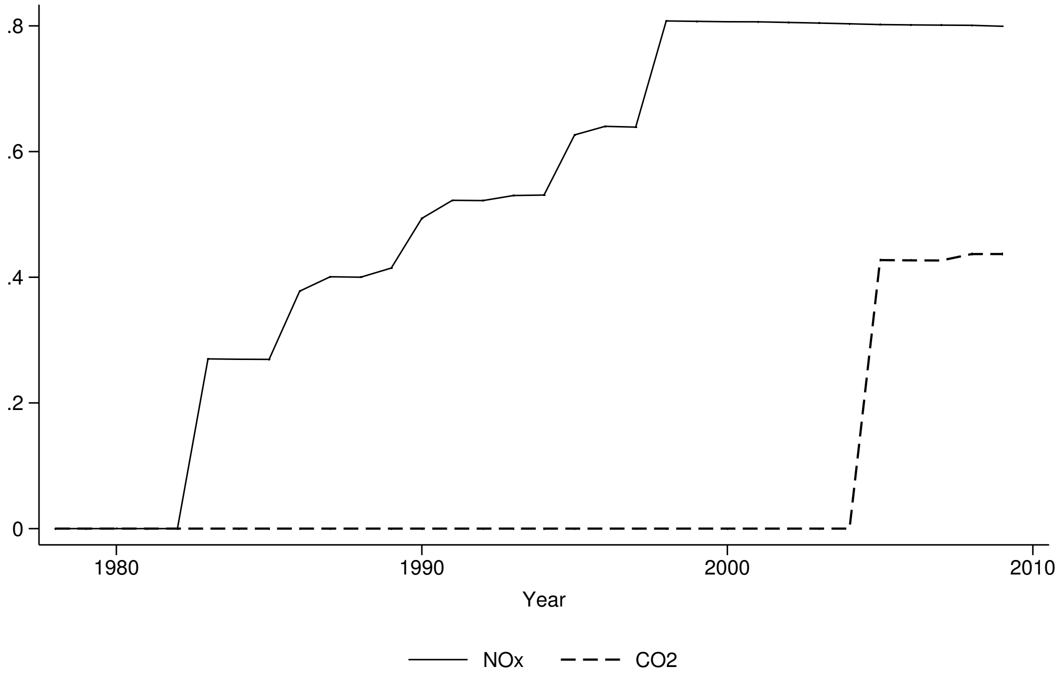

Figure 3.3: Average firm-level development of the weighted average NO_X and CO_2 dummy variables for all firms, 1978-2009. *Source:* Authors' calculations, based on PATSTAT, Popp (2006), and World Bank Group, Ecofys (2014).

3.4 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.

3.4.1 Empirical Model

Given the hypotheses stated in Section 3.2 and the variables described in Section 3.3.1, our empirical model can be specified as follows:

$$\begin{aligned} PAT_{ijt} = exp(&\beta_0 + \beta_1 \, ln\, P_{it-1} + \beta_2 \, ln\, K_{ijt-1} + \beta_3 \, ln\, RD_{it-1} + \beta_4 \, ln\, TPAT_{it-1} \\ &+ \beta_5 \, ln\, M_{it-1} + \beta_6 \, CO2_{it} + \beta_7 \, NOx_{it} + \tau_t + \eta_i) + u_{ijt} \end{aligned} \tag{3.6}$$

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 3.1. 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 3.2-3.4. $CO2$ 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 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 3.6. 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 (PSM) 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 3.6 are defined as:

$$\eta_i = \theta_1 \, ln \, P\bar{A}T_{ij} + \theta_2 \, D(P\bar{A}T_{ij} > 0) \tag{3.7}$$

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).

3.4.2 Empirical Results

The estimation results of our empirical model are presented in Table 3.6. We estimate the model defined in Equation 3.6 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 Criteria (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 3.6. 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 3.6 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

Table 3.6: Baseline results for CCT, EI-CCT, and AP-CCT.

	CCT		EI-CCT		AP-CCT	
	Poisson	NegBin	Poisson	NegBin	Poisson	NegBin
Energy price$_{t-1}$ (log)	-1.094 (1.145)	-1.839^{***} (0.684)	-0.513 (1.759)	-1.250 (1.095)	-1.514 (1.056)	-2.155^{**} (0.845)
Knowledge stock$_{t-1}$ (log)	0.844^{***} (0.049)	0.954^{***} (0.038)	0.883^{***} (0.066)	0.996^{***} (0.053)	0.892^{***} (0.051)	0.964^{***} (0.049)
Public R&D$_{t-1}$ (log)	-0.039^{***} (0.013)	-0.066^{***} (0.009)	-0.059^{***} (0.016)	-0.088^{***} (0.013)	-0.033^{**} (0.015)	-0.048^{***} (0.012)
Total patents$_{t-1}$ (log)	0.319^{***} (0.024)	0.390^{***} (0.018)	0.325^{***} (0.025)	0.371^{***} (0.022)	0.310^{***} (0.018)	0.341^{***} (0.017)
Electricity prod.$_{t-1}$ (log)	-0.020 (0.049)	-0.059 (0.037)	0.017 (0.083)	-0.011 (0.067)	-0.062 (0.054)	-0.091^{*} (0.048)
CO_2 regulation	0.808^{**} (0.335)	0.519^{***} (0.171)	1.138^{***} (0.416)	0.777^{***} (0.254)	0.761^{***} (0.281)	0.502^{**} (0.208)
NO_X regulation	0.457^{***} (0.158)	0.518^{***} (0.135)	0.239 (0.217)	0.311 (0.201)	0.621^{***} (0.203)	0.631^{***} (0.182)
Pre-sample mean	-0.256 (0.408)	-0.924^{**} (0.363)	0.235 (0.461)	-0.657 (0.487)	-0.963^{***} (0.331)	-1.171^{***} (0.334)
Pre-sample dummy	0.219^{*} (0.128)	0.150 (0.101)	-0.092 (0.209)	0.069 (0.138)	0.163 (0.112)	0.057 (0.097)
Constant	2.083 (5.637)	6.370^{*} (3.266)	-1.102 (8.735)	3.147 (5.392)	4.483 (5.173)	8.029^{**} (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^{***} (0.000)		1055^{***} (0.000)		387^{***} (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.

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 technological 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 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 3.7. 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

Table 3.7: Robustness results for different pre-sample specification and exclusion of top innovative firms.

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

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 3.7, our main results carry over. In addition, the weak statistical significance of electricity production in the AP-CCT model is back and NO_X regulation is shown to be statistically significant in all models.

Table 3.8: Robustness results for different lagged and forward values of the energy price, public R&D expenditures, and electricity production.

	CCT	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 3.6. 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 variables are depicted in Table 3.8. 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.

3.5 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 technological 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 build 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 one 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 CCT in electricity production processes. Another promising path for additional research is the analysis of spillover effects among the firms.

Chapter 4

Innovation in Green Energy Technologies and the Economic Performance of Firms

4.1 Introduction

Recent empirical economic literature has focused to a great extent on the determinants and inducement mechanisms of innovation in green energy (GE) (or environmental, or eco-) technologies. A large number of contributions provides a robust understanding of factors determining and policies inducing GE innovation (see, for example, Jaffe and Palmer, 1997, Johnstone et al., 2010, Popp, 2002, Verdolini and Galeotti, 2011). However, little attention has been devoted to the economic effects of GE innovation, especially to the relationship between innovating in GE technologies and the economic performance of the innovating firms. Understanding this relationship helps to answer the widely debated question in the literature on green innovation (see, for example, Marin and Lotti, 2016, Wörter et al., 2015), whether firms gain (forgo) economic opportunities by innovating (not innovating) in GE technologies.

This article empirically investigates the impact of innovation in GE technologies on the economic performance of firms. In addition, the impact of GE innovation is compared to the one of non-GE innovation. I analyze a panel of 8,619 patenting firms from 22 European countries over a period of 8 years from 2003 to 2010. Economic firm performance is measured in terms of productivity. Using productivity as performance indicator has several advantages. First, results from production function approaches are easily interpretable and comparable to other studies (Bloom and Van Reenen, 2002). Second, firm performance is mainly driven by productivity trends which are closely linked to innovation dynamics (Cainelli et al., 2011). Furthermore, compared to data on market valuation, data on productivity is available for a large number of firms including medium- and small-sized ones. I specify a panel data model based on an extended Cobb-Douglas production function in which productivity is a function of capital, labor, and innovation output. Firm accounts data is taken from the AMADEUS database provided by Bureau van Dijk (BvD). Innovation at the firm level is measured using patent data from the Organisation for Economic Co-operation and Development (OECD) REGPAT database.

