May 2023

The Role of Energy Storage in the Transition Toward a Carbon-Neutral Economy

Siyu Feng
University of Wisconsin-Milwaukee

THE ROLE OF ENERGY STORAGE IN THE TRANSITION TOWARD A CARBON-NEUTRAL ECONOMY

by

Siyu Feng

A Dissertation Submitted in

Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

in Economics

at

The University of Wisconsin-Milwaukee

May 2023

ABSTRACT

THE ROLE OF ENERGY STORAGE IN THE TRANSITION TOWARD A CARBON-NEUTRAL ECONOMY

by

Siyu Feng

The University of Wisconsin-Milwaukee, 2023
Under the Supervision of Professor Itziar Lazkano

Energy transitions to less-carbon intense technologies, such as wind and solar energy, in the electricity, sector are crucial to realizing international climate goals because the electricity sector has been one of the main global carbon emitter for decades, and environmental plans in most countries involve electrifying heavily polluting industries with clean electricity generation. The intermittency problem of renewable energy has been the main stumbling block on the path, and energy storage is now referred to as the key in these transitions because it can boost renewable energy use while also improving the efficiency of conventional power plants (Hall and Bain, 2008). However, existing large-scale energy storage is still expensive. Innovation has been playing a decisive role in reducing costs and expanding capacity.

Referring to a conversion of electrical energy from a power network to a storable form for later use (Price, 2011), energy storage is relatively newly developed, compared with generation technologies. Economists have been seeking to contribute to the understanding of innovation and its links with environmental policies and outputs, such as the key determinants of innovation in energy storage and which policies are successful at promoting it. My dissertation focuses on the innovation in energy storage, especially its role in the transition toward a carbon-neutral economy.

Using patent data from 1978 to 2019 across 1881 regions, Chapter 1 studies the innovation trend in energy storage at the global level and estimates the main determinants. Results show an overall positive trend in storage patents, indicating its

importance in the electricity sector. In addition, the results highlight the role of energy prices and past innovation in shaping innovation. Specifically, a one-unit increase in electricity prices leads to a 15.54% reduction in the ratio of storage to electricity generation patents. These results imply the need for a combination of energy policies and innovation policies to boost innovation in energy storage.

In Chapter 2, I examine the impact of market-based environmental policies on innovation in energy storage. My results highlight the role of environmental taxes, feed-in tariffs for solar energy, and tradable certificates for CO_2 emissions in promoting firms' patenting activity, whereas renewable energy certificates and energy efficiency certificates discourage it. These results imply the need for more stringent market-based environmental policies to incentivize innovation in energy storage.

Chapter 3 focuses on the role of energy storage in realizing energy transitions and whether energy storage subsidies successfully accelerate such transitions. While many point to energy storage as the solution to the intermittency problem of renewable resources, the relationship between energy storage and nonrenewable resources receives far less attention. By modifying the theoretical model of directed technical change, a subsidy to energy storage is presented as a mechanism that benefits both clean and dirty sectors and influences the optimal allocation. Finally, it might play a more important role in energy transitions by easing the substitution between clean and dirty inputs than encouraging innovation directly.

To

my parents,

and my grandparents.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

'No man is an island', so I would like to acknowledge and thank the people who supported me along the way, believed in me, and pushed me to the finish line. I would not have made it without you.

First and foremost, I would like to express my heartfelt gratitude to my advisor, Professor Itziar Lazkano, for her unwavering support and guidance throughout this journey. Thanks to her expertise, hard work, and involvement, I have been able to receive excellent graduate training in environmental and energy economics and to develop many important skills. Yet, the reach of her supervision has stretched far beyond the academic and professional aspects. Her wisdom, generosity, and kindness have made a profound impact on my career and my life. I will always cherish the opportunity to learn from her.

I am grateful to my committee members, Professor Matthew McGinty, Professor Rebecca Neumann, and Professor Jangsu Yoon, for their invaluable feedback and insights that have helped me to shape and refine my ideas. I also want to extend my appreciation to all the professors in the UWM economics department whose courses I have been fortunate to take, as well as to all employees who make it a wonderful place of learning.

I would also like to thank my cohort and friends at UWM for becoming my allies in the pursuit of a PhD. I thank my dear friends Mingyue, Sinem, Yuting, Qi, and others who have stood by my side through thick and thin and have been a constant source of laughter and joy.

Finally, I am indebted to my family. I wish to express my deep appreciation to my parents and grandparents, who have always been with me through all the ups and downs of life and the driving force behind everything I do.

I look forward to the new summits that this world has to offer me, and am ready to love the journey and love the grind.

Chapter 1

Innovation Trends in Electricity Storage: What Drives Global Innovation?

1.1 Introduction

Climate change concerns such as heat waves and rising sea levels present a great macroeconomic challenge that requires a drastic reduction in carbon emissions to fully mitigate. As the electricity sector is the single largest carbon emitter worldwide,[1] energy transitions to less-carbon intense technologies within the sector are crucial to realizing climate change goals. The intermittency problem of renewable energy like wind and solar, leading to high costs and low capacity, has been the main treadstone on the path. Energy storage technologies are now referred to as the key in these transitions because they can boost renewable energy use while also improving the efficiency of conventional power plants. Unfortunately, existing technologies are expensive, and their expansion is limited. To resolve these issues, innovation in electrical storage has received global attention.

[1]In 2018, global electricity generated 41.7% of total carbon emissions. In the same year, 37% of carbon emissions and 31% of total greenhouse gas emissions in the U.S. came from the electricity sector (International Energy Agency, 2020).

Energy storage technologies include a range of systems able to store electrical energy for later use. The earliest form of energy storage is pumped hydropower, which dominates global capacity but offers limited expansion opportunities. Newer systems such as batteries are easier to scale. However, their high cost prohibits widespread adoption. For example, a transition to 100-percent renewable energy requires storage capacity costs to drop 90 percent, roughly $20 per KWh (Ziegler et al., 2019). In addition, the International Energy Agency (2020) estimates that international climate goals require 266 GW of storage capacity by 2030. As of 2017, global storage capacity was 176.5 GW and only 2.9 GW were added in 2019. Innovation has played a decisive role in making batteries cheaper and promoting the development of new storage systems such as compressed air-energy storage and flywheels. In this paper we document these innovation trends and study the drivers of innovation.

Our goal is to identify the key determinants of innovation in electrical storage. To do so, we first build a novel patent dataset from 1978 to 2019 and describe innovation trends in electricity storage. Then, we study the drivers of innovation by estimating a dynamic regional log-log induced innovation model.

Our global dataset includes energy storage and electricity generation patents, which are drawn from the Organisation for Economic Cooperation and Development (OECD) patent database. Our dataset is unique because we identify technologies related to electricity storage by creating a new list of storage International Patent Classification (IPC) codes. Overall, our dataset includes 219,265 patent applications across 1,881 NUTS3/TL3 regions in 93 countries from 1978 to 2019. Out of these, there are 12,701 electricity storage patents. We also consider energy prices and macroeconomic variables such as government R&D, electricity consumption, and GDP.

To study the main drivers of innovation, we estimate a log-log regression model following Popp (2002). Our model combines information on both market demand and technological opportunity including energy prices, past innovation, spillover effects, electricity consumption, generation capacity, and R&D spending. We also use citation-adjusted knowledge stocks to incorporate the rates of decay and diffusion of existing patents. This innovation model is helpful for two reasons. First, it overcomes the difficulty of specifying a structural model of poorly-understood R&D processes in different regions. In addition, we can interpret the estimated coefficients as elasticities. Thus, our results show the causal effect of different variables in the ratio of storage to electricity generating patents.

Our analysis shows an overall positive trend in storage patents, indicating its growing importance in the electricity sector. Most innovation is directed at improving batteries which have been the main electrical energy storage vessel used in the last decades. Not surprisingly, Japan, the U.S. and Germany lead innovations in the electricity sector.

Our empirical results highlight the importance of energy prices and past innovation to determine innovation in storage. First, we find a positive energy price effect on the share of storage to electricity patents. Prior literature finds a strong and positive impact of energy prices on cost reducing and clean energy patents. This literature contributes to the understanding of the relationship between environmental policy and innovation, which focuses on either pollution abatement control expenditures (see e.g. Brunnermeier and Cohen, 2003; Lanjouw and Mody, 1996; Johnstone et al., 2010) or energy prices (see e.g. Newell et al., 1999; Popp, 2002). For example, Crabb and Johnson (2010), Knittel (2011), Kim (2014), and Aghion et al. (2016) focus on the automobile industry, while Verdolini and Galeotti (2011a), Noailly (2012), Ley et al. (2016), Girod et al. (2017), and Costantini et al. (2017) study energy-efficient and environmentally friendly technologies. These and other related papers use an average energy price index as the price instrument. In addition, we find that a one-unit increase in electricity price leads to a 15.54% reduction in the share of storage patents relative to electricity generation patents. This result is consistent with the directed technological change model developed by Acemoglu et al. (2012) and the empirical findings of Stevens and Tang (2021) who study how renewable policies affect the number of patent applications in complementary technologies such as combustion mitigation and storage technologies. Using country-level patent data from 25 OECD countries between 1992 and 2015, they estimate a negative binomial model and find evidence of a negative electricity price effect on storage technologies. Their focus is on the heterogenous impact of renewable policies such as feed-in-tariffs and certificates on complementary technologies, whereas our focus is on the determinants of innovation in electricity storage. These results suggest that we cannot rely on price policies to increase the share of patenting in energy storage.

Second, we emphasize the importance of past innovation to promote current inventive activity. In line with Popp (2002), who finds that the quality of existing knowledge has a strong and significant positive effect on innovation, we find that one more citation-adjusted past patent leads to almost 14.03% more innovation in the storage to electricity ratio. In addition, we find a strong relationship between storage technologies and past innovation in renewable and fossil-fuel technologies. These results suggest that policies that improve the quality of research in storage technologies may be important to boost further innovation in storage.

Our paper contributes to the understanding of induced innovation in the energy sector.[2] A large share of this literature has empirically examined the drivers of energy-efficient and renewable innovation. For example, using U.S. energy patent data from 1950 to 1994, Popp (2002) finds a strong and positive impact of energy prices on innovation in the energy sector. He also finds that the quality of existing patent applications shapes the direction of innovation. We follow Popp (2002)'s methodology to study the determinants of innovation in electricity storage. Another key study is Acemoglu et al. (2012) as they set up the framework to study induced innovation in the energy sector by incorporating market sizes along with energy prices. In addition, they theoretically establish that environmental policy is a strong determinant of innovation, where carbon taxes and research subsidies encourage energy-efficient innovation. Building on this framework, Aghion et al. (2016) provide empirical evidence for path dependence of clean energy innovation and find that carbon taxes promote the innovation using patent data in the automobile industry. Furthermore, Acemoglu et al. (2016) study the structure and time path of optimal policies in the transition to clean technology in the US energy sector using a quantitative model. While many have

[2]See Popp (2019) for an excellent review of the literature.

focused on the invention of clean technologies and energy-efficient conventional technologies in energy generation and transmission, energy storage has received far less attention.

Hall and Bain (2008) refer to energy storage as “the key to unlocking the door of renewable energy.” Fabrizio et al. (2017) examine the impact of demand- and supply-pushed policies on energy storage innovation using international panel data. For a given country, they find that only demand-pull policies promote domestic innovation in energy storage. Building on the framework of Acemoglu et al. (2012) and using a firm-level dataset of patents, Lazkano et al. (2017a) is one of the first to empirically analyze the importance of electricity storage in the energy sector. While their focus is on the role of electricity storage in fostering innovation in both conventional and renewable electricity generation, our focus is on studying the determinants of innovation in storage technologies.[3]

The paper is organized as follows. In the next section, we describe our patent dataset. In section 1.3 we discuss innovation trends according to statistics. Section 1.4 introduces our model and empirical strategy, and section 1.5 analyzes the estimation results. Finally, section 1.6 concludes the paper.

1.2 Patent Data Selection

We use patent applications drawn from the OECD patent database to measure research output and past innovation. One advantage of using patent data is that patent citations offer a good proxy of innovation quality and can be used to measure knowledge stocks because they confirm that the improvement over previous technologies (Verdolini and Galeotti, 2011a). Patent applications contain detailed information including application and grant year, the inventor country and NUTS3/TL3 region,[4]

[3]Our dataset is different than the one created by Lazkano et al. (2017a). They rely on the list of IPC codes created by the Wold Intellectual Property Organization (WIPO) to identify storage patents. In contrast, we create our own list of IPC codes building on Price (2011) in addition to the ones listed by WIPO. This results in a more extensive dataset of electricity storage patents.

[4]We adopt “NUTS3/TL3 region” definition to conduct our regional analysis. The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic

technology type, International Patent Classification (IPC) codes, their backward and forward citations.[5]

To create our unique dataset, we rely on IPC codes that identify the type of technological invention. Specifically, we select IPC codes related to energy storage.[6] Price (2011) defines energy storage as the conversion of electrical energy from a power network to a storable form for later use. Storage technologies capture electricity, store it in a different form of energy (chemical, thermal, or mechanical), and then release it when needed. Our focus is on storage technologies that benefit the electricity industry; those widely used in the supply side of electricity market.[7] We review the most common methods of energy storage in Appendix A.1, which we lean on to build a list of storage patents. Most of these patents are also electricity patents, however, this is not the case for all storage patents. We provide the complete list of the selected IPC classes used to extract patents in tables A.2.1 and A.2.2 in Appendix A.2. From this list, we identify storage patent applications and group them into four different categories according to their technology types: "General," "Fuel cells," "Hydro" and "Wipo." All patents related to batteries and fuel cells are in "General" and "Fuel cells", respectively. The group "Hydro" includes patents related to technologies storing electricity as hydropower. Finally, patents of other storage technologies identified by the IPC green inventory of the World Intellectual Property Organization (WIPO) are added into group "Wipo."

Overall, our dataset includes 219,265 patent applications across 1,881 regions in 93

territory of the EU and the UK for the purpose of socio-economic analyses of the regions", where NUTS 3 is small regions for specific diagnoses. See https://ec.europa.eu/eurostat/web/nuts/background. Similarly, "TL3" is the OECD Territorial Database used to classify regions within OECD member countries.

[5] Usually there are two types of citations. Backward citations are patent cited or referenced by the current patent, while forward citations are patents citing or referencing the current patent.

[6] We allocate each patent to every technology type it relates to. When a patent has J IPC classifications, we assign one patent to each one of these technologies. For example, consider a patent with three IPC codes, two related to storage and one related to renewable energy. In this case, we assign one patent to storage technologies and one patent to renewable technology.

[7] We identify storage technologies related to electricity supply, for example, short-term storage, fuel cells and electrolyser, rather than technologies mainly adopted by the demand side, for example hydrogen. The storage technologies used in the electricity sector are invented by firms affiliated with a variety of industries. For example, top innovative companies include energy companies such as General Electric Company, technology companies such as Siemens, companies from the automobile industry such as Toyota, or material companies such as Mitsubishi Chemical Corporation.

countries from 1978 to 2019.[8] Out of these patents, there are 12,701 storage patent applications.[9] Among all types of technologies, some appear to be more cost- or capacity-efficient. We analyze current trends in energy storage technology innovation through patent data.

1.3 Trends and Summary Statistics

In this section, we present descriptive statistics with a focus on innovation trends in electricity storage relating to invention country and technology type.[10]

1.3.1 Patenting trends over time

Figure 1.1 shows that from 1978 onwards, patenting in electricity storage technologies has slowly and stably increased with a steady growth since the 90s. There is a significant decline in 2011, which is followed by a sharp increase. The reason could be that the global electricity sector has faced some major changes since 2000s, including the shale gas boom and a global push to reducing fossil fuels. In addition, the intermittency challenge of renewable energy has led innovation effort towards storage as it is key to unlocking the door of renewable energy (Hall and Bain, 2008). The sharp decline in recent years can be partially explained by the application-to-grant time lag of patenting publication, as documented by Lanzi et al. (2011).[11]

Next, Figure 1.2 shows patenting in energy storage technologies and electricity generation technologies as a percentage of the entire electricity sector. There is no substantial change in storage patenting relative to patenting in generation technologies.

[8] We allocate each patent to the region of its inventor. When a patent has N inventors in multiple regions, we assign $1/N$ patents to each region. For example, consider a patent with two inventors, one located in U.S. region 1 and the other one in Japan region 1. In this case, we assign 0.5 patents to U.S. region 1 and 0.5 patents to Japan region 1.

[9] We also identify renewable energy generation technologies and fossil-fuel energy generation technologies according to Johnstone et al. (2010).

[10] As is common with patent data, our dataset presents truncation bias. To correct this truncation bias, we calculate the application-grant empirical distribution and adjust our sample with calculated weights following Hall et al. (2005).

[11] We show trends from 1978 to 2017 because the last-two-year data would be strongly biased by the time lag of patenting publication

Innovation activities in the three most innovative countries, Japan, the U.S., and Germany show a trend most consistent with the global trend in Appendix A.3 Figure A.3.3. These figures show more fluctuations than the total patenting trend in Figure 1.1. Overall, they present an increasing trend since the 1990s and suffered the decline in 2011. As the most innovative country, innovation in Japan has increased by leaps and bounds from 1978 while innovation in the U.S. started to boom after 2011. In contrast, innovation in Germany remained relatively stable until 2015 when the share of storage patents decreased.[12] The share of storage technologies in the U.S. and Germany follows the same trend as the full sample, while in Japan, patenting in storage overtook patenting in generation technologies in the late 1990s. Overall, these figures show a positive trend in electricity storage patents, which suggests the increasing importance of these technologies in the electricity sector. While the importance of storage continue to increase, generation technologies continue to dominate innovation activities in the sector.