My work is related to two strands of empirical literature on innovation and economic firm performance. The link between innovation and economic performance at the firm level has been analyzed in a large number of empirical economic articles (see, for example, Bloom and Van Reenen, 2002, Blundell et al., 1999, Comanor and Scherer, 1969, Ernst, 2001, Griliches, 1981, Griliches et al., 1991, Hall et al., 2005, Lanjouw and Schankerman, 2004, Scherer, 1965). The majority of these investigations identifies a positive relationship between innovative output and economic performance. However, since these studies focus on general innovation, the results cannot be simply transferred to GE innovation. There are fewer articles exploring the relationship between GE (or environmental or eco) innovation and economic firm performance. Ayari et al. (2012) investigate the impact of renewable energy innovation (patents) on firm performance (return on assets, stock market return) using a panel of 154 firms from 14 European countries (1987-2007). They find evidence that renewable energy innovation has a significant positive impact on both measures of firm performance. Marin (2014) analyzes the effect of environmental and non-environmental innovation (patents) on firm performance (value added) for a panel of 5,905 Italian firms (2000-2007). He shows that environmental innovation in most cases has no significant effect on firm performance, while non-environmental innovation has a positive effect. In a very similar study Marin and Lotti (2016) analyze the same relationship using a larger and longer panel of 11,938 Italian firms (1996-2006). They find positive impacts of both environmental and non-environmental patenting, while observing a substantially lower return for environmental patents. Wörter et al. (2015) examine the link between environmental innovation (patents) and performance (value added) on the industry-level. Their analysis is conducted on a panel of 22 manufacturing industries from 12 OECD countries (1980-2009). In contrast to Ayari et al. (2012) and Marin and Lotti (2016), they find that green innovation is negatively related to performance for most industries. Overall, the empirical evidence concentrating on GE innovation can thus be described as ambiguous.

This study contributes to the existing literature in three respects. First, I provide new evidence on the unsolved question how innovation in GE technologies impacts firms' economic performance. Second, the impact of GE and non-GE innovation on performance is compared. Moreover, as robustness check I distinguish two subgroups of GE technologies: (a) Renewable Energy Sources (RES) and (b) Energy Efficiency (EE) technologies. Third, I base my analysis on a comparatively large and broad panel of 8,619 European patenting firms including 968 GE patenters from 22 countries over an estimation period of 8 years (2003-2010) and a patent count period of 32 years (1977-2010).

The remainder of the article is structured as follows. Section 4.2 outlines the theoretical background my analysis is based on. Section 4.3 presents and discusses the data. Section 4.4 describes the empirical strategy employed. Section 4.5 discusses the results of the econometric estimations and of the robustness tests. Finally, Section 4.6 summarizes the main findings and concludes.

4.2 Theoretical Background

Innovative activity in market economies to large parts exists because private profit-maximizing firms allocate resources to the research and development (R&D) of new products and processes, for which they see innovation opportunities and market success and consequently expect a positive impact on future economic performance, that is positive private returns (Dosi, 1988). The resulting innovation output of private firms is widely believed to be an important source of economic wealth and growth in economies (see, for example, Romer, 1986, 1990). In addition, innovation in the subgroup of GE technologies is acknowledged to be a crucial factor for handling climate change while maintaining reasonable economic growth (so called green growth) (see, for example, Acemoglu et al., 2012, Jaffe et al., 2002, Popp et al., 2010).

Private profit-maximizing firms decide about R&D investments solely on the basis of private returns. Therefore, a firm deciding about two R&D investment projects, one a GE option and one a non-GE option, would always choose the option with the higher private return, even though the GE option might have higher social returns (the sum of both private and non-private returns). Higher social returns for a GE compared to a non-GE option can result from higher non-private economic returns due to positive innovation spillovers and the internalization of negative environmental externalities (Dechezleprêtre et al., 2014). As a consequence, private R&D investments in GE technologies depend on the private return of these investments compared to the private return of non-GE investments.

In economic theory, arguments can be found in favor and against higher private returns of GE compared to non-GE innovation. Higher returns may be expected because: (a) GE technologies are newer and less explored than other technology fields. Therefore, research in GE technologies builds on a lower knowledge stock than research in more mature technologies. This could imply greater development perspectives and opportunities for high marginal private returns (Popp and Newell, 2012). (b) GE technologies bear the potential of having an impact on many sectors and becoming general purpose technologies. General purpose technologies are expected to generate large economic gains (Helpman, 1998). (c) Markets are increasingly shaped by strict environmental regulations. This induces a larger demand for GE technologies and hence increases the probability of higher private returns from GE innovation (Colombelli et al., 2015).

Contrariwise, lower returns could arise because: (a) GE technologies often are new to a firm and lie outside their traditional technological scope. In addition, adjustments of business processes, working routines, employment, and organizational structures may be necessary. This could lead to large adjustment costs (Noci and Verganti, 1999). (b) Financial markets are usually imperfect with regard to technological innovation. These market imperfections are even more pronounced for GE innovation due to the higher technical risk and uncertainty about market developments. This may imply high costs of capital (Wörter et al., 2015).

Thus, I derive two rival hypotheses: H1: Private economic returns measured in terms of productivity are higher for GE than for non-GE innovation, and H2: Private economic returns measured in terms of productivity are lower for GE than for non-GE innovation. This work aims to find out which of these hypotheses is right.

4.3 Data

4.3.1 Data Sources

To analyze the impact of GE innovation on the economic performance of firms, I combine two different databases and construct a unique firm-level data set that matches patent applicants at the European Patent Office (EPO) to firm accounts.

The first performance-related database is BvD's AMADEUS which contains annual financial data taken from the registries of approximately 19 million firms from 44 Western and Eastern European countries (Bureau van Dijk, 2015). It covers all sectors with exception of the financial one and contains up to ten recent years of information per firm. The database includes firm-level financial information in a standardized format for 26 balance sheet items, 26 profit and loss items, and 26 financial ratios.[34] First, I use information on sales as a measure of economic performance respectively productivity.

[34] The coverage of the items varies across countries and time.

Second, I collect information on the number of employees as a measure of labor input and information on total assets as a measure of capital input. A GDP deflator from the World Bank's World Development Indicators (The World Bank, 2015) is used to deflate all nominal values. To avoid double-counting firms and subsidiaries, I consider only firms that report unconsolidated statements.

In order to measure innovation activities at the firm level, I extend the financial data with patent data from the OECD REGPAT database (OECD, 2015).[35] The REGPAT database covers patent applications filed at the EPO from 1977 to 2011, derived from the EPO's Worldwide Patent Statistical Database (PATSTAT, Autumn 2014). To avoid a truncation downward bias towards the end of the sample period, I consider only patents filed until 2010. Using EPO patent applications ensures that applications for low-value inventions are excluded from the analysis. Application costs for multinational EPO patent applications are generally higher than for applications filed at national institutions. Accordingly, patent applications filed at the EPO often constitute innovations of high value that are expected to be commercially profitable and thus justify the relatively high application fees (Johnstone et al., 2010).

The financial data is combined with the EPO patent information using the OECD Harmonised Applicants' Names (HAN) database (OECD, 2014). This database provides a grouping of patent applicants' names constructed by harmonising names and matching them against company names from business register data. The business register data stems from the ORBIS database from BvD. Since AMADEUS is a component of the ORBIS database, the HAN database allows me to match EPO patent information to AMADEUS company names. The intersection of the AMADEUS and REGPAT databases then results in a panel of 11,001 firms from 27 countries[36] over a period of 34 years (1977 to 2010) that applied for at least one patent at the EPO during this period.

I count GE and non-GE (all patents except GE ones) patent applications filed by these firms at the EPO over the period 1977 to 2010.[37] I date the patents based on their priority date which refers to the first filing date of the invention worldwide since this date 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 (Griliches, 1990, OECD, 2009). The GE patents are

[35] 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).

[36] The countries are (sorted by country code): Austria (AT), Belgium (BE), Switzerland (CH), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), United Kingdom (GB), Greece (GR), Hungary (HU), Ireland (IE), Iceland (IS), Italy (IT), Liechtenstein (LI), Luxembourg (LU), Latvia (LV), Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Romania (RO), Russian Federation (RU), Sweden (SE), and Slovenia (SI).