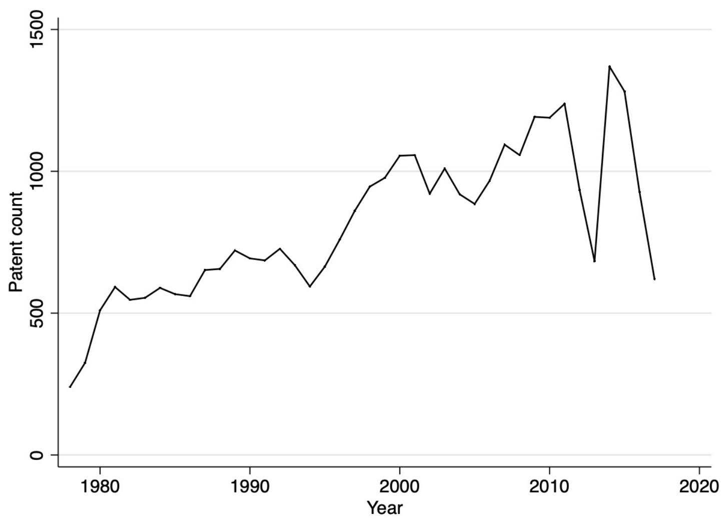


Figure 1.1: Patenting trend in electricity storage technologies, 1978-2017.

[12]Starting in 2015, the number of storage and generation patents decrease in Germany. While the number of electricity patents also decreased temporarily, by 2017 the number of applications return to their 2015 level. The last few years of our sample suggest that patent applications in the electricity sector moved away from generation and storage technologies.

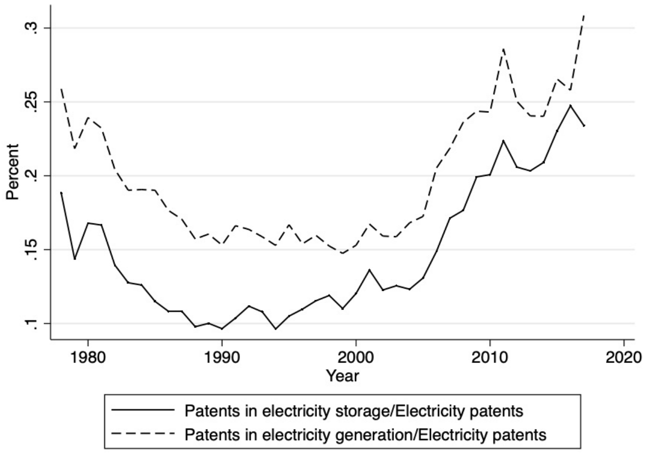


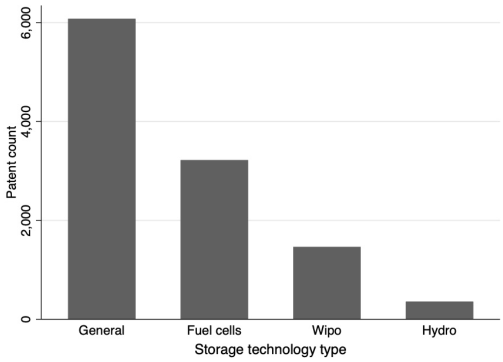
Figure 1.2: Percentage of patents in electricity storage over total electricity patents, 1978-2017.

1.3.2 Patenting by technology type

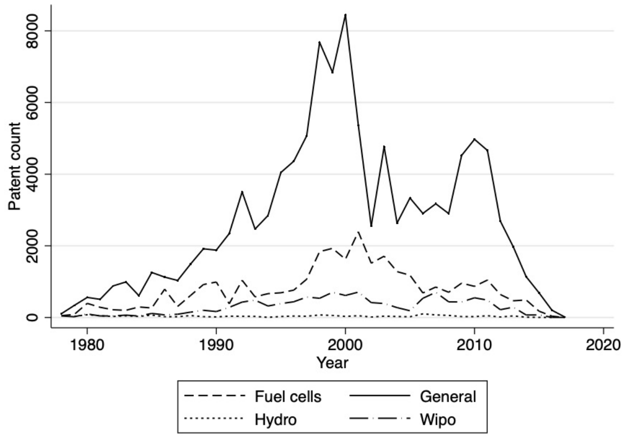
To understand the nature of patents in electricity storage, we turn our attention to different technology types. Looking at individual IPC codes in Appendix A.3 Figure A.3.1, we find that innovation in electricity storage mainly happens in IPC "H02J007/00" related to technologies for battery efficiency.[13] Most of top 10 technologies are related to either "General" or "Fuel cells." This is consistent with Figure 1.3a where we group patents according to the main four different technology types. Batteries in group "General," compromise most patents and more than twice as many as those in "Fuel cells" group. Fuel cells have the efficiency advantage and can operate for long periods without maintenance, so they attract high innovation effort to reduce their costs. Perhaps motivated by high efficiency, low prices, and little location limitations, batteries attract the most innovation effort. Besides, technologies in batteries are well developed so that they may provide better opportunities for further technological improvement. Therefore, general storage technologies have been the main electrical energy storage vessel used in the last decades by analyzing patenting either by single technology or by technology type.

Not surprisingly, different electricity storage technology types are experiencing

[13]H02J007/00 is technologies of circuit arrangements for charging or depolarising batteriesor for supplying loads from batteries. See details in Table A.2.1 in Appendix A.2.



(a)The number of patents



(b)Trend in patenting

Figure 1.3: Patenting by technology type of of electricity storage technologies, 1978-2017.

different patenting trends. As shown in Figure 1.3b, battery technologies have been leading innovation efforts and registered a blowout type growth of innovation in 1990s. There is no significant change if we consider patents in each technology type as a percentage of those in all electricity storage technologies, which indicates that innovation effort continues to develop technologies, and we have a large prospect for the development of new and improved technologies.

1.3.3 Patenting by inventor country

Next, we analyze patenting in different inventor countries. Most patent applications come from a small number of countries, mainly Japan, the U.S., Germany and Korea, with 5,671, 1,558, 1,110 and 1,105 storage patents, respectively. Figure 1.4 shows the total number of patents in the top seven inventor countries. This is hardly surprising, given that they are also the top inventors in the overall electricity sector. Lanzi et al. (2011) shows that the U.S. leads innovation in efficiency-improving technologies, while our data shows that Japan leads innovation in storage patents. France follows with 371 patents, and it is then followed by Switzerland, the UK, Italy and Canada. All the other countries have a significantly lower number of patent applications in electricity storage technologies over the whole sample period. This is in line with our expectation given that most of the R&D investment happens in the developed OECD countries and electricity storage technologies have high location requirements, high costs, or both. We also calculate the Herfindahl-Hirschman Index (HHI) of storage patents to describe the concentration of storage patents across countries and regions.[14] Over time, there is a higher concentration in the late 1970s and late 2010s, and a close to zero concentration from 1980s to 2010. Note, however, that while concentration is higher during these times, the HHI index is still close to zero. As expected, we find lowest concentration in the countries with most storage patents (Japan, the U.S., Germany and Korea). Overall, we find a very low country-level and regional-level concentration, which indicates that storage innovation is located in areas with broad technological competencies.

Finally, we analyze the distribution of storage technology types in different countries, shown in Appendix A.3 Figure A.3.2. There is a certain degree of country specialization. For instance, both the U.S. and Finland have high counts of type "General," while the U.S. is also specialized in "Fuel cells" and Finland is more specialized in "Wipo." Patenting in Ireland, on the other hand, focuses more on "Hydro" compared to other countries. Limitations on location might be a convincing explanation for some storage technologies such as pumped storage hydropower. Potentially, innovation opportunities would also lead to some specialization.

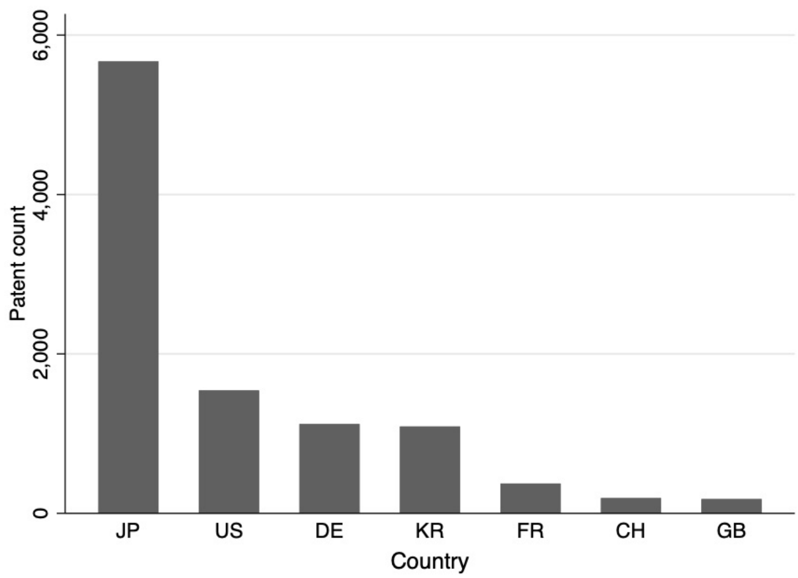


Figure 1.4: Patenting in electricity storage technologies in top 7 countries, 1978-2017.

[14]The mean concentration of storage patents at the country level is .0014 with standard deviation .0201, whereas the mean concentration at the regional level is .0038 and standard deviation is .0252.

1.4 Econometric Model and Methodology

Next, our goal is to study the determinants of innovation in electricity storage. Building on endonenous growth theory and induced innovation hypothesis,[15] we follow the econometric model of Popp (2002), which combines information on both market demand and technological opportunity. Using this model, we focus our estimation at region-level for two reasons. First, there are incentives to innovate at the firm level regionally (Asheim and Gertler, 2009; Isaksen and Trippl, 2017; Parrilli et al., 2020). Second, there are regional policies and market influences that shape the incentives to innovate in different locations. By focusing our attention to 1,881 NUTS3/TL3 regions, we exploit the variation in our dataset.[16]

A structural model to address the research question is impractical in our study since our sample covers 1,881 regions and their R&D process varies vastly.[17] We estimate a log-log regression of storage patent applications on energy prices, a lagged knowledge stock, R&D investment, and the other determinants of innovation following Popp (2002), where the estimated coefficients can be interpreted as elasticities. Equation 1.1 describes our baseline model:

$$\log\left(\frac{SPAT_{i,t}}{EPAT_{i,t}}\right) = \varphi_i + \gamma(1-\lambda)\log P^*_{j,i,t} + \theta \log K_{h,i,t-1} + \eta(1-\lambda)\log Z^*_{i,t} + \tau + \varepsilon_{i,t}, \tag{1.1}$$

[15] A microeconomic hypothesis first proposed in 1932 by John Hicks, where a change in the relative prices of the factors of production induces invention directed to economizing the use of expensive facotrs.

[16] The country-level and firm-level analyses are carried out in Appendix A.5 Table A.5.3 and Appendix A.6 Table A.6.4-A.6.5. The country-level analysis in Table A.5.3 shows less variation and less significance than our baseline estimates in Table 1.1. The variation in the data diminishes at the country level because we have a small number of top innovative countries and a large number of countries with lower innovation activity. For example, when we calculate the knowledge stocks at the country level, there is little variation among most countries. Our firm-level analysis in Appendix A.6 Table A.6.4-A.6.5 presents two alternative specifications based on a sub-sample of 690 firms with at least three storage patents. In Table A.6.4 we estimate our baseline model at the firm level and the results are consistent with our baseline estimates and an even stronger significance than in our regional analysis. Note, however, that the number of observations is small because few firms have generation and electricity patents, which is used to calculate the dependent variable. Table A.6.5 addresses this concern by considering the total number of storage patents as the dependent variable. The number of observations is higher and the results are consistent with our main results.

[17] Since the observations with zero patents cannot be used due to the log transformation of the data, we also estimate an exponential feedback model in which the dependent variable is the number of storage patents in region i and year t. The estimation results in Table A.7.6 Appendix A.7 confirm the importance of technological opportunity as a determinant of innovation in energy storage.

where,

$$P^*_{j,i,t} = P_{j,i,t} + \lambda P_{j,i,t-1} + \lambda^2 P_{j,i,t-2} + ... + \lambda^{t-1} P_{j,i,1}, \tag{1.2}$$

$$Z^*_{h,i,t} = Z_{h,i,t} + \lambda Z_{h,i,t-1} + \lambda^2 Z_{h,i,t-2} + ... + \lambda^{t-1} Z_{h,i,1}\,. \tag{1.3}$$

$SPAT_{i,t}$ represents the number of patent applications in electricity storage technologies in region i and year t, while $EPAT_{i,t}$ represents the number of patent applications in the entire electricity sector (or in electricity generation) in the same region and the same year. We use the $\frac{SPAT_{i,t}}{EPAT_{i,t}}$ percentage as the dependent variable, rather than the total number of storage patent applications to alleviate the impact of exogenous changes on the patenting behavior for the whole sector. For example, a change in patenting law, such as a federal law that reduces the application fee for small inventors, will affect both storage and electricity patents.[18] It also offers more instructive information about the importance of energy storage in the industry. Another feature of our analysis is that we incorporate the quality of patents using citation data as an explanatory variable but not explained variable. We do so because storage technologies are new compared to renewable and fossil fuels and it takes time to build citations.[19]

$P_{j,i,t}$ is the normalized real price of energy j in region i and year t. In our baseline model, instead of including prices of different kinds of energy inputs such as oil, coal and natural gas, we focus on the price of electricity because there is a high correlation between the electricity price and input prices.[20] In addition, we consider alternative price variables in other specifications.[21]

[18]In our baseline specification we follow Popp (2002) and use the ratio that can alleviate policies and changes that affect the entire industry since we cannot include regional fixed effects in the log-log model. In our robustness analysis, Appendix A.6 Table A.6.5 and Appendix A.7 Table A.7.6, the dependent variable is the number of patent applications.

[19]We also construct dependent variables using citation-weighted patents. Both raw storage patents and citation-adjusted storage patents follow the same trend, and we confirm that our estimation results are consistent with raw patent counts and citation-adjusted patent counts.

[20]We use electricity (MWh) industry total price drawn from International Energy Agency (2021).

[21]One might argue that intertemporal energy price variations or future energy prices also matter. We stick to an annual average price level in the baseline model following two reasons: (a) Innovation is not a short-term activity. Researchers, for instance, may not stop working on new storage technology when they expect a low oil price in the following years. (b) We found no a commen way to predict future energy prices. It is outside of the scope of our work to focus on how to make equitable predictions on future energy prices.

The variable $K_{h,i,t-1}$ represents the lagged stock of knowledge in technology h (storage, renewable or fossil fuels), which represents the available knowledge that researchers can build upon in region i and year t. We consider two options: a simple summation of patent applications and the summation of citation-adjusted patent applications. As shown by Popp (2002), citations to earlier patents are contained when a new patent is granted, therefore citation-adjusted knowledge stocks incorporate the diffusion of each newly patented innovation, as well as its decay as a patent becomes obsolete. Following Popp (2002), we first estimate the rates of decay and diffusion of knowledge using an exponential model. Then we construct the knowledge stock variable for each region with the estimated rates of decay and diffusion.[22] In addition to the internal knowledge stocks, we consider the role of technology spillover effects, $S_{h,i,t-1}$, which are calculated by adding past patents by other regions in a country in technology h at time t. In our robustness analysis, we explore alternative definitions of spillover regions.[23] We also calculate the spillover measure of Jaffe (1986) that accounts for technology relatedness in a region. For each pair of regions in a country and year, we calculate weights based on their patent shares in storage, renewable and fossil-fuel technologies, which are then used to construct a regional spillover measure.[24]

Z is a vector of independent variables and τ is a time trend. We include total government R&D spending in the baseline model. Since funding decisions can related to energy prices, we use a one-year lag as an instrument. Besides, we consider different proxies for electricity demand and other controls, such as GDP and different R&D spending in electricity generation, in alternative specifications.

Expected future prices and other expected future independent variables are following

[22] We follow Popp (2002) in using citations to estimate knowledge stocks instead of the perpetual inventory method that estimates R&D-based knowledge stocks. Since we measure innovation output with patent applications (instead of R&D spending), patent-based knowledge stocks are consistent with the dependent variable. In addition, we have patent data at the inventor level, which allows us to estimate the decay and diffusion of knowledge at the regional level. See Appendix A.4 for further details about the construction of our knowledge stocks.

[23] We consider two alternatives that expand the geographical region to a larger region based on the World Bank's income classification. The geographical regions are either six GEO regions or twenty GEO subregions, which are listed in Appendix A.10 Table A.10.8.

[24] On average, each region has none-zero technology relatedness with 87% of other regions in the same country (see Figure A.10.4). Therefore, each region receives a large percentage of the innovation effort made by a peer region.

an adaptive expectations model which depend on all past values, where λ is the weight on previous observations and tells how quick the reaction is to exogenous shocks. Finally, by combining equations 1.1, 1.2 and 1.3 we obtain the following dynamic AR(1) model:

$$\begin{aligned}\log\left(\frac{SPAT_{i,t}}{EPAT_{i,t}}\right) &= \lambda\log\left(\frac{SPAT_{i,t-1}}{EPAT_{i,t-1}}\right)+(1-\lambda)\varphi_i+\gamma(1-\lambda)\log P_{j,i,t}\\ &+ \theta\log K_{h,i,t-1}-\lambda\theta\log K_{h,i,t-2}+\eta(1-\lambda)\log Z_{i,t}\\ &+ \tau_t+\varepsilon_{i,t}-\lambda\varepsilon_{i,t-1}\,. \end{aligned} \tag{1.4}$$

We pool all regions to get single estimates for each parameter and to obtain a concise presentation of results. To estimate the underlying short dynamic panel model, we use System Generalized Method of Moments (system GMM) and limit the maximum 5 lags of the dependent variable as instrumental variables for the first-order difference to avoid weak IV problems.[25] Applying this model, it is possible to cover the whole series of past independent variables in adaptive expectations and to find the adjustment weight λ.[26] Finally, by estimating this model, we can find the causal effect of electricity price, knowledge stock, and other variables to patents of electricity storage as a percentage of total electricity patents.

1.5 Results and Discussion

In this section, we present our main results of the baseline model followed by alternative specifications to validate our results. To study what drives innovation in

[25]System GMM can be applied as long as there is no autocorrelation in first-difference errors and $|\Delta y_{i,t-1}, \Delta y_{i,t-2}, ...|$ are not correlated with individual fixed effects. For our model, we have tested the zero autocorrelation in first-difference errors and the overidentifying restrictions are also valid. We assume that the second condition is also satisfied since we pool countries in our sample and most of them do not yet reach the steady state. Popp (2002) finds a median lag of 4.86 years. and a mean lag of 3.71 years according to their estimated λ. Therefore we limit a lag of 5 here since little correlation between innovations and potential drivers tends to exist when the time distance is long.

[26]In addition to the system GMM estimation, we also conduct a simpler pooled OLS estimation with region and year dummies as a robustness check in Appendix A.8 Table A.8. These results confirm our main results, this is, that the price effect and past innovation are important determinants of innovation activity in storage technologies.

electricity storage, our baseline model includes energy prices, past innovation and total government R&D spending. The alternative specifications that follow use different energy prices such as coal and natural gas, different variables related to the demand of electricity, spillovers and a series of sub-samples. Since we take logs for all variables, the estimated parameters can be directly interpreted as short-run elasticities. Standard errors for each coefficient are included in parentheses.

We present the baseline estimates using data from all regions in Table 1.1. All specifications include electricity price, the lagged knowledge stock of storage, total government R&D spending and a time trend. We also consider two dependent variables: in columns (1)-(2) and (5)-(6) the dependent variable is the share of storage patents in electricity generation patents, whereas columns (3)-(4) and (7)-(8) use storage as a percentage of all electricity related patents. In addition, columns (1)-(4) include only the lagged stock of knowledge of electricity storage while columns (5)-(8) also include the knowledge stocks of renewable and conventional electricity generation technologies.[27] Finally, we calculate knowledge stocks from past patents in two different ways: a simple accumulation, and a citation-adjusted accumulation.

We highlight two main results from our estimations in tables 1.1-1.3. First, an increase in the electricity price leads to a reduction in the share of storage patents. Then we find evidence on the importance of past innovations to promote storage patent applications. In the following subsections we describe these results in detail.

1.5.1 Innovation and energy prices

Our results show that an increase in the price of electricity leads to a reduction in the *share* of storage patents. This result is robust to the use of different knowledge stocks and dependent variables, however, it is only statistically significant when we consider the share of storage patents over electricity generation patents with citation-adjusted knowledge stocks (Table 1.1 columns 2 and 6, and Table 1.3 column

[27] The construction of lagged knowledge stocks for renewable and fossil-fuel technologies is consistent with that of storage knowledge stocks. For example, all three stock variables in column (5) are simple accumulated while those in column (6) are all citation-adjusted.

2). This result is consistent with the directed technological change model developed by Acemoglu et al. (2012) who incorporate the market size and prices as determinants of technical change.[28] One explanation could be that increasing electricity prices lead to opposing forces. On the one hand, intermittent renewable energy becomes more attractive, which encourages innovation in storage. On the other hand, as conventional electricity generation becomes more expensive, more innovation effort goes towards lowering the cost of generation, including efficiency-improving conventional technologies and highly dispatchable generation, which discourages innovation in storage. Therefore, as electricity prices increase, there is a disproportionate investment in conventional technologies and thus the *share* of storage patents hinders. Based on our evidence alone, we are unable to identify these mechanisms. Thus, we do not imply that electricity prices hinder innovation in electricity storage but that the *share* of innovation in storage decreases. Instead, we conclude that we cannot rely on price policies to increase the *share* of innovation in electricity storage.

In our baseline model, we use the price of electricity to proxy price information, which may create a potential endogeneity problem. For example, policymakers and inventors may take energy prices into account in their decision making, which would lead to a correlation between energy prices and other independent variables. To address this potential endogeneity issue, we consider three alternative energy prices in Table 1.2: energy price index, coal price, and natural gas price. We create the fixed-weight energy price index following Linn (2008), where we include production inputs such as coal and natural gas as instrumental variables.[29] Our estimation results with the price index in Table 1.2 panel A show an insignificant but positive price elasticity effect for both specifications (storage-generation and storage-electricity ratios). In addition, we find a positive price effect at 15% significance level when accounting for citation-adjusted knowledge stocks (Table 1.2 panel A, column 4). Prior literature finds that higher

[28]This result is also consistent with the empirical findings of Stevens and Tang (2021) who find a negative electricity price effect on complementary technologies such as storage. Lazkano and Pham (2021) also finds a changing relationship between different energy prices and innovation in conventional technologies.

[29]See the construction of the fixed-weight input price index in Appendix A.9.

energy prices foster innovation towards renewable and efficiency-improving technologies (e.g. Newell et al., 1999; Popp, 2002; Verdolini and Galeotti, 2011a; Noailly, 2012; Ley et al., 2016). In our case, a higher energy price index leads to an increase in the storage to electricity patent ratio. Since electricity patents include technologies of different cleanliness levels, our results do not necessarily imply an increase in environmentally friendly innovations in response to higher energy prices. In contrast, results from panel B and panel C show that an increase in either coal or natural gas price lower innovation in the share of electricity storage. Given that electricity, coal and natural gas prices are highly tied to the price of conventional electricity generation, a price increase leads to a reduction of the share of innovation going to storage.[30]

The price effect we study in this paper may stimulate supply or demand for storage and electricity technologies, unfortunately, we are unable to distinguish between these two channels. Fabrizio et al. (2017) show the importance of considering supply-push and demand-pull policies to understand domestic innovation and transfer of storage technologies. Using international patent data, they evaluate the impact of innovation-supporting policies focused in either the supply of storage technologies or the demand for products based on storage technologies. They found that after implementing demand-pull policies, but not supply-push policies, the transfer of storage technologies increased.

To conclude our price effect analysis, we explore the heterogeneous impact of energy prices in regions with higher shares of renewable and fossil-fuel energy. In Table A.12.14, we include the interaction between electricity price with the share of electricity from renewable and fossil-fuel energy. We find a positive and significant interaction between the electricity price and the share of fossil-fuel energy in the storage to generation ratio, whereas a statistically insignificant interaction between the price and the share of renewable energy. These results suggest that regions with higher fossil-fuel

[30] As technologies become more expensive to develop, policy stringency has to increase disproportionately to have a further effect. As shown by Popp (2002), there are diminishing returns to research which suggests that more R&D spending is needed for new innovation. We test the linear and monotonic price effect assumption in our model by including a squared price term into our baseline specification. Our results in Appendix A.12 Table A.12.13 show no evidence of statistical significance of the squared price term.

energy react more strongly to an increase in electricity price than regions with higher renewable energy.[31] This is in line with Aghion et al. (2016) who find a heterogenous response to the fuel price effect based on a firm's past innovation in the automobile industry.

1.5.2 Innovation and knowledge stocks

Our second result emphasizes the importance of past innovation in current patent applications. From our baseline estimates in Table 1.1, the sign of estimates differ for simple and citation-adjusted knowledge stocks. In Table 1.1, simple accumulated knowledge stocks in columns (1), (3), (5) and (7) show a strong negative influence. However, when using citation-adjusted knowledge stocks in columns (2), (4), (6) and (8), their signs change to positive. This suggests that the rate of knowledge decay and diffusion, i.e. the usefulness of knowledge, plays an important role in shaping the direction of innovation. In addition, λs in specifications with citation-adjusted knowledge stocks, for example 0.2752 in column (4) and 0.2919 in column (8), are much lower than those estimated with simple knowledge stocks, 0.4897 in column (3) and 1.7100 in column (7). Since λ represents the weight placed on past observations in adaptive expectations, a smaller λ means a shorter lag structure. Thus, using simple accumulated knowledge stocks might overestimate the lag structure of exogenous shocks. Popp (2002) estimates a much higher $\lambda = 0.829$ in the weighted regression. This means that our estimates suggest a relatively quick reaction to price change of patenting in electricity storage within the energy sector.

In contrast to Popp (2002), we do not find a significant positive sign of the lagged

[31] From our model, we cannot identify the mechanisms that link the impact of electricity prices in renewable technologies, and their link to storage patents. Recent empirical studies identify some of these complex relationships. For example, using firm-level patent data from European countries, Noailly and Smeets (2015) find that increases in fossil-fuel prices and fossil-fuel past innovation led to an increase in the conventional-renewable technology gap through the innovation rate of mixed firms. From their results, they conclude that helping small firms should be the focus of policies, such as taxes that increase the electricity price, aimed at increasing renewable innovation. Lazkano et al. (2017a) also uses firm-level patent data to study the technology gap between conventional and renewable technologies. They find that if the average firm had an additional storage patent two years ago, their probability to apply for a renewable patent or an efficiency-improving conventional patent increases. A structural model that identifies the mechanisms that link electricity storage to different electricity generation technologies and their prices would shed more light on these complex links.

knowledge stock in all specifications. Our baseline estimates show a statistically significant and positive effect only of citation-adjusted storage knowledge stock on the share of storage innovation, and the significance stands out after controlling for past innovation in generation technologies. In this case, we find a significantly positive elasticity, 14.03% as shown in column (8). One possible reason is that we use the number of storage patents as a percentage over either generation patents or electricity patents as the dependent variable, different sensitivities and the interaction of patenting activities in electricity storage and generation would lead to the ambiguity of signs. Note also that electricity storage benefits both conventional and renewable technologies, which may not move in the same direction. Thus, our empirical results may capture these effects.

Knowledge spillovers of research from other regions can play an important role on a region's success (e.g. Grossman and Helpman, 1991; Jaffe, 1986; Jaffe et al., 1993; Audretsch and Feldman, 2004a). To account for this, we calculate two different measures of spillover effects: innovation by all the other regions in a given country and the regional-level spillover measure of Jaffe (1986).[32] We present our empirical results in Appendix A.10 tables A.10.9-A.10.10. These results show the importance of spillover effects in electricity storage within a country. Specifically, we find that past storage innovation within a country has a statistically positive impact on the share of electricity-related innovation dedicated to storage. Our results in Table A.10.10 confirm the importance of regional spillover effects in the development of storage technologies.

[32] We also consider other definitions of geographic spillover localization: GEO subregional (past innovation in the geographic subregion minus own NUTS3/TL3 region) and GEO regional (past innovation in the geographic subregion minus own NUTS3/TL3 region). We do not find strong empirical evidence of cross-boarder spillovers with these two definitions.

Table 1.1: Baseline estimates using data from 1978 to 2019 for all regions.

	Dependent variable:							
	Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-0.6980***	-0.6791***	-0.7632**	-0.6202**	-0.8257***	-0.715***	-0.6842†	-0.8098***
	(0.2314)	(0.1835)	(0.3069)	(0.2636)	(0.2381)	(0.1854)	(0.4458)	(0.2094)
Electricity price	-0.0785	-0.1467**	-0.1015	-0.0121	-0.0643	-0.1554**	0.0204	-0.0546
	(0.0830)	(0.0691)	(0.1072)	(0.0963)	(0.0869)	(0.0683)	(0.1306)	(0.0832)
K^S_{t-1}	-0.1676***	0.0241	-0.4500***	0.0620*	-0.2024***	0.0496†	-1.6940***	0.1403***
	(0.0275)	(0.0234)	(0.0458)	(0.0323)	(0.0426)	(0.0303)	(0.5780)	(0.0380)
K^R_{t-1}					-0.0188	-0.0028	0.5056**	-0.0697*
					(0.0429)	(0.0223)	(0.2113)	(0.0377)
K^{FF}_{t-1}					0.0713	-0.0601**	0.8969**	-0.1592***
					(0.0593)	(0.0296)	(0.3855)	(0.0457)
Total R&D	0.0872***	0.0454*	0.0579	-0.0663*	0.0925***	0.0575**	0.0267	-0.0158
	(0.0304)	(0.0236)	(0.0415)	(0.0373)	(0.0326)	(0.0235)	(0.0542)	(0.0301)
Time Trend	0.0131***	0.0074*	0.0166***	0.0048	0.0134***	0.0080**	0.0133*	0.0076*
	(0.0046)	(0.0038)	(0.0064)	(0.0052)	(0.0043)	(0.0038)	(0.0074)	(0.0043)
λ	0.1848***	0.1118***	0.4897***	0.2752***	0.1960***	0.1137***	1.7100***	0.2919***
	(0.0503)	(0.0392)	(0.0559)	(0.0406)	(0.0576)	(0.0407)	(0.6300)	(0.0371)
N	2215	2628	2483	2974	2005	2612	2263	2958
chi2	55	19	118	76	56	23	69	131

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Table 1.2: Estimates with alternative energy prices.

	Dependent variable: Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Panel A: with energy price index				
Constant	-0.7423*	-0.8484**	-0.9304†	-1.3490**
	(0.3826)	(0.3974)	(0.5863)	(0.6456)
Energy price index	0.0406	0.0413	0.0525	0.0798†
	(0.0323)	(0.0325)	(0.0477)	(0.0508)
K^S_{t-1}	-0.0308***	0.02997	-0.0987***	0.0166
	(0.0093)	(0.0248)	(0.0117)	(0.0305)
Total R&D	0.0084	-0.0082	-0.0564	-0.1421***
	(0.0321)	(0.0309)	(0.0456)	(0.0498)
Time trend	0.0059*	0.0037	0.0073†	0.0043
	(0.0034)	(0.0034)	(0.0050)	(0.0055)
λ	0.1425***	0.1238***	0.2585***	0.2105***
	(0.0414)	(0.0404)	(0.0424)	(0.0433)
N	2219	2625	2506	3002
chi2	26	15	111	44
Panel B: with coal price				
Constant	-0.3490*	-0.4256**	-0.4093†	-0.5307*
	(0.1949)	(0.1844)	(0.2707)	(0.3103)
Coal price	-0.0988†	-0.1201**	-0.0534	-0.0678
	(0.0601)	(0.0551)	(0.0792)	(0.0743)
K^S_{t-1}	-0.0304***	0.0345	-0.0992***	0.0190
	(0.0087)	(0.0250)	(0.0115)	(0.0308)
Total R&D	0.0369†	0.0181	-0.0190	-0.0876**
	(0.0252)	(0.0242)	(0.0386)	(0.0440)
Time trend	0.0068**	0.0037	0.0083*	0.0050
	(0.0031)	(0.0034)	(0.0047)	(0.0055)
λ	0.1433***	0.1267***	0.2616***	0.2191***
	(0.0391)	(0.0400)	(0.0416)	(0.0442)
N	2219	2625	2506	3002
chi2	30	20	111	44
Panel C: with natural gas price				
Constant	-0.3685*	-0.4585**	-0.4031†	-0.5256*
	(0.1956)	(0.192)	(0.2739)	(0.3133)
Natural gas price	-0.0507	-0.0536	-0.0158	-0.0193
	(0.0443)	(0.0435)	(0.0557)	(0.0592)
K^S_{t-1}	-0.0308***	0.0298	-0.0993***	0.0171
	(0.0089)	(0.0258)	(0.0116)	(0.0307)
Total R&D	0.0370†	0.0191	-0.0202	-0.0895**
	(0.0252)	(0.0251)	(0.0388)	(0.0440)
Time trend	0.0083***	0.0060*	0.0087*	0.0057
	(0.0031)	(0.0035)	(0.0049)	(0.0053)
λ	0.1443***	0.1262***	0.2616***	0.2171***
	(0.0419)	(0.0400)	(0.0413)	(0.0438)
N	2219	2625	2506	3002
chi2	31	16	108	44

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

1.5.3 Robustness tests

One of the main advantages of storage is that it allows the seller to time the sale of the energy to match consumers' needs. Thus, the variation in demand over time might be another key predictor of storage patents. We consider different proxies from both production (i.e. generation and capacity) and consumption to capture that.

First, columns (5)-(8) Table 1.1 include lagged knowledge stock of renewable generation technologies and fossil-fuel generation technologies. In previous work, Lazkano et al. (2017a) has shown that the total number of electricity storage patents increases with past innovation in renewable and efficiency-improving conventional technologies. In contrast, when we study patenting in storage as a percentage of all electricity patents, we find that citation-adjusted knowledge stocks of renewable and fossil-fuel generation technologies reduce the share of storage patents (see Table 1.1 column (8)). This does not necessarily imply that our results contradict prior work. Note that using the number of storage patents as a percentage over either generation patents or electricity patents as the dependent variable could be a possible reason, since past innovation renewable and conventional technologies might encourage generation technologies more.

Next, we include the market share of electricity generated from renewable and fossil fuels sources in Table 1.3. There is a significantly positive effect of the market share of renewable energy for the ratio of storage to electricity sector, while the effect of the fossil-fuel market share is positive but insignificant. This result implies that policies directed at increasing the share of electricity generation from renewable resources have the potential to promote the development of storage technologies.

We then incorporate generation, capacity and consumption at the macroeconomic level. Table A.11.11 in Appendix A.11 includes the quantity of electricity generation, capacity and consumption in different panels. All three variables show significant and positive influence on the share of storage over generation. While other baseline estimates are consistent with the estimations that include these three variables, it also suggests the existing base of knowledge as a more important channel.

Table 1.3: Estimates with market shares of renewable-energy and fossil-fuel electricity generation.