[37] If a single patent is filed by multiple firms, I 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.

identified by using International Patent Classification (IPC) codes from the "IPC Green Inventory" (WIPO, 2015a,b). The inventory provides IPC codes for patents relating to so-called Environmentally Sound Technologies. Combining these codes with the energy technology structure developed at the IEA (IEA, 2011), I count GE patents from two groups: RES and EE. The RES group contains five RES technologies: solar energy, wind energy, geothermal energy, ocean energy, and fuel cells. The EE group contains three EE technologies: energy efficiency in residential and commercial buildings, appliances and equipment, energy efficiency in transport, and other energy efficiency[38]. Table 4.1 provides an overview on the considered technologies.

Table 4.1: Green energy technologies.

Renewable energy sources technologies
Wind energy
Solar energy
Geothermal energy
Ocean energy
Fuel cells
Energy efficiency technologies
Energy efficiency in residential and commercial buildings, appliances and equipment
Energy efficiency in transport
Other energy efficiency

To investigate the effect of firms' GE and non-GE knowledge, I construct a GE knowledge stock (GKS) and a non-GE knowledge stock (NKS) for firm i at time t using the perpetual inventory method following Cockburn and Griliches (1988) and Peri (2005):

$$GKS_{it} = GPAT_{it} + (1-\delta)\, GKS_{it-1} \quad and \tag{4.1}$$

$$NKS_{it} = NPAT_{it} + (1-\delta)\, NKS_{it-1}, \tag{4.2}$$

where $GPAT_{it}$ (respectively $NPAT_{it}$) is the number of GE (respectively non-GE) patent applications and δ is a depreciation rate accounting for the fact that knowledge becomes obsolete as time goes by. The depreciation rate is set to 10% as is often assumed in the literature (see, for example, Verdolini and Galeotti, 2011).[39] [40]

[38] Following the IEA energy technology structure, the other energy efficiency group includes waste heat recovery and utilization, heat pumps, and measurement of electricity consumption.

[39] The initial knowledge stock GKS_{it_0} (respectively NKS_{it_0}) is given by $GKS_{it_0} = GKS_{it_0}/(g+\delta)$ (respectively $NKS_{it_0} = NKS_{it_0}/(g+\delta)$) where $GPAT_{ijt_0}$ (respectively $NPAT_{ijt_0}$) is the number of patent applications in 1977, the first year observed. The growth rate g is the pre-1977 growth in patent stock, assumed to be 15%, and δ again represents depreciation of 10%.

[40] I test the robustness of the regression results against the utilization of different depreciation rates in the calculation of the knowledge stocks in Section 4.5.2, Table 4.10.

The availability of the AMADEUS financial firm information is limited. The first available year is 2003. Since I count patents filed until 2010, I use AMADEUS data from 2003 to 2010. For approximately 22% of the matched firms I have no information on sales, employment, and/or total assets. For the remaining firms, there are missing values for some years. Because of these missings, the number of firms and years and, by this, the number of observations that can be used for the econometric estimations is lower than in the base sample with 11,002 firms and 34 years. The resulting estimation data set is an unbalanced panel of 8,619 firms from 22 countries[41] over a period of 8 years (2003 to 2010), that have filed at least one EPO patent between 1977 and 2010. In total, these 8,619 firms filed 3,021 GE patents and 100,835 non-GE patents at the EPO between 1977 and 2010. The GE patents were filed by a subset of 968 firms from 17 countries[42] since not every firm in the full sample applied for a GE patent. The non-GE patents were filed by a subset of 8,345 firms from 22 countries which shows that almost every firm in the full sample filed a non-GE patent.

Table 4.2 reports summary statistics for the full sample of 8,619 patenting firms. The mean values of sales and total assets suggest the presence of some major firms as the means lie well above the threshold for the AMADEUS classification of a very large firm. The knowledge stock values demonstrate the difference in patent counts between GE and non-GE technologies, reflecting that just about 11% of the sampled firms are GE patenters. The standard deviations of the knowledge stock of GE and non-GE technologies have a similar level of about 10% of the mean value. The last row shows that I have on average almost 6 years of data for each firm.

Table 4.2: Summary statistics.

	Mean	Std. dev.	Min.	Max.
Sales (million EUR)	186.83	2526.82	0.00	323387
Employees (100s)	3.56	38.85	0.01	2888
Total assets (million EUR)	335.96	4091.64	0.00	310898
GE knowledge stock	0.15	1.35	0.00	108
Non-GE knowledge stock	6.11	63.92	0.00	3627
Observations per firm	5.70	1.93	1.00	8

Note: Sales and total assets are both in 2006 million. The knowledge stock variables are calculated using the patent data from 1977 to 2010.
Source: Authors' calculations, based on AMADEUS and REGPAT databases.

Table 4.3 reports correlations between the variables sales, employees, and total assets as well as GKS and NKS. The highest correlation persists between GKS and NKS (0.552). This shows that the development of GKS is positively related to those of the significantly larger group of NKS. The two knowledge stocks are all only weakly correlated to the

[41] The countries are AT, BE, CH, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HU, IT, LI, LU, LV, NL, NO, PL, SE, and SI.
[42] The countries are AT, BE, CH, CZ, DE, DK, ES, FI, FR, GB, IT, LU, LV, NL, NO, PL, and SE.

measure of firms' performance, labor, and capital input. As expected, there is also a positive correlation between the firm indicators themselves, the one between sales and total assets (0.621) being the highest.

Table 4.3: Correlation matrix.

	Sales	Employees	Total assets	GKS	NKS
Sales	1				
Employees	0.202	1			
Total assets	0.621	0.282	1		
GKS	0.101	0.101	0.121	1	
NKS	0.080	0.106	0.131	0.552	1

Source: Authors' calculations, based on AMADEUS and REGPAT databases.

4.3.2 Descriptive Statistics

Figure 4.1 shows the development of yearly GE and non-GE patenting activities of all firms during 1977 and 2010. GE patent applications are shown on the left axis and non-GE applications on the right axis. Both variables show an increasing trend from 1977 to 2010. The number of yearly non-GE patent applications increases monotonically and it can be seen that the yearly increases become significantly larger since the beginning of the 1990s. Yearly non-GE patent applications peak after a small drop at about 8,000 in 2009. The development of the yearly number of GE patents in my sample is characterized by two periods of growth. While they remain fairly stable well below 100 at the beginning, there is a steep increase to over 100 yearly GE patents at the end of the 1990s. After a phase of stagnation at the beginning of the 2000s, again an increase to over 300 yearly GE patents from 2005 to 2008 can be observed. Overall, the development of GE patents is less steady than the one of non-GE patents.

Table 4.4 shows the distribution of firms by GE and non-GE patents. In the range from one to 1,000 or more patents, it can be seen how many firms have filed at least a certain number of patents. As stated before, the sample contains 8,619 firms of which 968 firms have filed at least one GE and 8,345 firms at least one non-GE patent. Only about 13% (1,059) of the non-GE firms have filed ten or more non-GE patents while the respective figure lies at 5% (51) for GE patents, that is the majority of firms has filed less than ten patents, even more so with regard to GE patents. There are some particularly innovative firms in the sample as 439 firms have filed 25 non-GE patents or more, 121 firms 100 or more and still 51 firms 250 or more. Finally, 12 firms have filed 1,000 or more non-GE patents. Concerning GE patents, there are 15 firms which have filed 25 or more patents and 2 firms which have filed 100 or more patents.

Figure 4.1: Number of yearly GE (left axis) and non-GE (right axis) patent applications filed at the EPO by all firms. *Source:* Authors' calculations, based on AMADEUS and REGPAT data.

Table 4.4: The distribution of firms by GE and non-GE patents.

	1 or more	10 or more	25 or more	100 or more	250 or more	1,000 or more
Firms (GE)	968	51	15	2	0	0
Firms (Non-GE)	8,345	1,059	439	121	51	12

Source: Authors' calculations, based on AMADEUS and REGPAT data.

Table 4.5 gives complementary information on the distribution of the firms with regard to technology, firm size[43], industry[44], and country. The GE patenters in the sample are more involved in EE than RES innovation as 73% of GE firms have patented in the field of EE technologies and only 41% in RES technologies. GE firms tend to be larger compared to the non-GE sample. While 31% of GE firms are categorized as very large, only 17% of the non-GE sample are. The distribution among industries and countries

[43] AMADEUS groups firms into the three size categories very large, large, and medium. For firms to be classified as very large, they have to satisfy at least one of the following criteria: Operating revenue of at least 100 million EUR, total assets of at least 200 million EUR, at least 1000 employees, or the firm has to be publicly listed. The respective criteria for large companies are: at least 10 million EUR operating revenue, at least 20 million EUR total assets, or at least 150 employees. For medium sized firms these criteria are: at least 1 million EUR operating revenue, at least 2 million EUR total assets, or at least 15 employees.