	Dependent variable: Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-0.4439*	-0.6013**	-0.4302	-0.7221**
	(0.2360)	(0.2349)	(0.3367)	(0.3637)
Electricity price	-0.1224*	-0.1581**	-0.1055	-0.0982
	(0.0657)	(0.0673)	(0.0961)	(0.1018)
K^S_{t-1}	-0.0339***	0.0267	-0.0973***	0.0162
	(0.0089)	(0.0246)	(0.0125)	(0.0304)
Elect from ren	-0.0056	-0.0030	0.0136†	0.0169**
	(0.0051)	(0.0050)	(0.0086)	(0.0083)
Elect from ff	0.0019	0.0020	0.0012	0.0038
	(0.0022)	(0.0021)	(0.0026)	(0.0031)
Total R&D	0.0297	0.0150	-0.0250	-0.0884**
	(0.0265)	(0.0250)	(0.0402)	(0.0435)
Time trend	0.0120***	0.0097**	0.0034	-0.0002
	(0.0039)	(0.0040)	(0.0063)	(0.0059)
λ	0.1484***	0.1291***	0.2504***	0.2058***
	(0.0372)	(0.0393)	(0.0462)	(0.0463)
N	2168	2573	2449	2942
chi2	34	22	117	54

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Finally, we analyze the impact of R&D spending in renewable and fossil fuels, as well as macroeconomic variables GDP and GDP per capita in Appendix A.11 Table A.11.12. In panel A we find that R&D in renewable technologies has a significantly positive effect. It confirms that innovation in storage would also benefit from innovation toward improving renewable technologies, and the links between them. We then take GDP for the size of each economy and GDP per capita for its productivity level as macroeconomic controls. These results are in line with our baseline findings. Our results suggest that, in contrast to energy prices and knowledge stocks, macroeconomic variables such as GDP and GDP per capita may not be the first-hand determinant of innovation in electricity storage directly.

The shares of patents in electricity storage in Figure 1.2 present an opposite-direction development before and after 1990. We split the data into an early-period (from 1978 to 1990) sub-sample and a later-period (from 1990 to 2019) sub-sample to check the asymmetry of the estimation results. Table A.12.15 in

Appendix A.12 presents the baseline specification results with these two subsamples. The estimation results during 1978-1989 show little significance when innovation in energy storage received little attention. During these years, past innovation in energy storage plays the main role in boosting innovation in storage technologies. The later-period results based on 1990-2019 data are in line with our baseline estimation results in Table 1.1, which present evidence for the negative price effect and the importance of quality-adjusted knowledge stocks. This is expected as innovation in storage technologies draw more attention during this time period.

As the distribution of patent applications in Section 1.3 shows, most patent applications in energy storage come from a small number of countries. To ensure the overall results are not influenced by one country, we estimate our baseline specifications with two sub-samples: (1) regions in all countries but the U.S.; (2) regions in the three most innovative countries (Japan, the U.S. and Germany). Tables A.12.16-A.12.17 in Appendix A.12 present these results. Our main results in Table 1.1 are robust to the exclusion of the U.S.. When we focus on the three most innovative countries, we find that past innovation has a stronger importance to determine storage innovation. Remember that in our baseline estimations, past innovation in renewable and fossil fuels lead to less innovation in storage whereas more storage innovation leads to a higher share of storage innovation (Table 1.1 column 8). Our firm-level analysis of the most innovative firms in Table A.6.5 also confirms a positive and significant effect of past innovation in storage. In the most innovative countries, however, we find that past innovation hinders the share of storage to electricity innovation (Table A.12.17 column 8). Recall the evolution of storage to electricity ratio in Figure A.3.3, where all countries show an increasing trend starting in 2000. The ratio decreases in Germany starting in 2015, due to a reduction in storage patents and an increase in electricity patents, whereas in Japan this ratio decreases in the last few years. The negative past innovation effect in the most innovative countries could be driven by the decrease in the storage-electricity ratio in Germany.

Overall, these estimations show that our main results are robust to a number of different model specifications and assumptions.

1.6 Conclusion and Policy Implications

Energy storage has received much attention to achieve clean energy transitions. Innovation in energy storage has dramatically increased in the last three decades. Using patent data from 1978 to 2019 across 1,881 regions, we document the evolution of innovation in storage focusing on different technology types. Innovation in battery technologies still dominates innovation efforts, though fuel cells are attractive because of high efficiency and durability. In addition, technologies such as flywheels with a higher storage capacity continue to draw attention to transition towards a less-carbon intense grid. Overall, innovation offers many technological possibilities for large-scale, and hopefully, cheaper energy storage.

Our empirical analysis draws attention to energy prices and past innovation to foster global innovation in energy storage. We find that an increase in the average energy price leads to more storage patenting, whereas an increase in the price of electricity leads to a reduction in the share of storage patents relative to all electricity patenting. We also find that this electricity price effect varies with the regional share of renewable and fossil fuel energy. There is a negative (but insignificant) price effect in regions with a high share of renewable energy, while regions with a high share of fossil-fuel energy present a strong positive effect. These results suggest that we cannot rely on price policies to increase the share of patenting in energy storage. Finally, we also find strong evidence of the importance of past innovation. Specifically, we find that the quality of past innovation is important to promote the share of storage innovation. This suggests that policies aimed at improving the quality of R&D in storage can be an important tool to boost the share of storage innovation.

Chapter 2

Do Market-based Environmental Policies Encourage Innovation in Energy Storage?

2.1 Introduction

Energy transitions to less-carbon intense technologies are crucial to realizing climate change goals. Since the electricity sector is one of the largest carbon emitters, most environmental plans involve electrifying heavily polluting industries with clean electricity generation (IEA, 2021a). For example, one solution to the energy crisis in the European Union is to maximize generation from existing low-emission sources, and to deploy new wind and solar projects (IEA, 2022a). The penetration of renewables in the energy sector is fast growing with the help of innovation and policy interventions. Unfortunately, the intermittency problem of renewables, where renewable energy cannot always consistently produce energy at all hours of the day, continues to be a limiting determinant to their expansion. Therefore, technologies in electrical storage have received global attention as they can help reduce the intermittency problem to boost renewable energy use.

Governments have introduced various market-based policies in an effort to promote renewables and accelerate energy transitions.[1] The number of countries adopting direct policy support has tripled from 48 in 2004 to at least 147 by 2017 (IRENA, IEA and REN21, 2018). Well-designed policies lead to increased deployment and cost reduction. For example, the trading scheme in Italy helped to install 6700 MW of wind capacity by the end of 2011 (IRENA, IEA and REN21, 2018). With efficient feed-in tariffs (FITs), the global average price of wind energy in 2016 was USD 40/MWh, down from USD 80/MWh in 2010 (IRENA, IEA and REN21, 2018). However, climate objectives still require a scale-up deployment of renewables. The share of renewables in global electricity generation reached almost 29% in 2020, but to meet the Net Zero Emissions by 2050 Scenario, it needs to reach more than 60% by 2030 (IEA, 2022b). As energy storage is playing a decisive role in resolving the intermittency problem, policy support that encourages innovation in energy storage is crucial to realize energy transitions.

My goal is to examine the effects of the stringency of market-based environmental policies on innovation in energy storage. To do so, I first build a global firm-level patent dataset from 1978 to 2019, and then I combine it with the Environmental Policy Stringency (EPS) index generated by the Organisation for Economic Cooperation and Development (OECD). The EPS dataset covers twenty-eight OECD and BRICS (Brazil, Russia, India, China, South Africa) countries from 1990 to 2015. Since policy data is unavailable until 1990 and after 2015, I use patent data from 1978 to 1989 as the pre-sample period to determine pre-sample patenting behavior, and patent data from 1990 to 2015 as the sample period. I adopt a negative binomial model to test the impact of market-based environmental policies on patent applications in storage technologies.

My patent pool consists of patent applications of electrical storage technologies drawn from the OECD patent database in the ten most innovative countries which account for about 90% of all storage innovation at the global level.[2] I identify battery and fuel cell

[1] There has been a debate between price and quantity with regarding to optimal environmental policy instruments. A large share of literature has discussed this topic (see e.g. Weitzman, 1974; Kete, 1994; Pizer, 1997; Pizer and Prest, 2020). This work focuses on market-based instruments, i.e. price-based instruments, and their effects on storage innovation as they do not prescribe that firms use specific technologies and allow firms greater flexibility in research choice.

[2] As shown in Section 2.2.1 and Figure 2.1a, the top ten countries in storage innovation are: Japan, the United States, Korea, Germany, France, Switzerland, Canada, Italy, the United Kingdom, and China.

technologies based on International Patent Classification (IPC) codes as they have little location limitations and attract high innovation effort in the last several decades. Overall, my dataset includes 9,970 storage patent applications from 2,194 unique firms. These firms present different specialty levels; only 7.54% of them are specialized in developing storage technologies while more than 90% are mixed firms also innovating in renewable or fossil-fuel generation technologies, or both. In addition to patents, I measure the stringency of market-based environmental policies using the EPS dataset. This dataset distinguishes between three types of market-based environmental policies: environmental taxes, FITs and trading schemes; and scores policy instruments on a scale of 0 (not existing) to 6 (most stringent) based on the comparison against the distribution of values for the same type of instrument. This allows me to use continuous measures of the stringency and compare them across countries and over time.

As the dependent variable is a count of patents, I estimate a negative binomial model to examine the relative effectiveness of policies for innovation in energy storage. This model helps overcome the overdispersion problem of my data. In addition to policy measures, the model combines information on both market demand and technological opportunity including energy prices, past innovation and spillover effects (see e.g. Popp, 2002; Acemoglu, 2002; Acemoglu et al., 2012; Feng and Lazkano, 2022). Following Aghion et al. (2016), I use the pre-sample behavior as a firm fixed effect to address the problem that knowledge stocks may not be strictly exogenous. Finally, I transform the estimated coefficients to report them as percentage changes. Thus, my results show the relative effect of different policy measures on a firm's patenting activity.

The empirical results highlight three interesting findings. First, a firm is expected to apply for 60.9% more storage patents when the composite market EPS within the country increases by one unit. While the overall effect is positive, I find that some policies encourage innovation in storage whereas others discourage it. Specifically, environmental taxes, FITs for solar power and tradable CO_2 certificates strongly promote firms' patenting activity in energy storage. I find that a more stringent environmental tax policy strongly fosters a firm's patenting activity in storage by

119.7%. This contributes to the understanding of the relationship between environmental taxes and storage innovation. Barradale (2010) shows that investors have better belief in the future of policies without the direct link to public finance. Johnstone et al. (2009) prove this potential concern with tax policies using a tax dummy and find no effect of tax measures on renewable innovation. My results complement theirs because I use a continuous tax proxy. One possible reason is that a more stringent tax policy may affect investors' anticipation more than the existing of a tax policy. In addition to environmental taxes, FITs for solar energy and tradable certificates for CO_2 emissions also present a significant positive effect. A firm's patenting in energy storage is expected to increase by 14.5% with a one-unit higher stringency of FITs for solar and by 18.2% with that of tradeble certificates for CO_2 emissions. This is consistent with the induced innovation theory and the directed technical change model as they would increase the overall costs of conventional technologies and improve a transition towards renewable energy (Acemoglu, 2002; Acemoglu et al., 2012). Prior literature also finds a positive influence of such policies on other types of energy innovation (see e.g. Johnstone et al., 2009; Rogge and Hoffmann, 2010; Schmidt et al., 2012; Borghesi et al., 2015; Cui et al., 2018). While previous work focuses on the direction and adoption of the overall environmental or low-carbon innovation, my focus is on the innovation in energy storage.

Second, my results show that some policies are discouraging storage innovation. Specifically, renewable energy certificates and energy efficiency certificates discourage firm-level storage innovation. A firm's storage patenting is expected to drop by 28.14% with a one-unit higher stringency of renewable energy certificates and by 83.56% with that of energy efficiency certificates. The significant negative impacts are unexpected but not surprising, as more than 90% of sample firms are mixed firms. Such certificates might change the allocation of investment and innovation effort in firms which innovate both generation and storage technologies.

Finally, my results emphasize the heterogenous policy effects in firms of different specialties. Firms with a higher innovation share in renewable technologies react less to environmental taxes but more to tradable certificates for CO_2. Environmental taxes and tradable certificates for CO_2 encourage patenting activities in energy storage directly, but the sensitivity alters in firms with different levels of specialization in renewable technologies. Besides, some policies such as FITs show a stronger influence with longer lags while the significance of policies such as trading schemes vanishes with longer lags. It suggests that policies may affect different stages in the process of storage innovation.

Using continuous measures of the stringency for policy options, this paper contributes to the understanding of links between environmental policy and innovation in energy storage. A large share of the innovation literature has empirically examined the impact of environmental policies on innovation in renewable energy.[3] Early studies show that differences between policies matter, even among market-based options. Due to the heterogenous nature of policies adopted, researchers often use binary variables to indicate the presence of policies. For example, Johnstone et al. (2009) use dummies for police types such as tax credits as they only find possible continuous variables to represent the policy stringency of R&D expenditures, FITs and renewable energy certificates. They emphasize the importance of public policy and find that different policy instruments are effective for different renewable energy sources. In contrast, I focus on continuous policy proxies for the stringency which can help governments optimally allocate investments. As an important complement to intermittent renewable energy, energy storage technologies are still at a relatively earlier stage of the technology life cycle, and has received far less attention. Fabrizio et al. (2017) separate energy storage policies into demand-pull policies that focused on the demand for products based on these technologies and supply-push policies that focused on the supply of a given set of technologies. They create dummies for their presence and examine their impact on energy storage innovation. For a given country, they find that only demand-pull policies promote domestic innovation in energy storage. While they focus on energy storage policies from demand and supply side (those to increase demand and those to support research effort), my focus is on studying the effects of

[3]Popp (2010) and Popp (2019) provide an extensive review of this topic.

three distinct types of market-based environmental policies.

The paper is organized as follows. In the next section, I describe the patent dataset as well as policy measures. Section 2.3 introduces the model and empirical strategy, and section 2.4 analyzes the estimation results. Finally, section 2.5 concludes the paper.

2.2 Data

2.2.1 Patent applications

My dataset includes energy storage and electricity generation patents drawn from the Organisation for Economic Cooperation and Development (OECD) patent database from 1978 to 2019. As patent values can be addressed by citation and pre-sample variables, I use the number of patent applications (also referred as "patent counts" hereafter) related to storage technologies to measure storage innovation.[4] This dataset identifies storage technologies that are widely adopted by the supply side of electricity market based on International Patent Classification (IPC) codes. I focus on patents of battery and fuel cell technologies in this study because, compared to hydro technologies, they have little location limitations and attract high innovation effort in last several decades. I identify battery and fuel cell technologies following the list of storage IPC codes in Feng and Lazkano (2022). The complete list of the selected IPC classes used to extract patents in this study can be found in Appendix B.1 Table B.1.1. I focus on patent applications by firms from the ten most innovative countries – Japan("JP"), the United States("US"), Korea("KR"), Germany("DE"), France("FR"), Switzerland("CH"), Canada("CA"), Italy("IT"), the United Kingdom("GB"), and China("CN") – as most patent applications come from these countries. As expected, nine of ten are OECD countries given that most of the R&D investment happens in the developed OECD countries and electricity storage technologies require unique locations,

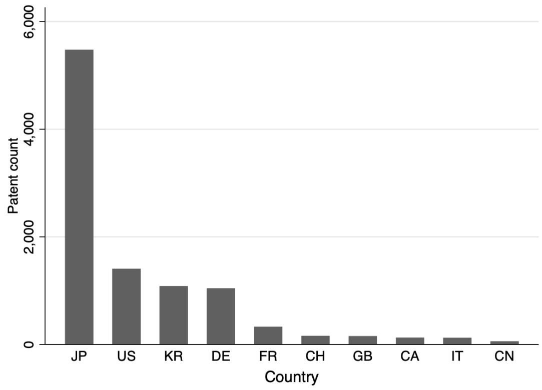
[4]Though patent counts do not directly indicate heterogenous values of different patents, the citation information in patent dataset can offer a good proxy of innovation quality and be used to measure knowledge stocks (Verdolini and Galeotti, 2011b). An alternative is R&D investments, which measure the input of innovation but cannot easily be classified by technology.

high costs, or both. China also stands in the top position as the investment in technological R&D has been continuously increasing after the State Council put forward the strategy of "innovation-driven development" and the strategy of scientific and technological innovation (Xin-gang and Wei, 2020).

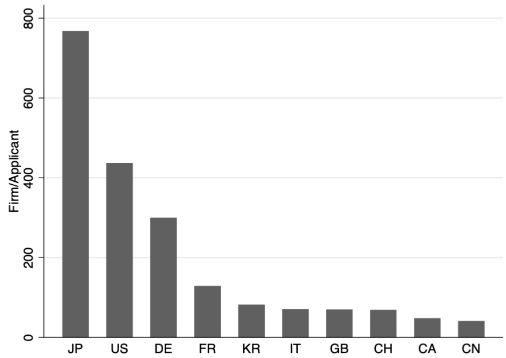
Overall, the data includes 9,970 storage patent applications from 2,194 unique firms in ten countries.[5] The distribution of patent applications and inventor firms in each of the ten inventor countries is presented in Figure 2.1. Figure 2.1a shows the total number of storage patents. Most patent applications come from top four countries: the U.S., Korea, Germany, and especially Japan. I present the patenting trend for these four countries in Figure 2.2. Japan has a substantial technological development in storage technologies since late 1980s and has remained high since then. Germany and the U.S. have kept a constant trend through the sample period while Korea starts to catch up after 2000. Figure 2.1b shows the total number of firms in each country. Consistent with the distribution of storage patent applications, Japan, the U.S. and Germany have the highest numbers of firms. Korea has a relatively lower number of firms, which suggests that Korea might have a more concentrated allocation of innovation in storage technologies.