[44] AMADEUS assigns firms to industries using NACE (for the French term "nomenclature statistique des activités économiques dans la Communauté européenne"), the standard European industry classification system.

is very similar between GE firms and the non-GE sample. 50% and 54% respectively are classified as manufacturers which is thus the most prominent industry group. Other well represented groups are professional, scientific and technical activities, wholesale and retail trade as well as construction. Concerning the country distribution of the non-GE firms, Germany (32%) and France (30%) dominate the sample followed by Spain (11%) and Italy (10%). It is interesting to note that GE patenters disproportionately come from Germany (38%).

Table 4.5: Distribution of firms by technology, size, industry, and country.

Technology	RES	EE	GE			
No. of GE firms	399	704	968			
% in GE firms	41%	73%	100%			
Size	**Very Large**	**Large**	**Medium**	**All**		
No. of GE firms	296	305	367	968		
% in GE firms	31%	32%	38%	100%		
No. of non-GE firms	1,399	2,684	4,262	8,345		
% in non-GE firms	17%	32%	51%	100%		
Industry	**Manufacturing**	**Professional, scientific and technical activities**	**Wholesale and retail trade**	**Construction**	**Other**	**All**
No. of GE firms	485	159	126	70	128	968
% in GE firms	50%	16%	13%	7%	13%	100%
No. of non-GE firms	4,559	977	1,357	346	1,106	8,345
% in non-GE firms	54%	12%	16%	4%	13%	100%
Country	**DE**	**FR**	**ES**	**IT**	**Other**	**All**
No. of GE firms	369	290	72	65	172	968
% in GE firms	38%	30%	7%	7%	18%	100%
No. of non-GE firms	2,630	2,542	894	834	1,445	8,345
% in non-GE firms	32%	30%	11%	10%	17%	100%

Source: Authors' calculations, based on AMADEUS and REGPAT data.

4.4 Empirical Strategy

To empirically evaluate the impact of GE innovation on firm performance, I follow the approach by Bloom and Van Reenen (2002) who measure firm performance by productivity. I use a panel data model based on a standard Cobb-Douglas production function for firm i at time t, extended by innovation respectively knowledge as an additional input:

$$Q_{it} = AL_{it}^{\alpha}K_{it}^{\beta}I_{it}^{\gamma}, \tag{4.3}$$

where Q is the output, L is the labor input, K is the capital input, I is the knowledge stock, and A is a constant. The parameters α, β, and γ are elasticities with respect to labor, capital, and knowledge respectively.

The elasticity with respect to labor accounts for the effect on output caused by growth in labor input. The elasticity with respect to capital accounts for the effect in output caused by growth in capital input. These parameters measure the corresponding single factor productivity (SFP) growth. The elasticity with respect to knowledge measures the total factor productivity (TFP) by accounting for the effect in output not caused by the growth in labor and capital input. This is in line with the conventional view that TFP is the measure of the rate of technical change (Krugman, 1996). Precisely, since I will use sales as a proxy for output, I measure revenue productivity which includes both changes in factor productivity as well as in markups as firms are able to raise prices for new innovations (Bloom and Van Reenen, 2002).

Expressing 4.3 in logarithms yields:

$$ln\,(Q)_{it} = ln\,(A) + \alpha ln\,(L)_{it} + \beta ln\,(K)_{it} + \gamma ln\,(I)_{it}\,. \tag{4.4}$$

In the empirical application, I use sales as a proxy for output Q, the number of employees engaged as a proxy for labor L, and total assets as a proxy for capital K. The knowledge stock I is proxied by the firm's GE knowledge stock (GKS), capturing GE specific knowledge, and the respective non-GE knowledge stock (NKS), capturing non-GE knowledge. This allows a separate assessment of the productivity impact of GE and non-GE innovation. Including the non-GE knowledge stock also controls for differences in the firms' overall propensity to patent innovations. The knowledge stocks are included in levels and not in logarithmic form since a substantial number of firms have knowledge stocks of zero (Wooldridge, 2002). In the complete sample of 8,619 firms the share of zero observations is 91% for the GE and 17% for the respective non-GE knowledge stock. Thus, this share is substantial especially with respect to the GE knowledge stock.[45] In order to mitigate any reverse causality problems and to account for the fact, that the impact of innovation on productivity is dynamic and comes with a certain time lag (Bloom and Van Reenen, 2002), the knowledge stock variables are lagged by two

[45] In a robustness test, I address this approach. I use an alternative specification that includes the logged total knowledge stock instead of the separated GE and non-GE stocks in levels. Therefore, the problem of zero knowledge stocks is less pronounced. Using the total knowlege stock in logs does not change the sign and significance of the coefficients so that I continue to use the knowledge stocks in levels in the main specification.

years.[46] To control for correlated unobserved heterogeneity, I include year fixed effects T_t and firm-specific fixed-effects η_i. The baseline specification to be estimated then is given by:

$$\begin{aligned} ln\left(Q\right)_{it} = &\, ln\left(A\right) + \alpha ln\left(L\right)_{it} + \beta ln\left(K\right)_{it} + \gamma_1\left(GKS\right)_{it-2} + \gamma_2\left(NKS\right)_{it-2} \\ &+ T_t + \eta_i + u_{it}, \end{aligned} \tag{4.5}$$

where u_{it} is a standard varying error term (across time and firms). I estimate (4.5) using OLS and fixed-effects (within) regression (least-squares dummy-variable regression) with standard errors cluster-robust to heteroscedasticity (Section 4.5.1). To test the robustness of the baseline model, I use alternative specifications with modifications (Section 4.5.2).

4.5 Results

4.5.1 Baseline Results

The baseline results of estimating the Cobb-Douglas production function (4.5) are presented in Table 4.6. Initially, the full sample of 8,619 firms is used. Column (1) gives the OLS estimates of the production function. As the independent variables employment and total assets enter the estimations in log form, the estimated coefficients can be interpreted as elasticities. The coefficients on employment and total assets are both positive and statistically significant at the 1% level. This result is in line with general expectations. As one would also expect, the sum of the coefficients is close to unity suggesting constant returns to scale. Column (2) has the results of the fixed-effects estimator which controls for time-invariant unobserved heterogeneity between firms by including firm-specific fixed effects. Again the coefficients on employment and total assets are both positive and statistically significant while slightly smaller for employment and slightly higher for total assets. The estimated elasticities of 0.639 and 0.469 suggest that a 10% increase in employment or capital is associated with a 6.4 and 4.7% increase in productivity respectively.

Column (3) reports the results from adding the firm's GE knowledge stock and the corresponding non-GE stock as proxies for a firm's knowledge. As the knowledge stocks enter the estimation in levels, the estimated coefficients have a percentage interpretation when they are multiplied by 100, commonly called semi-elasticity. The GE knowledge stock is negative and significant at the 5% level. The coefficient suggests that an increase of the stock by 1 would lead to a 3.6% decrease in productivity. A doubling of the stock

[46] I test the robustness of my results against other lag structures in Section 4.5.2, Table 4.9.

Table 4.6: Estimated coefficients of the Cobb-Douglas production function. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)	(4)
Firms	All	All	All	GE patenters
Employees (log)	0.700^{***}	0.639^{***}	0.643^{***}	0.441^{***}
	(0.029)	(0.055)	(0.055)	(0.094)
Total assets (log)	0.408^{***}	0.469^{***}	0.469^{***}	0.730^{***}
	(0.027)	(0.047)	(0.046)	(0.167)
GE knowledge stock$_{t-2}$			-0.036^{**}	-0.031^{**}
			(0.014)	(0.012)
Non-GE knowledge stock$_{t-2}$			0.001^{***}	0.001^{***}
			(0.000)	(0.000)
Year dummies	yes	yes	yes	yes
Firm dummies	no	yes	yes	yes
Adj. R-Squared	0.581	0.896	0.896	0.915
No. observations	39152	39152	39152	4482
No. firms	8619	8619	8619	968

Note: Column (1), (2), and (3) present the results using the population of all patenting firms. Column (4) presents the results for the subset of firms with GE patents. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parentheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

with respect to its sample average (0.15) would lead to a 0.5% decrease in productivity. In contrast, the corresponding non-GE stock is positive and significant at the 1% level. Here an increase of the stock by 1 would result in a 0.1% increase in productivity. A doubling of the stock with respect to its sample average (6.11) would result in a 0.6% increase in productivity. Thus, the marginal effect of GE innovation is negative while the marginal effect of non-GE innovation is positive indicating that sales markets do not provide sufficient incentives to increase firms' GE innovation activities but do provide enough incentives to increase firms' non-GE innovation activities. The results suggest, that there is a positive return in terms of productivity for non-GE innovation, but a negative return for GE innovation. Thus, hypothesis H2 can be confirmed: Private economic returns measured in terms of productivity are lower for GE than for non-GE innovation. The findings are in line with the aforementioned examinations by Marin (2014), Marin and Lotti (2016), and Wörter et al. (2015).

The last column (4) gives the results of the previous specification for the subset of the 968 GE patenters. Using this specification, I test if the results in column (3) are robust or mainly driven by the shift from a firm without any GE patents to a firm with GE patents. Again the estimate on the GE knowledge stock is negative and significant although slightly smaller than in column (3). Likewise the coefficient on the respective stock in non-GE patents is still positive and significant but slightly lower. The lower estimates on employment and higher estimates on total assets indicate that the GE patenting firms are on average more capital intensive than the non-GE patenting firms. In fact the GE patenters have on average a 37% higher capital to labor ratio compared to the complete sample.

4.5.2 Robustness Tests

In order to test the sensitivity of the baseline results presented in Table 4.6, I conduct a number of robustness tests based on the main model in column (3).

Table 4.7: Differentiating by technology group. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)	(4)
Firms	All	RES patenters	All	EE patenters
Employees (log)	0.643^{***}	0.508^{***}	0.642^{***}	0.343^{***}
	(0.055)	(0.165)	(0.055)	(0.100)
Total assets (log)	0.469^{***}	0.714^{***}	0.469^{***}	0.707^{***}
	(0.046)	(0.174)	(0.046)	(0.238)
RES knowledge stock$_{t-2}$	-0.055^{*}	-0.061^{**}		
	(0.031)	(0.025)		
Non-RES knowledge stock$_{t-2}$	0.001^{**}	0.001^{***}		
	(0.000)	(0.000)		
EE knowledge stock$_{t-2}$			-0.044^{**}	-0.029^{*}
			(0.022)	(0.016)
Non-EE knowledge stock$_{t-2}$			0.001^{**}	0.001^{**}
			(0.001)	(0.000)
Year dummies	yes	yes	yes	yes
Firm dummies	yes	yes	yes	yes
Adj. R-Squared	0.896	0.896	0.896	0.937
No. observations	39152	1816	39152	3344
No. firms	8619	399	8619	704

Note: Estimations are based on the same specification as in column (3) of Table 4.6. Column (1) and (3) present the results using the population of all patenting firms. Column (2) and (4) present the results for the subset of firms with RES respectively EE patents. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parentheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

First, I repeat the main specification differentiating between two subgroups of GE technologies: RES and EE technologies. Column (1) and (3) in Table 4.7 present results using the population of all patenting firms. Overall, the estimated coefficients are similar but show differences between the two technology groups. The negative coefficients of the RES and EE knowledge stocks are higher compared to the coefficient of the GE knowledge stock, even more so for the RES knowledge stock. Thus, patents in the field of RES have a more pronounced negative impact on productivity than EE patents. This finding may be explained by different maturity levels of RES and EE markets. Again in contrast, the corresponding coefficient of the non-RES and non-EE knowledge stocks are small, but positive and significant.

Column (2) and (4) give the results for the subset of firms with RES respectively EE patents. Doing this, I test again if the results in column (1) and (3) are robust or mainly driven by the shift from non-RES respectively non-EE patenters to RES- respectively EE patenters. The coefficient on the RES knowledge stock is negative and significant and increases slightly in absolute terms compared to column (1). Contrary, the coefficient on the EE knowledge stock decreases slightly compared to column (3) but still remains negative and significant. The coefficients on the respective stocks in non-RES and non-EE patents do not change compared to columns (1) and (3). The estimates on employment and total assets show that both RES and EE patenters are on average more capital intensive than non-GE firms, with EE patenters having the highest capital-intensity. The sum of the coefficients is 1.22 in column (2) and 1.05 in column (2), suggesting higher returns to scale in tangible factors for RES than EE patenters.

Table 4.8: Differentiating by firm size. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)
Firms	Very large	Large	Medium
Employees (log)	0.686***	0.652***	0.606***
	(0.140)	(0.066)	(0.063)
Total assets (log)	0.530***	0.541***	0.412***
	(0.105)	(0.063)	(0.070)
GE knowledge stock$_{t-2}$	−0.031*	−0.039	−0.056
	(0.017)	(0.040)	(0.113)
Non-GE knowledge stock$_{t-2}$	0.001*	0.000	0.004***
	(0.001)	(0.001)	(0.001)
Year dummies	yes	yes	yes
Firm dummies	yes	yes	yes
Adj. R-Squared	0.870	0.846	0.814
No. observations	8109	13956	17087
No. firms	1428	2775	4416

Note: Estimations are based on the same specification as in column (3) of Table 4.6. Column (1) presents the results for the subset of very large, column (2) for the subset of large, and column (3) for the subset of medium sized firms. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parentheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

The relationship between innovation and productivity may be dependent on a firm's size. Therefore, I conduct a second robustness test differentiating between the size of the investigated firms. Table 4.8 reports estimated coefficients of the main model for very large, large, and medium sized firms. The coefficient on the GE knowledge stock, which has been significant in all previous specifications, is only significant for very large firms. For very large firms it also has the same size as in the main specification. The coefficient on the non-GE knowledge stock, likewise always significant before, is highly significant for medium sized firms only, significant at the 10% level for very large firms and insignificant for large firms. Overall, the results are very similar in size but not always statistically significant. The results suggest that the (negative) impact of GE innovation on productivity tends to be more pronounced for larger firms whereas the (positive) productivity effect of non-GE innovation seems to be more important for smaller firms. Possible reasons for the lower levels of significance are that the sample sizes are smaller and the variation of the knowledge stocks is lower between firms of similar size.

Table 4.9: Different lags for the knowledge stocks. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)	(4)
Firms	All	All	All	All
Employees (log)	0.643^{***}	0.643^{***}	0.643^{***}	0.642^{***}
	(0.055)	(0.055)	(0.055)	(0.055)
Total assets (log)	0.469^{***}	0.469^{***}	0.469^{***}	0.469^{***}
	(0.046)	(0.046)	(0.046)	(0.046)
GE knowledge stock	-0.029^{**}	-0.028^{*}	-0.036^{**}	-0.034^{**}
	(0.013)	(0.015)	(0.014)	(0.017)
Non-GE knowledge stock	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{**}
	(0.000)	(0.000)	(0.000)	(0.001)
Year dummies	yes	yes	yes	yes
Firm dummies	yes	yes	yes	yes
Adj. R-Squared	0.896	0.896	0.896	0.896
No. observations	39152	39152	39152	39152
No. firms	8619	8619	8619	8619

Note: Estimations are based on the same specification as in column (3) of Table 4.6. Column (1), (2), (3), and (4) present the results for the current knowledge stocks and for knowledge stocks lagged one, two, and three years, respectively. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parentheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

As noted before, in the baseline specification I lag the knowledge stock variables by two years in order to mitigate any reverse causality problems and to account for the fact that innovative output does not immediately have an effect on a firm's productivity. In order to test the sensitivity of the knowledge stock results to other lag structures, I conduct a third robustness test and re-estimate the main model with the current knowledge stocks and with knowledge stocks lagged one, two (as used in the baseline specification depicted in Table 4.6), and three years. The results are given in Table 4.9. Overall, the results are robust to these modifications. The impact of additional GE innovation on productivity is still negative and the impact of additional non-GE innovation still positive. The higher point estimates on the two- and three-year lag compared to the zero- and one-year lag for both knowledge stocks[47] support the hypothesis of a time lag between innovation and its effect on performance. In other words, patented innovations take some time to enter the production function. Another explanation for the stronger negative impact of additional GE innovation for longer lags might be that marginal costs of GE innovation were higher and demand for GE innovation was lower in earlier periods (for a similar result and reasoning see Wörter et al., 2015).