Figure 2.3 presents the distribution of storage patents by firm. The median firm has one storage patent application. Out of the 2,194 firms, 575 firms have at least three patent applications accounting for 84% of total storage patents and 368 firms have at least five patents accounting for 77%. Inventor firms present different levels of specialty. As shown in Figure 2.4, only 7.54% of them are specialized in developing storage technologies while more than 90% are mixed firms also innovating generation technologies. Most of those mixed firms, 79.89%, conduct research on both renewable and fossil-fuel generation technologies alongside storage innovation. For such mixed

[5] In my data, "firm" includes entities from both private and public sector such as universities and national labs. One might argue that environmental policies may affect private and public entities differently. I pool all firms, i.e. entities, in the estimation following two reasons: (a) The OECD patent database does not offer enough information to identify private and public entities. (b) I identify 53 universities out of 2,194 unique firms, which have in total 107 storage patent applications out of 9,970. I estimate the model using storage patents from "non-university" firms in Appendix B.3. Table B.3.2 shows that both the magnitude and the significance of estimates are in line with baseline results, which provides no evidence on heterogenous policy effects. This is consistent with the previous finding of the high correlation between areas with strong science-based universities and private sector innovation (see e.g. Jaffe, 1989; Belenzon and Schankerman, 2013; Valero and Van Reenen, 2019).



(a)Total number of storage patents



(b)Total number of firms

Figure 2.1: Distribution in top ten countries, 1978-2019.

firms, environmental and renewable policies might, on the one hand influence investors' anticipation, on the other hand direct the allocation of research effort within a firm.

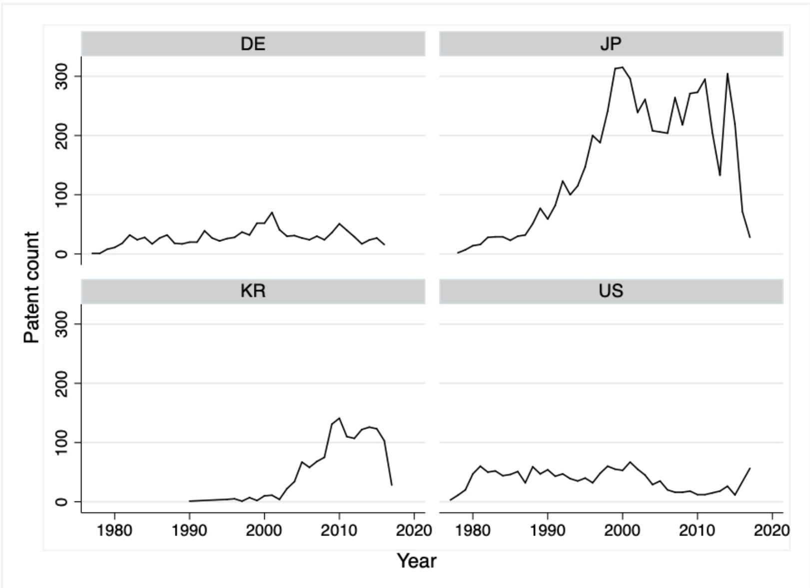


Figure 2.2: Patenting trend of storage technologies in top four countries, 1978-2019.

2.2.2 Environment policy measures

To measure the stringency of market-based environment policies, I use data drawn from the Environmental Policy Stringency (EPS) dataset gathered by the OECD (OECD, 2016). This dataset covers twenty-eight OECD and BRICS countries from 1990 to 2015.[6] It defines policy stringency as a higher cost of polluting or environmentally

[6]There is an updated version of the EPS index published on August 29th, 2022, which covers forty countries from 1990-2020 (see Kruse et al., 2022). I do not use this revised EPS index for two

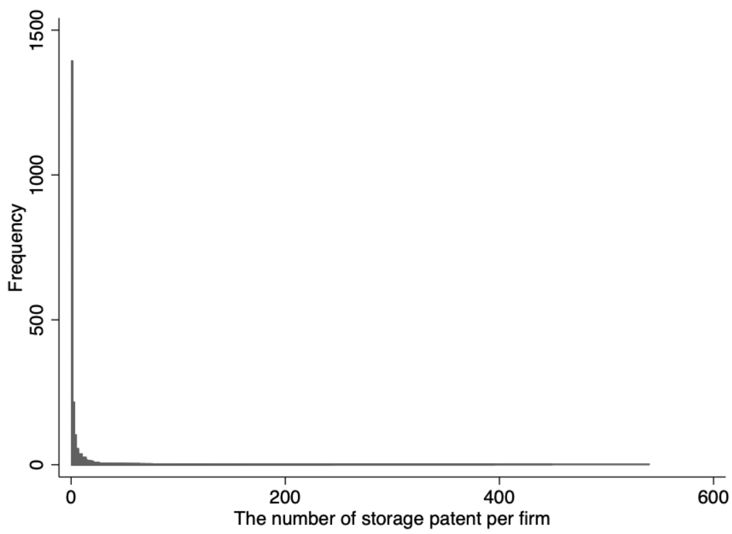


Figure 2.3: Distribution of storage patents by firm, 1978-2019.

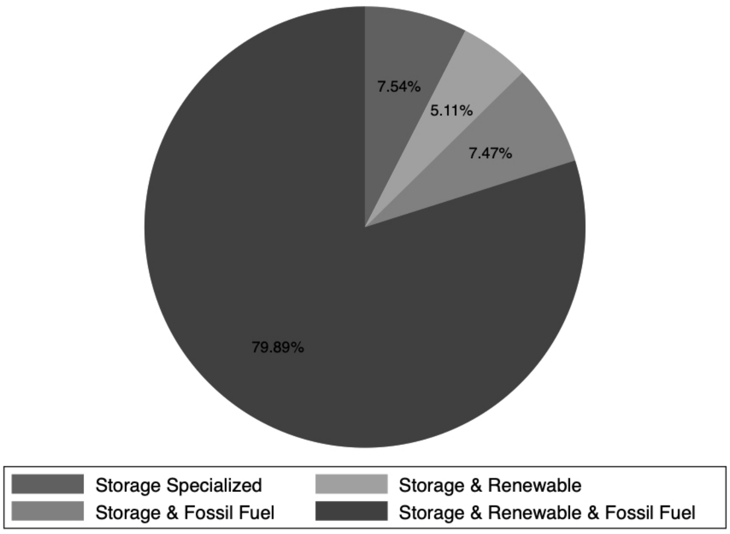


Figure 2.4: Specialty of firms in top ten countries, 1978-2019.

harmful behavior. For example for taxes, a higher price on a unit of pollutant implies higher stringency, while for subsidising instruments such as FITs, a higher subsidy is interpreted as more stringent. Based on quantitative data, it scores environmental policy instruments on a scale of 0 (not existing) to 6 (most stringent), and aggregates

reasons: (a) The revised index adopts a different taxonomy which includes a third subindex, technology support, in addition to market-based and non-market-based policies. Some market-based policies such as feed-in tariffs are no longer included into the market-based EPS subindex. (b) The policy selection of environmental taxes, which is the most important policy instrument in this paper, has changed to include less information than the 2015 version. For example, in the 2020 version, there are no environmental taxes instituted in Korea before 2000, and only a near-zero diesel tax in Canada from 2000 to 2018, whereas the 2015 version offers a great variation of the stringency of environmental taxes in these two countries (shown in Appendix B.2 Figure B.2.1a).

scores into composite EPS indexes. The score reflects the relative stringency – the country's position on each instrument relative to the other countries and years (Botta and Koźluk, 2014). In contrast to previous work, which relies on dummy variables to capture the effect of the implementation of most policies (see e.g. Johnstone et al., 2009; Fabrizio et al., 2017), this dataset allows me to measure continuous variables to represent stringency for most common environmental policies. With this, the stringency of environmental policies can be compared across countries and over time.

Following the taxonomy developed by de Serres et al. (2010), this dataset distinguishes three different market-based policy types: taxes, FITs and trading schemes. In this paper, I use a composite market EPS index, one composite indicator for each policy type, and six policy measures from the three types to study the impact of market-based environmental policies on innovation in electricity storage. The six policy measures are environmental taxes, FITs for solar power, FITs for wind power, tradable certificates for CO_2 emissions, renewable energy certificates and energy efficiency certificates. Table 2.1 shows the selected policy instruments and their measurements used for scoring.

Table 2.1: Policy instruments: measurements and summary statistics.

Policy	Information considered for scoring	Mean	St. Dev.
Market EPS		1.2891	0.0571
Environmental Taxes	Tax rate in EUR/tonne	1.625	0.0403
Feed-in Tariffs			
FIT Solar	EUR/kWh	1.5391	0.1337
FIT Wind	EUR/kWh	1.8125	0.1442
Trading Schemes			
CO_2 Certificates	Price of one CO_2 allowance	0.625	0.0908
Green Certificates	% of renewable electricity that has to be procured annually	0.5977	0.0857
White Certificates	% of electricity saving that has to be delivered annually	0.3867	0.0703

Note: Statistics come from scores of the top ten countries for period 1990-2015.

Environmental taxes are directly applied to the pollution source (tax on emissions of CO_2, NO_x, SO_x) and on input or output of a production process (diesel tax) to encourage activities in lower emissions.[7] I present the stringency of environmental taxes

[7]I do not use carbon taxes because they are just a recent policy choice for most countries, or they do not have high carbon taxes instituted. Therefore, I use the measure of total environmental taxes, which converts emissions of all pollutants to a price/ton emission value.

in each country over time in Appendix B.2 Figure B.2.1a. Countries started adopting environmental taxes in late 1970s and they are widely used. For example, the Environmental Protection Tax Law of People's Republic of China is implemented on January 2018 to reduce greenhouse gas emission (Hu et al., 2018).

Feed-in tariffs (FITs) for solar energy, as well as FITs for wind power, are subsidies for electricity production from renewable energy sources. They guarantee purchases of power generated from solar and wind at fixed prices over longer periods, and encourage the deployment of renewable electricity technologies. FITs are common internationally. Germany has been the front-runner to introduce FITs since the early 1990s (see Appendix B.2 Figure B.2.1b), such as the Electricity Feed-in Act (Strominspeisungsgesetz) between 1991 and 1999, and the Renewable Energy Sources Act (Erneuerbare-Energien-Gesetz) in 2000. For example, according to the Renewable Energy Sources Act (2000), "the compensation to be paid for electricity generated from solar radiation energy shall be at least 50.62 cent (Euro) per kilowatt-hour."

Tradable certificates for CO_2 emissions give holders the right to emit, and to trade the right under a cap-and-trade system. Such policies are more common in European countries as European Union Emissions Trading System (EU ETS) launched in 2005 is the world's first international emissions trading system, which drives a jump of the stringency of trading schemes, as shown in Appendix B.2 Figure B.2.1c, in EU countries in 2005 (Botta and Koźluk, 2014).

Renewable energy certificates legally convey the environmental attributes of one megawatt-hour (MWh) of electricity generated from a renewable energy source. Policies that issue such certificates are commonly used to incentivize deployment of large-scale renewable electricity, such as Renewable Energy Obligations (RO) in the U.K. and Renewable Portfolio Standards (RPS) in the U.S..

Energy efficiency certificates, also called "white tags," represent one MWh of energy saving through an energy efficiency activity of utilities. Though this type of tradable certificate is far less common than renewable energy certificates, it is also found in select states in the U.S. and some European countries, such as the U.K. and France.

On average, the top innovative countries in energy storage have a relatively low stringency for market-based environmental policies on a scale 0 to 6, while six of the them have an above-OECD-average market EPS. Figures 2.5 and 2.6 provide a sense of overall market-based environmental policy stringency, i.e. the composite Market EPS index, by showing the mean scores and its trend in each country. The mean scores in the top ten countries are low in terms of a scale of 0 to 6 and present a wide range. As shown in Figure 2.5, France has the highest mean market EPS, 1.80, while the lowest is China with 0.51. Overall, European countries such as France, Germany and Italy have relatively higher scores, Korea and Japan are about the average, while the U.S. and China stand the lowest. This is hardly surprising. As each country's EPS index in Figure 2.6 shows, European countries had ambitious market-based environmental policies from early 1990s, while other countries started around 2000 or even later.

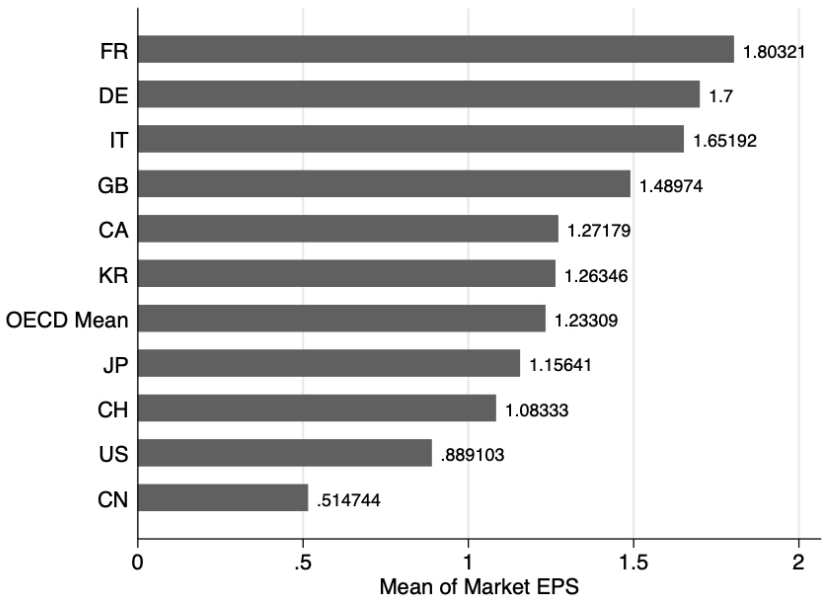


Figure 2.5: Mean market-based environmental policy stringency index for the top ten countries, 1990-2015.

To investigate the impact of market-based environmental policies on innovation in energy storage, I combine the patent data and EPS measures. Since policy data is only available from 1990 to 2015, the time period from 1978 to 1989 is defined as the pre-sample period to determine pre-sample variables, and that from 1990 to 2015 is defined as the

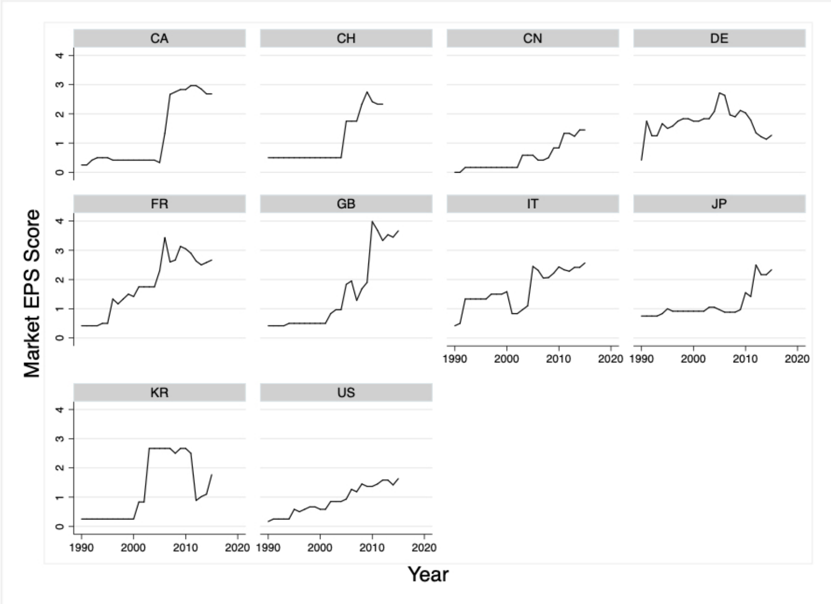


Figure 2.6: Market-based environmental policy stringency index for the top ten countries, 1990-2015.

sample period.[8]

2.3 Empirical Strategy

This section describes the econometric approach used to identify the effects of market-based environmental policies on innovation in energy storage. As the dependent variable is patent counts at the firm level, I estimate a firm-level count model (Asheim and Gertler, 2009; Isaksen and Trippl, 2017; Parrilli et al., 2020). The following equation describes the baseline model where j indexes country, i indexes inventor firm, and t = 1990, ..., 2015 indexes time (year):

$$\begin{aligned} PAT_{i,t} =& exp(\beta_1 Price_{j,t} + \beta_2 K_{i,t} + \beta_3 Spillover_{j-i,t} + \beta_4 Policy_{j,t} \\ &+ \beta_5 Firm_i + \beta_6 Time_t) + \epsilon_{i,t}. \end{aligned} \tag{2.1}$$

The dependent variable $\mathrm{PAT}_{i,t}$ represents the number of patent applications in battery and fuel cell technologies in firm i and year t.[9] The quality of patents are often proxied

[8]Patents data suffers truncation bias (a comparison between two data versions) as it usually takes several years to know just how many patents were applied for during any particular period. I do not have to worry about it as the sample uses patent data before 2015 and I have full patent data to 2019.

[9]I identify storage patent applications by firm. Each firm is only located in one country. For

by citation data. I abstract from this because it takes time (median 4 years in my patents data) to build citations and storage technologies are newer than generation technologies.

$\text{Price}_{j,t}$ is a country-level average energy price index in country j and year t. Following Linn (2008), I construct this fixed-weight energy price index with production inputs such as coal, natural gas and renewable energy.[10] I use this index rather than the price of any single energy input or electricity to avoid endogeneity concerns. While these prices could be much driven by new storage technologies, this index considers country characteristics, the energy mix, and fuel prices.

The variable $\text{K}_{i,t}$ represents the stock of knowledge in storage technologies, i.e. the available knowledge that researchers can build upon in year t. Literature confirms the importance of past innovation to promote current inventive activities (Popp, 2002; Acemoglu et al., 2012; Aghion et al., 2016; Feng and Lazkano, 2022, etc.). Echoing Popp (2002), I construct a citation-adjusted storage knowledge stock.[11] A storage patent usually has a term of 20 years from its earliest effective. Citations are contained when a new patent is granted so forward citations and backward citations could tell the diffusion of each newly patented innovation, as well as its decay as a patent becomes obsolete. Therefore, the citation-adjusted knowledge stock accounts for not only knowledge accumulation but also the quality of storage patents.