Table 4.10: Different depreciation rates for the knowledge stocks. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)	(4)
Firms	All	All	All	All
Employees (log)	0.642***	0.643***	0.643***	0.643***
	(0.055)	(0.055)	(0.055)	(0.055)
Total assets (log)	0.469***	0.469***	0.469***	0.468***
	(0.046)	(0.046)	(0.046)	(0.047)
GE knowledge stock$_{t-2}$	−0.026**	−0.036**	−0.042***	−0.046***
	(0.012)	(0.014)	(0.016)	(0.017)
Non-GE knowledge stock$_{t-2}$	0.001**	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.001)	(0.001)
Year dummies	yes	yes	yes	yes
Firm dummies	yes	yes	yes	yes
Adj. R-Squared	0.896	0.896	0.896	0.896
No. observations	39152	39152	39152	39152
No. firms	8619	8619	8619	8619

Note: Estimations are based on the same specification as in column (3) of Table 4.6. Columns (1), (2), (3), and (4) present the results for knowledge stock depreciation rates of 5%, 10%, 15%, and 20%, respectively. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parentheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

The final robustness test is done by utilizing different depreciation rates in the calculation of the knowledge stocks. Table 4.10 reports the main model estimates for depreciation rates of 5%, 10% (as used in the baseline estimation depicted in Table 4.6), 15%, and 20%. The higher the depreciation rate, the lower the importance of past knowledge. A depreciation rate of 100% would mean that the knowledge stock becomes a flow variable, that is only the patents from the current period contribute to a firm's productivity. For all specifications, the coefficients on the GE and non-GE knowledge stocks are significant at least at the 5% level. While the coefficient on the non-GE knowledge stock does not vary in size, the coefficient on the GE stock becomes more negative using higher depreciation rates. Hence, the negative effect of GE knowledge on productivity becomes larger when firms can rely on less previous GE knowledge. In other words, a larger GE knowledge stock mitigates the negative effect that an increase in GE knowledge has on

[47] For the non-GE coefficients, the increase concerns the fourth decimal place and cannot be seen in the presented output table.

productivity. An explanation might be that firms with a larger knowledge stock in GE technologies have lower R&D costs for the same amount of inventive output than firms with a lower knowledge stock.

4.6 Conclusions

In this article, I studied the effect of innovation in GE technologies on the economic performance of firms and compared it to the effect of non-GE innovation. I based my study on a panel of 8,619 patenting firms including 968 GE patenters from 22 European countries over the period 2003 to 2010. To construct the panel, I combined firm accounts data with data on firms' patent applications.

My results show that, all else equal, innovation in GE technologies has a negative impact on the economic performance of firms while innovating in non-GE technologies positively affects firms' economic performance. This confirms the hypothesis H2 that private economic returns in terms of productivity are lower for GE than for non-GE innovation, which corresponds to previous results found by Marin (2014), Marin and Lotti (2016), and Wörter et al. (2015). I also find evidence for different performance effects across GE technologies. My results reveal that the negative effect on firm performance is more pronounced for RES than for EE technologies. Moreover, my findings suggest that the negative relationship between GE innovation and performance is stronger for larger firms. Furthermore, the negative impact of GE innovation on performance is found to be stronger with a larger time lag between both. On the one hand, this supports the hypothesis of a time lag between innovation and its impact on performance. On the other hand, it indicates that marginal costs of GE innovation decreased and demand for GE innovation increased over time. Finally, the use of different knowledge depreciation rates shows that the negative impact of new GE patents on performance is less pronounced when firms can build on an existing stock of GE knowledge.

Given these results, the initial research question can be answered: since GE innovation guarantees lower private returns than non-GE innovation, firms forgo economic opportunities by innovating in GE technologies and gain economic opportunities by concentrating on innovation in non-GE technologies. However, as one can observe in the data, firms nevertheless have invested in GE technologies. Since the resources that firms can allocate to R&D investment projects are limited and since firms always choose the project with the highest private return, this observation evidences a potential crowding out of GE innovation at the expense of (more rewarding) non-GE innovation. Thus it seems that there where factors (for example political expectations, environmental regulation) that somewhat forced firms to use their scarce R&D funds for projects with comparatively low returns (Marin, 2014). Assuming that the non-private returns for the GE and the non-GE project are the same, this crowding out would be welfare decreasing. However, if the GE project has higher social returns (that is combined private and non-private returns) compared to the non-GE project, this crowding out would be welfare increasing. This then would be an argument for policy intervention aiming to increase private returns of GE innovation in order to promote socially beneficial green growth.

Appendix A

Supplementary Material for Chapter 2

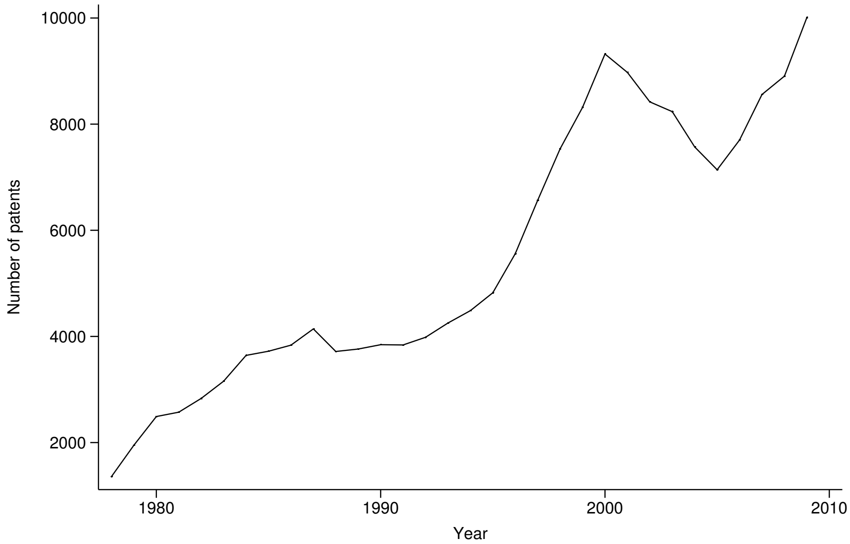

Figure A.1: Total number of green energy EPO patent applications of 26 OECD countries, 1978-2009.

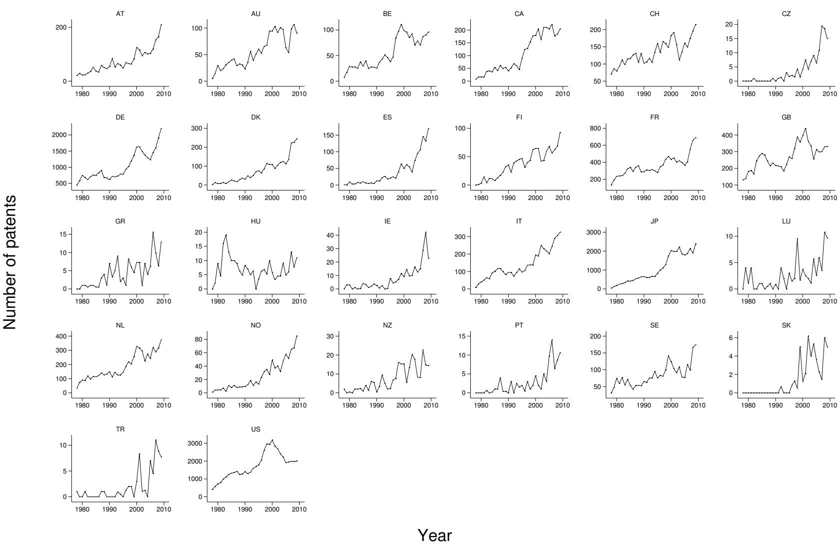

Figure A.2: Annual number of green energy EPO patent applications by country, 1978-2009. *Note*: The country codes are the same as in Table 2.1.

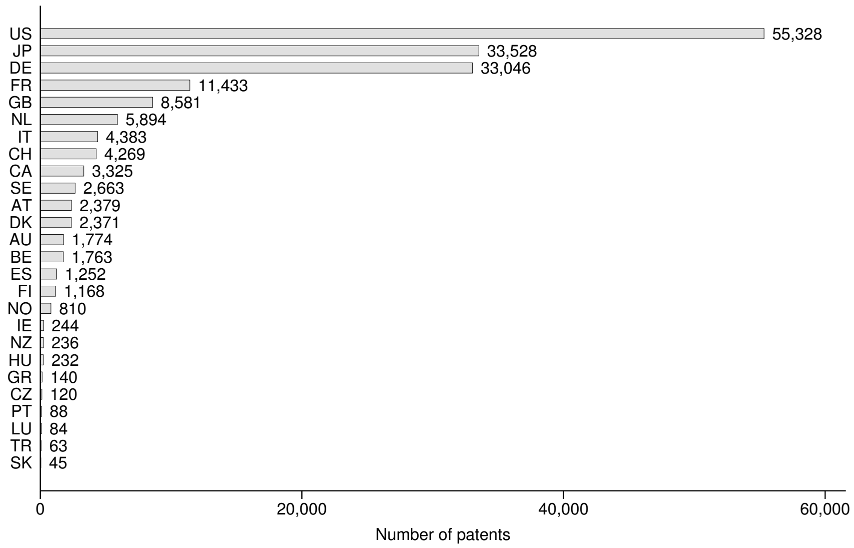

Figure A.3: Total number of green energy EPO patent applications over 1978-2009 by country. *Note*: The country codes are the same as in Table 2.1.

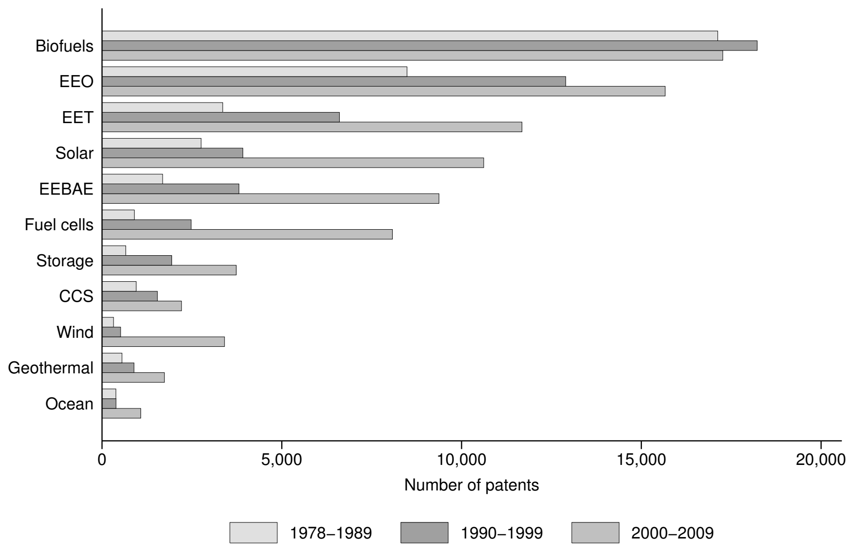

Figure A.4: Total number of EPO patent applications of 26 OECD countries over three time periods by green energy technology.

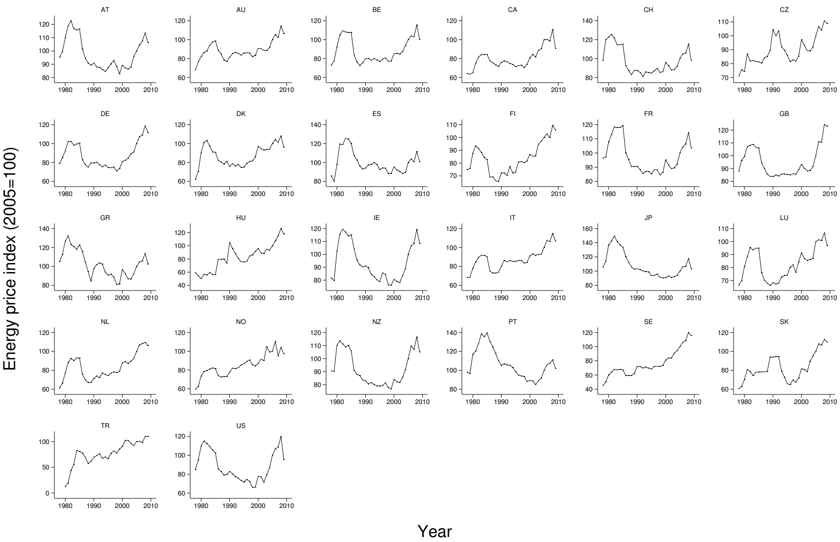

Figure A.5: Real total energy end-use price for households and industry by country (index: 2005=100), 1978-2009. *Note*: The country codes are the same as in Table 2.1.

Table A.1: Number of EPO patent applications by country and green energy technology.

Country	Biofuels	CCS	Fuel cells	Geothermal	Ocean	EEO	EEBAE	Solar	Storage	EET	Wind	Total
AT	318	33	55	64	46	434	307	263	69	722	66	2,379
AU	666	43	69	37	53	286	82	263	47	186	43	1,774
BE	907	22	35	28	17	248	151	167	20	115	52	1,763
CA	1,114	110	404	34	42	616	174	179	168	414	70	3,325
CH	1,021	58	182	210	55	1,074	365	438	109	687	68	4,269
CZ	25	2	2	5	6	30	10	9	5	25	1	120
DE	7,589	699	1,965	878	269	7,352	3,094	3,657	987	5,360	1,197	33,046
DK	806	39	122	24	43	295	127	200	50	91	574	2,371
ES	257	12	30	26	36	149	93	266	30	175	178	1,252
FI	281	18	36	49	27	403	97	73	43	101	39	1,168
FR	3,414	429	425	130	173	2,763	641	992	348	1,963	156	11,433
GB	3,244	304	369	116	197	1,883	671	619	166	796	216	8,581
GR	31	0	5	4	14	17	13	20	2	24	10	140
HU	94	2	2	13	4	40	13	26	11	21	5	232
IE	50	2	1	1	42	41	41	30	7	11	18	244
IT	921	52	196	90	80	917	403	467	93	1,035	128	4,383
JP	5,590	482	3,955	547	122	6,144	4,617	4,442	2,151	5,128	350	33,528
LU	8	1	7	1	1	21	16	12	4	7	6	84
NL	2,086	183	148	73	49	1,515	717	435	119	394	175	5,894
NO	139	126	23	27	83	161	32	90	10	46	73	810
NZ	96	4	7	5	2	37	9	15	14	43	2	236
PT	14	3	3	0	9	9	4	25	1	10	10	88
SE	481	67	54	104	70	703	211	236	144	489	104	2,663
SK	13	0	0	1	5	6	3	6	0	9	2	45
TR	8	0	5	1	1	9	11	13	2	8	5	63
US	23,438	2,009	3,353	713	405	11,889	2,965	4,348	1,729	3,781	697	55,328
Total	52,614	4,701	11,455	3,181	1,853	37,044	14,867	17,290	6,330	21,640	4,245	175,220

Note: The country codes are the same as in Table 2.1.

Table A.2: Number of EPO patent applications by green energy technology and time period.

Technology	1978-1984	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	Total
Biofuels	8,848	8,277	6,442	11,780	10,778	6,488	52,614
CCS	408	542	628	912	1,026	1,184	4,701
Fuel cells	434	465	687	1,792	4,522	3,555	11,455
Geothermal	312	244	357	532	723	1,013	3,181
Ocean	221	166	161	229	383	694	1,853
EEO	3,546	4,938	5,957	6,940	8,213	7,450	37,044
EEBAE	760	925	1,348	2,461	4,741	4,632	14,867
Solar	1,554	1,202	1,492	2,425	3,932	6,684	17,290
Storage	293	367	606	1,331	1,696	2,037	6,330
EET	1,430	1,926	2,576	4,027	5,450	6,229	21,640
Wind	197	123	149	367	1,059	2,348	4,245
Total	18,004	19,177	20,405	32,798	42,521	42,314	175,220

Table A.3: Total number of total EPO patent applications and total number of green energy EPO patent applications over 1978-2009 by country.

Country	Number of total patents	Relative share in sum of total patents	Number of green energy patents	Relative share in sum of green energy patents	Ratio of green energy patents to total patents
AT	27,813	1.19%	2,378	1.36%	8.55%
AU	19,492	0.83%	1,773	1.01%	9.10%
BE	27,320	1.17%	1,763	1.01%	6.45%
CA	35,753	1.53%	3,324	1.90%	9.30%
CH	65,331	2.79%	4,268	2.44%	6.53%
CZ	1,588	0.07%	120	0.07%	7.57%
DE	475,912	20.35%	33,045	18.86%	6.94%
DK	18,896	0.81%	2,370	1.35%	12.55%
ES	17,496	0.75%	1,251	0.71%	7.15%
FI	23,121	0.99%	1,167	0.67%	5.05%
FR	175,655	7.51%	11,433	6.53%	6.51%
GB	131,161	5.61%	8,580	4.90%	6.54%
GR	1,363	0.06%	139	0.08%	10.26%
HU	3,239	0.14%	231	0.13%	7.16%
IE	4,258	0.18%	244	0.14%	5.74%
IT	86,489	3.70%	4,383	2.50%	5.07%
JP	419,708	17.95%	33,527	19.13%	7.99%
LU	1,596	0.07%	84	0.05%	5.29%
NL	67,132	2.87%	5,894	3.36%	8.78%
NO	8,065	0.34%	810	0.46%	10.05%
NZ	2,925	0.13%	235	0.13%	8.05%
PT	1,050	0.04%	87	0.05%	8.37%
SE	48,335	2.07%	2,663	1.52%	5.51%
SK	347	0.01%	45	0.03%	13.08%
TR	1,927	0.08%	63	0.04%	3.29%
US	672,831	28.77%	55,328	31.58%	8.22%
Total	2,338,817	100.00%	175,220	100.00%	7.49%

Note: The country codes are the same as in Table 2.1.