$\text{Spillover}_{j-i,t}$ is knowledge spillovers from other firms in country j. While previous work confirms the role of knowledge spillovers on innovation success (e.g Grossman and Helpman, 1991; Jaffe et al., 1993; Audretsch and Feldman, 2004b), Feng and Lazkano (2022) find that knowledge spillovers in electricity storage influence only within the same

international companies, the dataset documents different names for firms in different countries. For example, General Electric Canada Inc. is located in Canada while General Electric Technology GmbH is in Switzerland.

[10]The energy price index is a country-level variable. For example, the price index of firm i in country j and year t is obtained from the average of the share of electricity production from energy inputs such as oil, natural gas and hydro power in country j over the sample period.

[11]A citation-adjusted stock of previous granted patents:

$$K_{i,t} = \sum_{s=1978}^{t} PAT_{i,s} exp[-\hat{\beta_1}\,(t-s)] * [1 - exp\left(-\hat{\beta_2}\,(t-s)\right)].$$

$\hat{\beta_1}$ and $\hat{\beta_2}$ stand for the rate of decay and diffusion of knowledge, which are estimated by the probability that a patent would be cited by subsequent patents. See Popp (2002) and Feng and Lazkano (2022) for further details about the construction of our knowledge stocks.

country. There is no evidence on them in greater geographic definitions such as subregions and regions. Therefore, I construct a country-level spillover, which is the accumulation of all citation-adjusted knowledge stock of storage technologies from other firms in country j, i.e. $\mathrm{K}_{j-i,t}$.[12]

$\mathrm{Policy}_{j,t}$ is a vector of policy variables. As described in section 2.2.2, I use continuous measures of policy stringency. I adopt a composite market EPS index, one composite indicator for each policy type namely environmental taxes, FITs and trading schemes, and six policy measures from the three types (environmental taxes, FITs for solar energy, FITs for wind power, tradable certificates for $\mathrm{CO_2}$ emissions, renewable energy certificates and energy efficiency certificates) in three baseline specifications, respectively.

Firm_i is the pre-sample patenting behavior that proxies for fixed effects. This variable is constructed to address the problem that knowledge stocks are not strictly exogenous, which would bias the standard fixed effects count data model (Hausman et al., 1984; Blundell et al., 1995). Following Aghion et al. (2016), the citation-adjusted knowledge stock in year 0, i.e. the last year of the pre-sample period (t = 1989 in this case), is taken as the pre-sample fixed effects in this study (shown as *Pre-sample Firm* in result tables). There are alternative ways to deal with the firm-level fixed effects. For example, a pre-sample average of the dependent variable suggested by Blundell et al. (1995), and the fixed-effect Poisson estimator confirmed by Aghion et al. (2016). Specifications with such alternatives are presented in robustness analysis. In addition, Time_t is a complete set of year dummies to account for year fixed effects.[13]

I adopt a negative binomial model as the baseline to address overdispersion of patent data.[14] I include a dummy variable, *Pre-sample Zero*, for firms without

[12] While one might be concerned that $\mathrm{K}_{i,t}$ and $\mathrm{Spillover}_{j-i,t}$ are endogenous because they include current patent applications, note that current patent applications are only a small portion of the overall stock because of the slow nature of the diffusion process. In addition, all explanatory variables are lagged to address such issues.

[13] One might argue that a country fixed effect is necessary to control for some country-specific characteristics such as financial markets. Table B.4.3 in Appendix B.4 shows estimations with a set of country dummies. Policy instruments keep the signs as in baseline estimations but most of them lose significance. Thus, country differences are important in terms of the effects here, but the identification comes from country differences in the stringency of environmental policies.

[14] Specify the mean and variance of a count data as follow:

$$E(Y) = \lambda, Var(Y) = \lambda * (1 + \delta),$$

pre-sample patents. This variable is used to address the potential that these firms behave in a structurally different way and the model may be biased because of the incidental parameter problem. Finally, there might be an endogeneity problem. Innovation in energy storage can help reduce the costs of renewable energy, scale up its deployment, and then reduce carbon emissions. $\text{Price}_{j,t}$ and $\text{Policy}_{j,t}$ could pose a simultaneity issue as they may respond to new storage technologies. Note, however, that the variables describe current prices and policies whereas innovation may only have an impact on the future. In addition, it takes time for any response to result in patenting behavior. Therefore, I use the lag of explanatory variables to control for potential endogenous links. As there is no common way to find an optimal lag, I use the first lag of all explanatory variables in the baseline and conduct specifications using different lag structures in the robustness analysis.[15]

2.4 Results and Discussion

In this section I present the main results of the baseline model followed by alternative specifications to validate my results. To study the impact of market-based environmental policies on innovation in energy storage, the baseline model includes energy prices, past innovation, knowledge spillovers and the stringency of market-based environmental policies. The alternative specifications that follow use different

where δ is the overdispersion parameter. My patent data shows overdispersion where $\delta = 1.87$. Therefore, I adopt the negative binomial model as it addresses overdispersion problem compared to the Poisson distribution.

[15]I conduct the Oster's bound analysis to evaluate the endogeneity of these variables. Specifically, to test whether the price index, fixed effects, and lags can fully address the potential bias due to endogeneity, I first estimate a linear regression model with the dependent variable $\log(\text{PAT}_{i,t}{+}1)$ and then I apply the Oster's bound analysis. The bound estimates (δ) of the lagged energy price index are close to zero in all specifications, which suggests that the extent of the bias is limited. For most policy instruments, the bound estimate is either much smaller than the linear coefficient, or close to zero. For example, the bound estimate of lagged environmental taxes is 0.0016, which is much smaller than its coefficient 0.0069 from the linear regression. This indicates that there is little evidence of endogeneity bias. The bound estimates of other lagged policy variables, such as FITs for solar energy with $\delta = 0.0009$, though not necessarily smaller than the controlled estimates, are close to zero and the R-squares of the controlled model are substantially larger. This suggests that policy variables help explain some variation in the dependent variable, though there might be a small degree of endogeneity bias present. Overall, the Oster's bound analysis gives me confidence that the variables I selected in my baseline model to address endogeneity.

estimators, and different lag structures. I report percentage impacts of explanatory variables along with the estimated parameters for ease of interpretation. Standard errors for each coefficient are included in parentheses.

2.4.1 Main results

Table 2.2 presents the main results of the negative binomial model using firm-level data from 1990 to 2015. I consider three different specifications: (1) a composite market EPS index, (2) one composite indicator for each policy type, namely environmental taxes, FITs and trading schemes, and (3) six individual environmental policy measures. Columns (1), (3) and (5) present the estimated coefficients, and columns (2), (4) and (6) show the expected change in the count of storage patents in terms of a percentage change. In line with the induced innovation theory and previous work, the energy price index, knowledge stocks, and knowledge spillovers significantly drive storage innovation (e.g. Jaffe et al., 1993; Popp, 2002; Audretsch and Feldman, 2004b; Verdolini and Galeotti, 2011b; Acemoglu et al., 2012).

Column (1) explains the first specification and shows the overall positive and significant effect of market EPS on storage patenting. Specifically, with a one-unit rise in the composite market EPS, a firm is expected to apply for 60.9% more storage patents. This suggests that firms tend to innovate more when they are located in a country where market-based environmental policies are overall valued and stringent. This implies that the both the existence and stringency of environmental policies are important to promote firm-level innovation in energy storage. Thus, we can boost improvements in storage technologies by increasing the stringency of existing policies. Column (3) explains the second specification for each policy type. I find significantly positive effects of environmental taxes and FITs but not trading schemes. Column (5) then shows estimates of the third specification with individual environmental policy measures, where I find that different market-based environmental policies lead to heterogeneous effects, even among the same policy type.

Results in Table 2.2 show strong evidence for the role of environmental taxes in promoting firms' storage patenting. As discussed in Section 2.2.2, the measure for environmental taxes applies additional costs based on emissions of CO_2, NO_x, SO_x and diesel (Botta and Koźluk, 2014). As shown in both columns (3) and (5), a more stringent environmental tax policy fosters patenting in energy storage. The effect is strong and positive, with a greater than 100% change, which the country-level analysis in Table 2.3 supports. This result contributes to the understanding of the relationship between environmental taxes and storage innovation. Previous work on energy innovation offers inconsistent evidence of the impact of environmental taxes. For example, Johnstone et al. (2009) find no effect of tax measures on renewable-energy-related innovation. My results may be different for two reasons. First, my analysis is based on a different policy proxy. While the tax dummy in Johnstone et al. (2009) does not reflect policy stringency, I use a continuous tax measure indicating both the existence and the stringency of environmental taxes. Rozendaal and Vollebergh (2021) also find a positive and significant tax effect on clean patenting in the car market, using a continuous excise tax. Thus, there might be more political obstacles for a stringent tax policy than other policies, which leads to no significant effect of the presence of a tax policy. Second, as a complementary technology, environmental taxes could influence innovation in energy storage differently. To explain this further, I conduct the same estimation using patent data on generation technologies. Appendix B.5, Table B.5.6 shows that there is no significant effect of environmental taxes on renewable generation technologies, which is in line with Johnstone et al. (2009). This is also consisted with Barradale (2010) who indicates that investors tend not to believe that policies depending on public finance would remain in place for a relative long time, such as tax policies. Therefore, higher costs caused by environmental taxes might have an impact on energy investors' perception of future viability, which leads to a non-significant environmental tax effect. Nevertheless, innovation in energy storage is currently in a fast-developing stage, and the next generation of energy storage technologies are given high expectations (Perdana et al., 2023). Storage investors then may anticipate a higher market share of renewable energy from stringent environmental taxes and invest more on advanced storage technologies to solve the intermittency problem of renewables.

Next, I discuss FITs which guarantee a set price for solar power and wind power. The composite index of FITs has an overall positive effect on a firm's storage patenting activities in Table 2.2 column (3). However, as shown in column (5), the impacts of FITs for solar power and for wind power differ. Specifically, only solar FITs have a significant effect on improving firm-level patenting activities. A firm is expected to apply for 14.5% more storage patents if the stringency of solar FITs increases by one unit, while wind FITs lead to a statistically insignificant reduction. This is consistent with Stevens and Rouhollahi (2021), who find a weakly positive impact of FITs for solar on storage technology patenting. They find no statistical significance for FITs for wind on other types of complementary grid technologies. These results suggest that guaranteed prices of wind energy may not additionally improve firm-level incentives to innovate in storage. In addition, these results support the idea that the impact of different FITs are technology-specific. Previous work has found a similar result when studying innovation in renewable energy. For example, Johnstone et al. (2009) find that the level of FITs has a positive influence on solar energy patenting, but not on other types of technologies. Likewise, Böhringer et al. (2017), focusing on the German feed-in tariff scheme, find both negative and positive technology-specific FITs effects. They indicate that FITs for solar and wind have an insignificant influence on renewable patent filings. A potential reason could be that since feed-in tariffs are often calculated based on the average cost of each respective technology, there are few revenue incentives for renewable electricity producers to deploy. In addition, there are few incentives for investors to invest in uncertain new technologies as pre-existing established technologies could be more attractive. Therefore, compared with other market-based environmental policies, FITs have limited impact boosting firm-level innovation in energy storage.

As with FITs, trading schemes also present heterogenous effects. The aggregate index for trading schemes is insignificant in column (3). However, tradable certificates for CO_2 emissions promote storage innovation. With a one-unit higher stringency, a firm's storage patenting is expected to increase by 18.2%. This is consistent with the induced innovation theory. With tradable CO_2 certificates, emitters can trade the right to emit under a cap-and-trade system. A more stringent policy on that requires a higher use of low-carbon-emission resources and a transition towards renewable energy. New storage technologies then become imperative to help lower costs by overcoming the intermittency problem and boost the expansion. In contrast, renewable energy certificates, and particularly white tags (written as *Certificates: Green* and *Certificates: White* respectively in tables) are strong hindrances for storage patenting. Renewable energy certificates require a certain share of renewable energy in utilities' portfolio, where a one-unit higher stringency reduces a firm's storage patenting by 28.14%.[16] White tags establish energy savings obligations for utilities and lead the storage patenting activities to a 83.56% reduction. One possible explanation is a firm's resource composition. Close to 90% of firms are mixed firms innovating both in electricity generation and storage technologies. Such certificates might change the allocation of investment and innovation effort within firms. To investigate this further, I estimate equation 2.1 using patent applications of generation technologies in Appendix B.5. White tags hinder firm-level generation innovation (see Appendix B.5 Table B.5.4). Specifically, a firm is expected to apply for 22.8% less generation patents, from both fossil-fuel and renewable technologies, when the stringency of white tags is one-unit higher. This could happen when prices or transaction costs of white tags are high. Though they are generally designed to improve energy efficiency, they could also create a financial burden for firms and discourage investment. Therefore, within a country's environmental policy framework, the inclusion of specific incentives or bonuses for renewable energy adoption and energy storage deployment might be an effective channel to further incentivize innovation. In contrast, renewable energy certificates strongly encourage patenting in both fossil-fuel and renewable generation technologies, by 30.3% and 39.2% respectively. This is hardly surprising as energy storage and generation

[16]This result is further confirmed by estimating my model with the 2020 version EPS data. These results show nearly identical results for tradable certificates for CO_2 emissions and renewable energy certificates. Note, however, that the updated 2020 index excludes white tags.

technologies are at different stages of maturity, which lead to distinct anticipation of investment and research effort for a successful innovation. Firms will then choose the least-costly technology option to meet these energy targets. Thus, for mixed firms, more stringent renewable energy certificates could alter their decision due to cost differences among technologies. In addition, previous work has reported inconsistent effects of renewable energy certificates on renewable generation and capacity, which ranges from a positive effect to a negative effect (see e.g. Carley, 2009; Johnstone et al., 2009; Shrimali and Kniefel, 2011; Hollingsworth and Rudik, 2019). Nevertheless, this study only finds negative influences of renewable energy certificates and energy efficiency certificates on firms' storage patenting behavior. Therefore, I am unable to draw the conclusion based on this evidence alone.

To conclude the results on how market EPS affects incentives of storage innovation, I estimate the baseline model using aggregate country-level data in Table 2.3.[17] Results are overall in line with firm-level results in Table 2.2 but with less significance. The composite indicator, Market EPS, presents a low impact on country-level incentives. Environmental taxes have a positive effect at the country level, but with a much smaller magnitude than at the firm level. Policies that affect firms' innovation incentives, such as FITs for solar energy, tradable certificates for CO_2 emissions and renewable energy certificates, are insignificant at country level. I keep the firm-level analysis as the baseline analysis for two reasons. First, the incentives to innovate happen at the firm level (see e.g. OECD, 2015; Hall et al., 2010). Second, as shown in Figure 2.1, most innovation happens in three countries, and so the variation in the data diminishes when I focus on the top ten countries.

2.4.2 Heterogenous policy effects

Figure 2.4 shows that 92.47% of the sample firms are mixed firms innovating both in storage and generation technologies. Technology-neutral environmental policies could

[17] Here K_{t-1} is the available knowledge that researchers can build upon in country j and year t. As mentioned in section 2.3, knowledge spillovers in electricity storage influence only within the same country. Therefore, I do not include any spillover here in greater geographic definitions. In addition, the variable *Pre-sample Zero* is no longer included because all countries have pre-sample patents.

Table 2.2: Firm-level baseline estimates using data from 1990 to 2015 for top 10 countries.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	-1.828***		-2.557***		-2.693***	
	(0.2274)		(0.2668)		(0.2722)	
Energy price index$_{t-1}$	2.1e-08**	0%**	2.4e-08**	0%**	3.0e-08***	0%***
	(9.3e-09)		(9.4e-09)		(1.0e-08)	
K_{t-1}	0.2941***	34.2%***	0.282***	32.6%***	0.2748***	31.6%***
	(0.0238)		(0.0235)		(0.0230)	
Spillovers$_{t-1}$	0.0041***	0.4%***	0.0013*	0.1%*	0.0009	0.1%
	(0.0005)		(0.0008)		(0.0008)	
Market EPS$_{t-1}$	0.4756***	60.9%***				
	(0.1456)					
Environmental Taxes$_{t-1}$			0.6955***	100.5%***	0.7869***	119.7%***
			(0.1117)		(0.1129)	
Feed-in Tariffs$_{t-1}$			0.101**	10.6%**		
			(0.0506)			
FIT Solar$_{t-1}$					0.1354*	14.5%*
					(0.0762)	
FIT Wind$_{t-1}$					-0.0543	-5.29%
					(0.0553)	
Trading Scheme$_{t-1}$			0.0844	8.8%		
			(0.1736)			
Certificates: CO_{2t-1}					0.1669*	18.2%*
					(0.0910)	
Certificates: Green$_{t-1}$					-0.3305**	-28.14%**
					(0.1618)	
Certificates: White$_{t-1}$					-1.805**	-83.56%**
					(0.8493)	
Pre-sample Firm	-0.0501	-4.88%	-0.0194	-19.2%	-0.0056	-0.56%
	(0.0492)		(0.0493)		(0.0483)	
Pre-sample Zero	-1.159***	-68.6%***	-1.154***	-68.45%***	-1.113***	-67.15%***
	(0.0986)		(0.0988)		(0.0983)	
Year	YES		YES		YES	
N	3894		3894		3894	
chi2	942		972		1004	

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

Note: The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

have different influences on firms specialized more in renewable energy and firms with a higher focus on conventional generation technologies. To understand heterogenous policy effects in different firm types, I construct two variables to proxy a firm's expertise in renewable energy: (1) Specialty$_{i,t}$ – the share of renewable patents (over the total number of generation patents) in firm i and year t; (2) Timing$_i$ – the time length since firm i

Table 2.3: Country-level baseline estimates using data from 1990 to 2015 for top 10 countries.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	1.368***		0.9824***		0.9161***	
	(0.1982)		(0.2285)		(0.2232)	
Energy price index$_{t-1}$	-7.2e-08***	0%***	-8.0e-08***	0%***	-7.3e-08***	0%***
	(9.7e-09)		(1.0e-08)		(1.3e-08)	
K$_{t-1}$	0.0079***	0.8%***	0.0066***	0.7%***	0.0064***	0.6%***
	(0.0004)		(0.0005)		(0.0005)	
Market EPS$_{t-1}$	0.0398	4.1%				
	(0.0796)					
Environmental Taxes$_{t-1}$			0.2489***	28.3%***	0.3425***	39.8%***
			(0.0801)		(0.0840)	
Feed-in Tariffs$_{t-1}$			-0.0107	-1.04%		
			(0.0301)			
FIT Solar$_{t-1}$					0.0146	1.5%
					(0.0355)	
FIT Wind$_{t-1}$					-0.0157	-1.55%
					(0.0229)	
Trading Scheme$_{t-1}$			-0.0927*	-8.85%*		
			(0.0547)			
Certificates: CO$_{2t-1}$					0.0337	3.4%
					(0.0411)	
Certificates: Green$_{t-1}$					-0.0443	-4.33%
					(0.0451)	
Certificates: White$_{t-1}$					-0.1469***	-13.66%***
					(0.0491)	
Pre-sample Country	0.0563***	5.8%***	0.0608***	6.3%***	0.0579***	6%***
	(0.0039)		(0.0041)		(0.0047)	
Year	YES		YES		YES	
N	205		205		205	
chi2	471		478		493	

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

Note: The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

applied for its first renewable patent.[18] These two variables capture the intensity of firm i in renewable energy innovation, and how long it has conducted renewable innovation.