Appendix B

Supplementary Material for Chapter 3

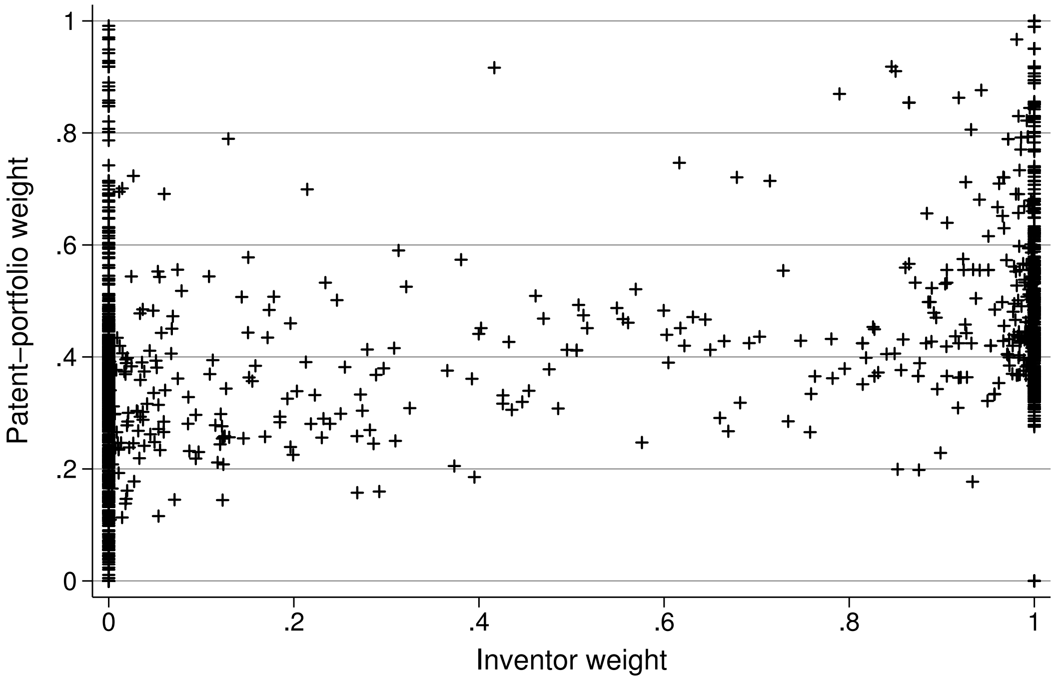

Figure B.1: Patent-portfolio weights versus inventor weights for the USA. *Source:* Authors' calculations, based on PATSTAT. *Note:* The figure shows combinations of patent-portfolio weights (y-axis) and inventor weights (x-axis) for the USA for all 3,648 firms.

Table B.1: 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 B.2: 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 B.3: 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 B.4: 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 B.5: 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).

Appendix C

Supplementary Material for Chapter 4

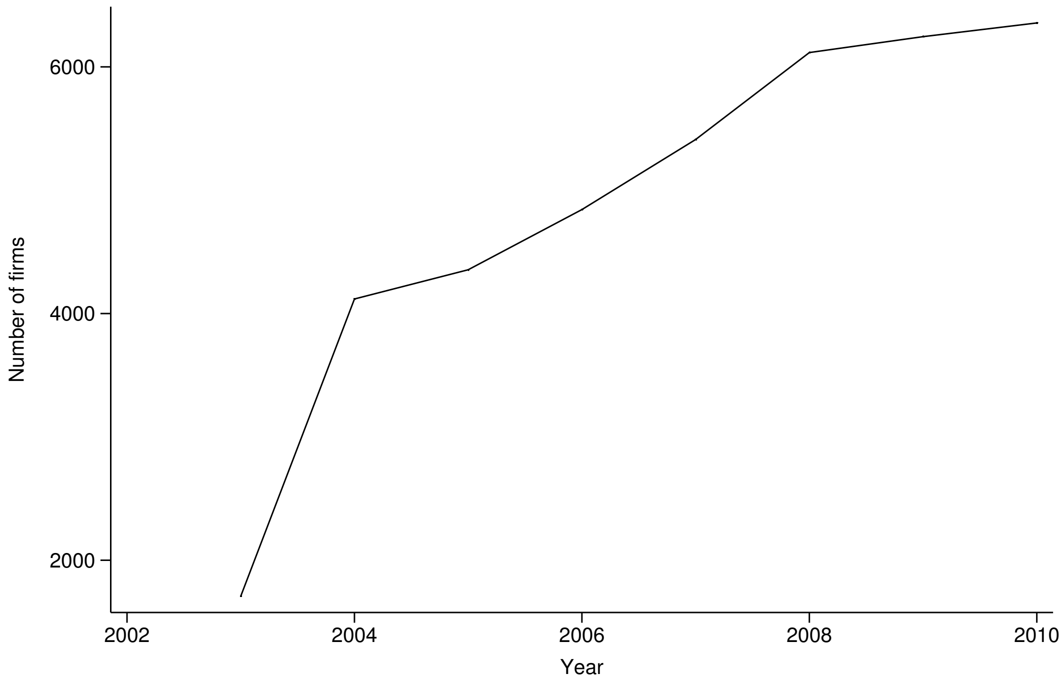

Figure C.1: Number of firms, 2003-2010. *Source:* Authors' calculations, based on AMADEUS and REGPAT data.

Table C.1: Number of yearly patent applications filed at the EPO by all firms by technology group.

Year	RES	EE	GE	Non-GE
1977	0	0	0	66
1978	0	3	3	212
1979	2	7	9	309
1980	1	9	10	390
1981	1	12	13	504
1982	4	14	18	530
1983	5	16	18	548
1984	7	20	24	647
1985	3	32	35	749
1986	7	26	27	891
1987	4	28	32	1,024
1988	3	25	28	1,140
1989	11	30	32	1,267
1990	5	33	38	1,268
1991	3	29	31	1,331
1992	5	40	45	1,390
1993	10	45	52	1,609
1994	8	42	47	1,768
1995	12	35	40	2,034
1996	11	33	40	2,487
1997	20	57	68	2,886
1998	25	62	77	3,419
1999	26	88	100	3,883
2000	41	108	119	4,278
2001	59	101	143	4,440
2002	51	94	134	4,911
2003	46	94	130	5,522
2004	63	110	168	6,142
2005	54	89	141	6,959
2006	82	142	207	7,324
2007	106	168	241	7,739
2008	132	181	261	7,558
2009	195	192	356	7,925
2010	189	207	336	7,691
Total	1,190	2,171	3,021	100,835

Source: Authors' calculations, based on AMADEUS and REGPAT data.

Table C.2: Country distribution of GE firms.

Country	No.	%
DE	369	38.12
FR	290	29.96
ES	72	7.44
IT	65	6.71
SE	49	5.06
AT	46	4.75
BE	24	2.48
NO	23	2.38
FI	6	0.62
CH	5	0.52
PL	5	0.52
GB	4	0.41
DK	3	0.31
LU	3	0.31
CZ	2	0.21
LV	1	0.10
NL	1	0.10
Total	968	100.00

Source: Authors' calculations, based on AMADEUS and REGPAT data.

Table C.3: Country distribution of non-GE firms.

Country	No.	%
DE	2630	31.51
FR	2542	30.46
ES	894	10.71
IT	834	9.99
SE	502	6.02
AT	313	3.75
NO	234	2.80
BE	184	2.20
FI	45	0.54
PL	37	0.44
CH	32	0.38
DK	25	0.30
GB	22	0.26
LU	17	0.20
EE	9	0.11
NL	9	0.11
CZ	6	0.07
HU	4	0.05
LV	3	0.04
GR	1	0.01
LI	1	0.01
SI	1	0.01
Total	8345	100.00

Source: Authors' calculations, based on AMADEUS and REGPAT data.

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