[18] Specifically, the construction of these two variables is as follows:

$$\text{Specialty}_{i,t} = \frac{\text{Renewable patents}_{i,t}}{\text{Generation patents}_{i,t}},$$

$$\text{Timing}_i = 1990 - s,$$

where s is the year when firm i filed its first renewable patents. A greater Timing$_i$ captures an "earlier" firm and the sign indicates whether the first renewable patent happens with any market-based environmental policy.

Table 2.4 shows baseline estimates of policy interactions with these two variables. Appendix B.6 Table B.6.7 and Table B.6.8 present the complete results of specifications with policy interactions, where the levels of interaction terms are also shown. Note that the composite indicator Market EPS, environmental taxes and FITs have larger coefficients on their levels in Table B.6.7 and Table B.6.8, and adding interactions does not take them away. Here in Table 2.4, I only show interaction terms. Overall, the composite indicator of market EPS, as presented in column (1), does not impact storage patenting differently given firms' various expertise in renewable energy. However, environmental taxes and tradable certificates for CO_2 have heterogenous effects when a firm is more specialized in renewable technology invention. In panel A column (5), firms with a higher innovation share in renewable energy react more strongly to tradable certificates for CO_2 but slightly less to environmental taxes. Interactions with the time length variable in panel B do not show statistical significance. One possible reason is that battery and fuel cell technologies are relatively newly developed, and whether a firm starts renewable innovation early or later may not be as important as its behavior in recent years.

These results suggest that the level of renewable specialization matters more than the time length specialization. Moreover, as seen in Table 2.2, environmental taxes and tradable certificates for CO_2 emissions encourage firms' patenting activities in energy storage directly, and their sensitivity to these results change with a firm's level of specialization in renewable technologies. This suggests that policies directed at increasing R&D investments for renewable energy can boost their expertise, and therefore create additional benefits to innovation energy storage. Thus, the combination of both types of policies creates an effective framework to boost innovation.

2.4.3 Robustness analysis

I further explore specifications with alternative firm fixed effects and different lag structures in this section to validate the baseline results.

In the baseline estimation, I use the knowledge stock in the last year of the pre-sample period (year 1989) as the firm fixed effect and a Pre-sample Zero dummy to address the

Table 2.4: Heterogenous policy effects in firms' expertise in renewable technologies.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Panel A: Interaction with Specialty$_{t-1}$						
xMarket EPS$_{t-1}$	-0.0159	-1.58%				
	(0.0138)					
xEnvironmental Taxes$_{t-1}$			-0.0076†	-0.76%†	-0.0111**	-1.1%**
			(0.0051)		(0.0050)	
xFeed-in Tariffs$_{t-1}$			-0.0135	-1.34%		
			(0.0129)			
xFIT Solar$_{t-1}$					-0.0034	-0.34%
					(0.0160)	
xFIT Wind$_{t-1}$					-0.0079	-0.78%
					(0.0118)	
xTrading Scheme$_{t-1}$			-0.0054	-0.54%		
			(0.0199)			
xCertificates: CO_{2t-1}					0.1119**	11.8%**
					(0.0465)	
xCertificates: Green$_{t-1}$					-0.0045	-0.45%
					(0.0103)	
xCertificates: White$_{t-1}$					-20.26	-100%
					(52.63)	
Panel B: Interaction with Timing$_{t-1}$						
xMarket EPS$_{t-1}$	0.0048	0.5%				
	(0.0185)					
xEnvironmental Taxes$_{t-1}$			-0.0025	-0.25%	0.0015	0.2%
			(0.0176)		(0.0175)	
xFeed-in Tariffs$_{t-1}$			0.0128†	1.3%†		
			(0.0087)			
xFIT Solar$_{t-1}$					-0.0027	-0.27%
			(0.0120)			
xFIT Wind$_{t-1}$					0.0056	0.6%
			(0.0100)			
xTrading Scheme$_{t-1}$			-0.0020	-0.2%		
			(0.0296)			
xCertificates: CO_{2t-1}					-0.0024	-0.24%
					(0.0132)	
xCertificates: Green$_{t-1}$					-0.0013	-0.13%
					(0.0253)	
xCertificates: White$_{t-1}$					-15.7	-100%
					(644.9)	

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

Note: Data from 1990 to 2015 in top 10 countries. The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

potential incidental parameter problem. There are alternative ways to proxy firm-level fixed effects. Blundell et al. (1995) suggest the pre-sample average of the dependent variable, while Aghion et al. (2016) choose a fixed-effect Poisson estimator.[19] I adopt both alternatives and use a Poisson Pseudo-Maximum Likelihood (PPML) estimator because of consistency and no asymptotic bias (Weidner and Zylkin, 2021). I present results in Table 2.5 and Table 2.6, and the main results hold. Estimates with average citation-adjusted knowledge stocks in the pre-sample period (year 1978-1989) in Table 2.5 show that the composite market EPS, environmental taxes and tradable certificates of CO_2 emissions significantly promote firm-level storage patenting while renewable energy certificates and white tags hinder it. The fixed-effect Poisson estimation in Table 2.6 validates the positive impacts of the composite market EPS and environmental taxes on firm-level storage patenting, but only significant influence of white tags among trading schemes.

I then conduct the baseline model with different lag structures and results are presented in Table 2.7 and Table 2.8. Table 2.7 uses the second lag of all explanatory variables and Table 2.8 uses the third lag. Results are in line with the baseline results where the composite market-based environmental policy stringency, particularly environmental taxes and tradable certificates of CO_2 emissions, significantly incentivize patenting activities in storage technologies. Moreover, further lags of feed-in tariffs show a stronger influence than their first lag. For example, from table 2.2 the stringency of FITs for solar energy in the last year increases a firm's storage patenting by 14.5% at a 10% significance level. Table 2.7 column (6) shows that FITs for solar energy two years before increase storage patenting by 25.3%, while the third lag in Table 2.8 shows a 42.8% increase, and both significant at 1%. In contrast, the significance of trading schemes vanishes with longer lags. This is hardly surprising as the innovation process can take years. It suggests that some policies such as FITs may affect the early stage in the process of storage innovation while other policies such as trading schemes impact the later stage to a higher degree. By understanding these relationships, policymakers could be able to develop more effective policies to support the development, as well as the deployment, of new technologies.

[19] Allison and Waterman (2002) indicate that conditional negative binomial model for panel data does not qualify as a true fixed effects method because it does not control for all stable covariates.

Table 2.5: Alternative firm-level fixed effects: pre-sample average fixed effects.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	-1.452***		-1.908***		-2.059***	
	(0.1951)		(0.2227)		(0.2281)	
Energy price index$_{t-1}$	2.3e-09	0%	2.3e-09	0%	1.1e-08	0%
	(7.7e-09)		(7.7e-09)		(8.6e-09)	
K$_{t-1}$	0.347***	41.5%***	0.3498***	41.9%***	0.3389***	40.3%***
	(0.0224)		(0.0228)		(0.0223)	
Spillovers$_{t-1}$	0.0043***	0.4%***	0.0023***	0.2%***	0.0021***	0.2%***
	(0.0004)		(0.0007)		(0.0007)	
Market EPS$_{t-1}$	0.1853†	20.4%†				
	(0.1221)					
Environmental Taxes$_{t-1}$			0.4277***	53.4%***	0.4769***	61.1%***
			(0.0969)		(0.0969)	
Feed-in Tariffs$_{t-1}$			0.0115	1.2%		
			(0.0432)			
FIT Solar$_{t-1}$					-0.0188	-1.87%
					(0.0623)	
FIT Wind$_{t-1}$					-0.0084	-0.84%
					(0.0438)	
Trading Scheme$_{t-1}$			0.0262	2.7%		
			(0.1584)			
Certificates: CO_{2t-1}					0.1576**	17.1%**
					(0.0787)	
Certificates: Green$_{t-1}$					-0.3101**	-26.67%**
					(0.1389)	
Certificates: White$_{t-1}$					-1.411*	-75.62%*
					(0.8261)	
Pre-sample Firm	-0.1609**	-14.86%**	-0.1563**	-14.47%**	-0.1322*	-12.39%*
	(0.0696)		(0.0700)		(0.0684)	
Pre-sample Zero	-1.289***	-72.44%***	-1.279***	-72.18%***	-1.259***	-71.62%***
	(0.0923)		(0.0932)		(0.0922)	
Year	YES		YES		YES	
N	5717		5717		5717	
chi2	1310		1315		1353	

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

Note: Data is from 1990 to 2015 for all firms in top 10 countries. The average citation-adjusted knowledge in the pre-sample period is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

2.5 Conclusion

Energy storage has received global attention as an important complement to intermittent renewable energy. Currently, innovation in energy storage is dramatically increasing but its use is still limited. Along with climate goals, governments have introduced various market-based policies to accelerate clean energy transitions. Using

Table 2.6: Alternative firm-level fixed effects: PPML estimator.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Energy price index$_{t-1}$	4.8e-09	0%	7.4e-09†	0%†	7.5e-09	0%
	(4.9e-09)		(4.8e-09)		(5.7e-09)	
K$_{t-1}$	0.106***	11.2%***	0.1043***	11%***	0.104***	11.%***
	(0.0050)		(0.0050)		(0.0050)	
Spillovers$_{t-1}$	0.0048***	0.5%***	0.0030***	0.3%***	0.0027***	0.3%***
	(0.0003)		(0.0004)		(0.0004)	
Market EPS$_{t-1}$	0.1802**	19.7%**				
	(0.0826)					
Environmental Taxes$_{t-1}$			0.4211***	52.4%***	0.4552***	57.7%***
			(0.0824)	(0.0818)		
Feed-in Tariffs$_{t-1}$			0.0404	4.1%		
			(0.0313)			
FIT Solar$_{t-1}$					0.0417	4.3%
					(0.0444)	
FIT Wind$_{t-1}$					-0.0136	-1.35%
					(0.0309)	
Trading Scheme$_{t-1}$			-0.174**	-15.97%**		
			(0.827)			
Certificates: CO$_{2t-1}$					-0.0058	-0.58%
					(0.0569)	
Certificates: Green$_{t-1}$					-0.1197	-11.28%
					(0.0906)	
Certificates: White$_{t-1}$					-0.2131*	-19.2%*
					(0.1185)	
Year	YES		YES		YES	
N	15315		15315		15315	
chi2	1212		1258		1282	

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

Note: Data is from 1990 to 2015 for all firms in top 10 countries. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

patent data from 1978 to 2015 combined with the EPS index generated by the OECD, I empirically examine the impacts of market-based environmental policies on innovation in energy storage in the ten most innovative countries. Overall, I find that the stringency of environmental policies, as measured by a composite market EPS index, encourages innovation in energy storage. Specifically, environmental taxes, FITs for solar energy and tradable certificates for CO_2 emissions strongly promote firms' patenting activity in energy storage, whereas renewable energy certificates and energy efficiency certificates discourage it. In addition, I find that firms with a high level of specialization in renewable technologies respond more to tradable certificates for CO_2

Table 2.7: Alternative lag structures: the 2nd lag.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	-1.715*** (0.2457)		-2.533*** (0.2817)		-2.686*** (0.2863)	
Energy price index$_{t-2}$	3.3e-08*** (1.0e-08)	0%***	3.3e-08*** (1.0e-08)	0%***	4.4e-08*** (1.1e-08)	0%***
K_{t-2}	0.2902*** (0.0257)	33.7%***	0.2571*** (0.0249)	29.3%***	0.2693*** (0.0246)	30.9%***
Spillovers$_{t-2}$	0.00463*** (0.0005)	0.5%***	0.0013† (0.0008)	0.1%†	0.0008 (0.0008)	0.1%
Market EPS$_{t-2}$	0.6864*** (0.1616)	98.7%***				
Environmental Taxes$_{t-2}$			0.7895*** (0.1173)	120.2%***	0.8854*** (0.1174)	142.4%***
Feed-in Tariffs$_{t-2}$			0.1292** (0.0563)	13.8%**		
FIT Solar$_{t-2}$					0.2255*** (0.0848)	25.3%***
FIT Wind$_{t-2}$					-0.112* (0.0645)	-10.6%*
Trading Scheme$_{t-2}$			0.1172 (0.1868)	12.4%		
Certificates: CO_{2t-2}					0.1778* (0.1028)	19.5%*
Certificates: Green$_{t-2}$					-0.4798*** (0.1801)	-38.11%***
Certificates: White$_{t-2}$					-21.08 (27135)	-100%
Presample Firm	-0.0844† (0.0550)	-9.1%†	-0.0086 (0.0541)	-0.86%	-0.0285 (0.0532)	-2.81%
Presample Zero	-1.14*** (0.1126)	-68.03%***	-1.107*** (0.1047)	-66.94%***	-1.09*** (0.1118)	-66.39%***
Year	YES		YES		YES	
N	3469		3469		3469	
chi2	753		793		837	

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

Note: Data is from 1990 to 2015 for all firms in top 10 countries. The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 2th lag of all explanatory variables is used.

emissions but less to environmental taxes. Finally, my results suggest that these policies may affect different stages in the process of storage innovation. Some policies such as FITs show a stronger influence with longer lags while the significance of other policies such as trading schemes vanishes overtime.

These empirical findings have several policy implications. First, governments could

Table 2.8: Alternative lag structures: the 3rd lag.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	-1.666***		-2.337***		-2.401***	
	(0.2643)		(0.2978)		(0.2998)	
Energy price index$_{t-3}$	3.0e-08***	0%***	2.9e-08***	0%***	3.2e-08**	0%***
	(1.1e-08)		(1.1e-08)		(1.2e-08)	
K_{t-3}	0.2549***	29%***	0.2279***	25.6%***	0.2386***	26.9%***
	(0.0262)		(0.0255)		(0.0249)	
Spillovers$_{t-3}$	0.0050***	0.5%***	0.0019**	0.2%**	0.0015*	0.1%*
	(0.0006)		(0.0009)		(0.0009)	
Market EPS$_{t-3}$	0.7863***	119.5%***				
	(0.1708)					
Environmental Taxes$_{t-3}$			0.7481***	111.3%***	0.8134***	125.6%***
			(0.1226)		(0.1227)	
Feed-in Tariffs$_{t-3}$			0.1513**	16.3%**		
			(0.0590)			
FIT Solar$_{t-3}$					0.3564***	42.8%***
			(0.0933)			
FIT Wind$_{t-3}$					-0.1849***	-16.88%***
			(0.0712)			
Trading Scheme$_{t-3}$			0.2232	25%		
			(0.1882)			
Certificates: CO_{2t-3}					0.1516†	16.4%†
					(0.101)	
Certificates: Green$_{t-3}$					-0.2405	-21.37%
					(0.1918)	
Certificates: White$_{t-3}$					-18.85	-100%
					(6060)	
Presample Firm	-0.0622	-6.03%	-0.0053	-0.52%	-0.0261	-2.58%
	(0.058)		(0.0569)		(0.0564)	
Presample Zero	-1.102***	-66.78%***	-1.073***	-65.79%***	-1.046***	-64.87%***
	(0.1179)		(0.1088)		(0.117)	
Year	YES		YES		YES	
N	3135		3135		3135	
chi2	625		660		699	

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

Note: Data is from 1990 to 2015 for all firms in top 10 countries. The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 3th lag of all explanatory variables is used.

focus on increasing the stringency of existing market-based environmental policies as part of the energy policy framework targeting innovation in energy storage. Six of the most innovative ten countries have an above-OECD-average market EPS. It suggests that countries with stronger market-based environment policies also promote developing patents in energy storage technologies. Second, governments interested in facilitating innovation in energy storage could strengthen direct carbon pricing instruments, i.e. carbon taxes and tradable CO_2 certificates (ETSs). My results show that such policies strongly and significantly increase patenting in energy storage These results provide another reason to enhance these policies among these ten countries. In 2021, though carbon prices rose quickly and hit record highs in many jurisdictions (World Bank, 2022), my stringency results support even higher carbon prices to encourage storage innovation. Finally, firms specialized in renewable energy respond differently to policies that directly encourage storage patenting. Therefore, increasing investments in R&D for renewable energy to help firms reach a higher expertise level will create additional benefits to innovation in energy storage.

Chapter 3

The Role of Energy Storage Subsidies to Boost Clean Energy Transitions

3.1 Introduction

Energy storage plays a key role in the transition to clean energy. In the transportation sector, electric vehicles, which rely on storage batteries, are the key technology to decarbonize road transportation. In the electricity sector, storage provides energy system flexibility. On the one hand, storage helps harness renewable energy like wind and solar, which generate energy intermittently. On the other hand, storage improves the efficiency of conventional technologies like natural gas and coal power plants. Thus, global energy storage deployment is scaling up to achieve climate and energy targets. To this end, policymakers globally have implemented policies like subsidies and mandates to boost growth in global energy storage deployment.[1]

Energy storage deployment includes a variety of technologies. In the electricity sector, the most widely deployed technology is pumped-storage hydropower followed by

[1]For example, from 2016 to 2021 hydrogen and fuel cells technologies have seen the most rapid increase of 140% in public R&D budgets among International Energy Agency countries. IEA Energy Technology RD&D Budgets database, `https://www.iea.org/data-and-statistics/data-product/energy-technology-rd-and-d-budget-database-2`.

grid-scale batteries, while in the transportation sector, electric vehicles commonly use lithium-ion batteries. The expansion of pumped-storage hydropower is geographically limited, whereas the production of batteries used in solar photovoltaic plants, wind farms and electric vehicles relies on nonrenewable minerals like cobalt, nickel, and lithium.[2] For example, IEA (2021b) finds that an electric car uses six times the mineral inputs of a conventional car and that an onshore wind plant uses nine times more mineral resources than a gas-fired plant. Thus, the global increase in the share of renewables and electric vehicles has led to a higher demand for minerals, which has resulted in a 50% increase on the average amount of minerals needed for a new unit of power generation capacity since 2010 (IEA, 2021b). To address mineral energy security and to reduce reliance on critical materials, we would like to highlight the role of innovation.

The newest innovation is sodium-ion batteries that are free of lithium and the sodium they need can be found anywhere. The first sodium-ion battery car (BYD Seagull) is scheduled to be released in April 2023 and mass production of sodium-ion batteries is expected for the second quarter of 2023. The global patent race for post-lithium-ion batteries over the past 10 years shows that patents for sodium-ion batteries dominate the race. In total, there are close to 10,000 patents for post-lithium-ion batteries. This one example shows how innovation can provide alternatives to batteries that rely on non-renewable materials such as lithium.

Our goal is to theoretically show that a research subsidy to energy storage has the potential to change the technical transition in energy sector beyond its ability to enable the use of intermittent renewable energy and electric vehicles. Acemoglu et al. (2012) is prominent in the literature to study induced innovation in the energy sector and many subsequent papers have built on or analyzed their work (see e.g. Acemoglu et al., 2014; Lazkano et al., 2017b; Lemoine, 2017; Wiskich, 2021). Their model considers two sectors

[2] IEA (2021b) states that "*the types of mineral resources used vary by technology. Lithium, nickel, cobalt, manganese and graphite are crucial to battery performance, longevity and energy density. Rare earth elements are essential for permanent magnets that are vital for wind turbines and EV motors. Electricity networks need a huge amount of copper and aluminium, with copper being a cornerstone for all electricity-related technologies.*"

(clean and dirty) and optimal policy to achieve energy transition relies on a carbon tax and a research subsidy to the clean sector. Within a stylized theoretical model of directed technical change, we consider a research subsidy to energy storage contributing to both clean and dirty sectors. Specifically, we adopt a proportional profit subsidy to energy storage, which shows in the expected profit from undertaking research in both clean and dirty sectors. Thus, we present energy storage as a mechanism that can promote innovation in both clean and dirty sector, then influence the optimal allocation.

Our results provide the evidence on the importance of a subsidy to energy storage, particularly when the elasticity of substitution between clean and dirty energy inputs is low. In other conditions unchanged, a storage subsidy would postpone the timing of adopting a clean innovation subsidy, and shorten its duration, which helps shoulder temporary financing and research burden in clean sector.

The paper proceeds as follows. In section 2, we present the the optimal environmental policy while section 3 presents the calibrations and discusses our results. Section 4 concludes.

3.2 Optimal Environmental Policy

According to Acemoglu et al. (2012), the relative benefit from undertaking research in clean sector c to dirty sector d in the decentralized equilibrium without any policy intervention is:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d}\left(\frac{p_{ct}}{p_{dt}}\right)^{\frac{1}{1-\alpha}} \frac{L_{ct}}{L_{dt}}\frac{A_{ct-1}}{A_{dt-1}}. \tag{3.1}$$

Defining $\varphi \equiv (1-\alpha)(1-\epsilon)$, equation 3.1 can be written as 3.2:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d}\left(\frac{1+\gamma\eta_c s_{ct}}{1+\gamma\eta_d s_{dt}}\right)^{-\varphi-1}\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{-\varphi}. \tag{3.2}$$

Under the assumption of DTC model, “dirty input production Y_d always grows without bound” and the economy under laissez-faire will lead to an environmental disaster. Acemoglu et al. (2012) implement the socially optimal allocation using a tax on dirty input (a "carbon" tax), a subsidy to clean innovation, and a subsidy for the use of all machines.

In addition to these three policy interventions, we include a research subsidy to energy storage in our study, which is a proportional profit subsidy but contributes to both sector. Therefore, given a carbon tax τ_t, a subsidy to clean sector q_t and a subsidy to energy storage q^s, the relative benefit ratio in equation 3.2 becomes:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \left(\frac{1 + q_t + q^s}{1 + q^s}\right) \frac{\eta_c}{\eta_d} \left(\frac{1 + \gamma\eta_c s_{ct}}{1 + \gamma\eta_d s_{dt}}\right)^{-\varphi-1} (1 + \tau_t)^{\epsilon} \left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{-\varphi}. \tag{3.3}$$

With different levels of a storage subsidy q^s, the optimal policies and the socially optimal allocation change. In the next section, we incorporate this subsidy into the calibration of this DTC model of Acemoglu et al. (2012).

3.3 Calibration

In this section we calibrate our model with a storage subsidy. Our goal is to compare our results to the standard Acemoglu et al. (2012) model, and therefore we select the same parameter values as in Acemoglu et al. (2012). Figure 3.1 describes those parameters and their values. Governments have invested in renewable energy research from the 1980s while subsidies to energy storage spurred in early 2000s. Some countries, for example the U.S. as shown in figure 3.1, have larger spur of R&D spending in energy storage in certain time periods. Therefore, we consider three levels of the storage subsidy, i.e. $q^s = 0.5q_t$, q_t, and $1.5q_t$. Our objective is to highlight the effects of different levels of the storage subsidy on the form of optimal environmental regulation and the resulting timing of a switch (of R&D and production) to clean technology.

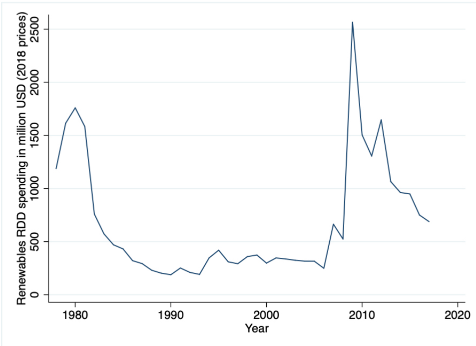
3.3.1 Results with subsidies to energy storage

Next, we apply different levels of storage subsidies in equation 3.3, and explore their effects on the optimal allocation. Note that the level of subsidies to energy storage only

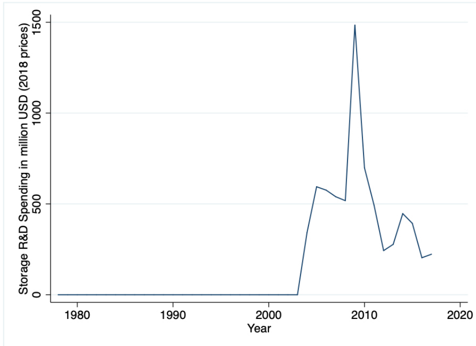
Table 3.1: Parameter choice.

Parameter	Value	Description
ϵ	3 10	Elasticity of substitution between two sector
ρ	0.001*dt 0.015*dt	Utility discount rate per period
σ	2	Coefficient of relative risk aversion
α	1/3	Factor share of machines
ψ	2/3	Cost of machines
γ	1	Innovation step size
η_d	0.02*dt	Probability of success in the dirty sector
η_c	0.02*dt	Probability of success in the clean sector
dt	5	Number of years in one period
t	80	Number of periods

Note: The parameter choice is the same as in Acemoglu et al. (2012).



(a)Renewable R&D Spending.



(b)Storage R&D Spending.

Figure 3.1: Public R&D Spending in the U.S., 1978-2019.

influence the subsidy to clean sector in the optimal allocation. Therefore, we present only the clean innovation subsidy in this section.

Figure 3.2 shows the subsidy to clean sector, i.e. q_t with the presence of a subsidy to energy storage for different values of the elasticity of substitution between two sector, ϵ, and the discount rate, ρ. Column (a), (b) and (c) present the optimal path of q_t when $q^s = 0.5q_t$, q_t, and $1.5q_t$, respectively.

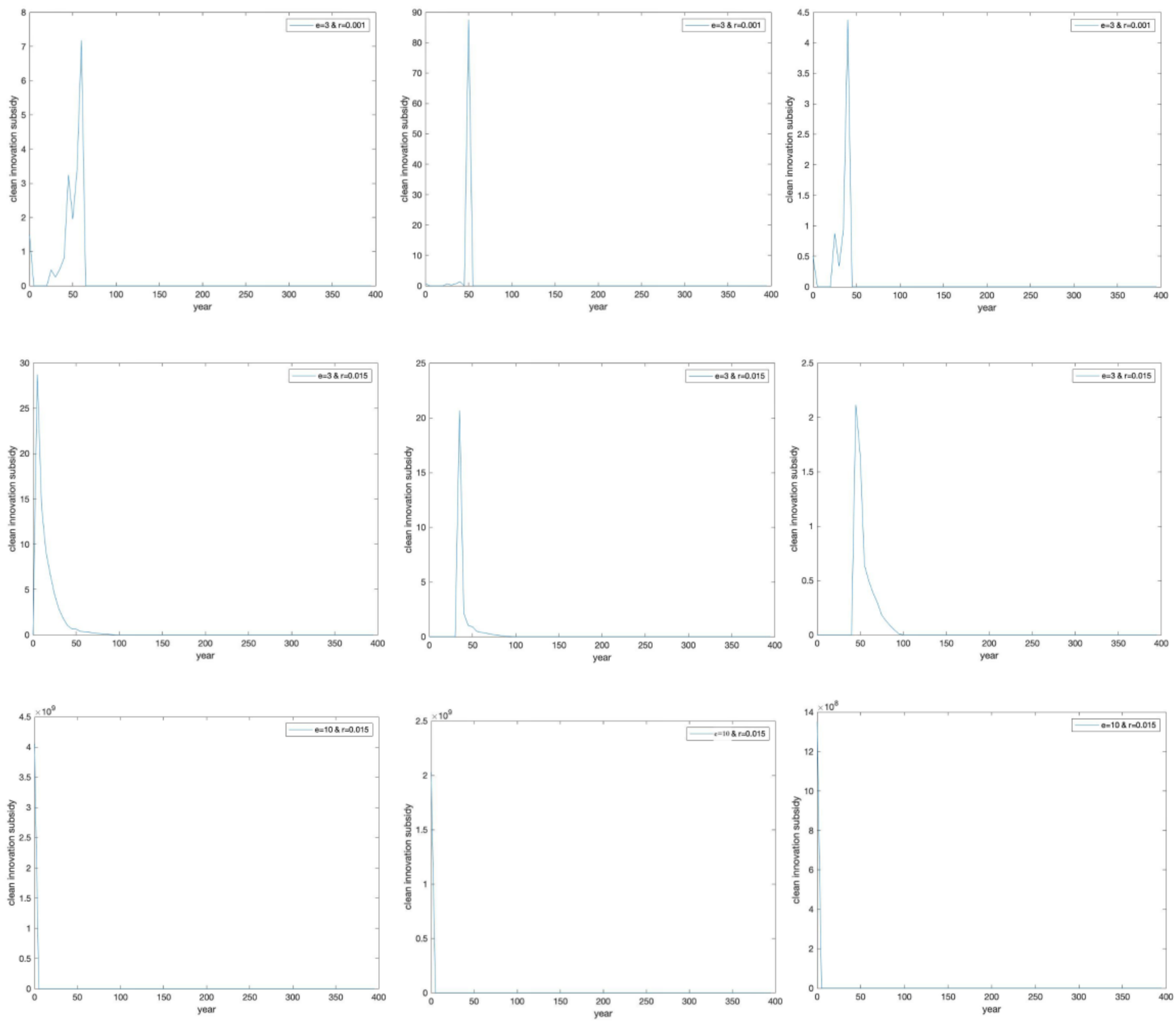
The first row shows that when $\epsilon = 3$ and $\rho = 0.001$, the optimal subsidy to clean research remains temporary, but is higher and of shorter duration than its baseline. In addition, the presence of a subsidy to energy storage postpones the timing of the clean innovation subsidy. Particularly when $q^s = q_t$, the high level of subsidy only lasts shortly (about 10 years) around year 50. This buys time for both policymakers and scientists. As shown in Acemoglu et al. (2012) Figure 1 panel A, without a q^s, we have to adopt the highest level of q_t immediately to achieve the clean transition and to avoid a natural disaster. It suggests that, to a certain extent, a subsidy to energy storage helps the clean sector to shoulder research burden, and complement the clean innovation. This result helps us understand the evolution of the relationship between clean, dirty, and storage technologies.

Row 2 is the scenario that includes an eventual natural disaster, i.e. when $\epsilon = 3$ and $\rho = 0.015$. Compared to the other two scenarios, the switch to clean research occurs at a later time, and the optimal subsidy is larger and lasts longer. Adding a subsidy to energy storage does not have significant impacts, but it lowers the required level of optimal subsidy when q^s is sufficiently high, in our case when $q^s = 1.5q_t$.

Similarly, in the third row, when $\epsilon = 10$, subsidizing energy storage does not substantially benefit the optimal allocation. This is not surprising. Energy storage technologies are now referred to as the key in clean transitions because they help reduce the intermittency problem of renewable energy. With a high ϵ, clean inputs easily substitute dirty inputs. As shown in Acemoglu et al. (2012) Figure 1 panel D, the clean sector takes over most of input production rapidly (around 30 years). In this case, there is no further incentive to innovate in storage technologies, and a subsidy to energy storage does not improve the optimal allocation.

3.3.2 Elasticity to substitution closer to one

Limited work empirically determines the elasticity of substitution between clean and dirty energy inputs. Goulder and Schneider (1999) find a value of 0.9. Using a steady-state assumption, Lanzi and Sue Wing (2010) estimate a value of 1.6 for the elasticity of substitution between clean and dirty inputs in the energy sector. Popp (2004) find the same value for the elasticity of substitution between fossil fuels and nonfossil fuels in the modified DICE model. Papageorgiou et al. (2017) estimate nested CES specifications using nonlinear estimation, which imply a value of 1.8 in the electricity-generating sector and a value of 3 in non-energy industries. Therefore, in addition to $\epsilon = 3$ and 10, we adopt an elasticity of substitution between clean and dirty



(a) $q^s = 0.5q_t$ (b) $q^s = q_t$ (c) $q^s = 1.5q_t$

Figure 3.2: Subsidy to clean sector in the optimal allocation with a subsidy to energy storage.

sectors that is closer to stylized facts, $\epsilon = 1.5$, to explore the optimal allocation and the effects of a storage subsidy.

Figure 3.3 shows the subsidy and the allocation of scientists to clean sector, the carbon tax, the share of clean inputs in total production and the increase in temperature in the optimal allocation when $\epsilon = 1.5$ and $q^s = 0$. Despite the presence and levels of a storage subsidy, the results confirm that it is difficult to avoid a natural disaster if the elasticity of substitution is sufficiently low. In this case, the clean innovation subsidy, as shown in Figure 3.4, is significant lower and of shorter duration with a higher storage subsidy.

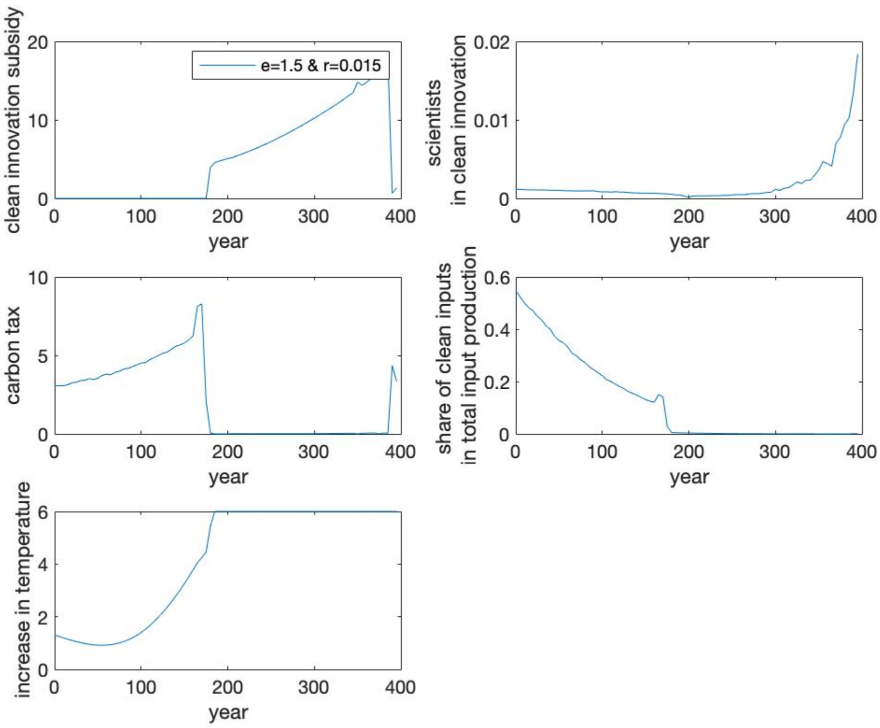
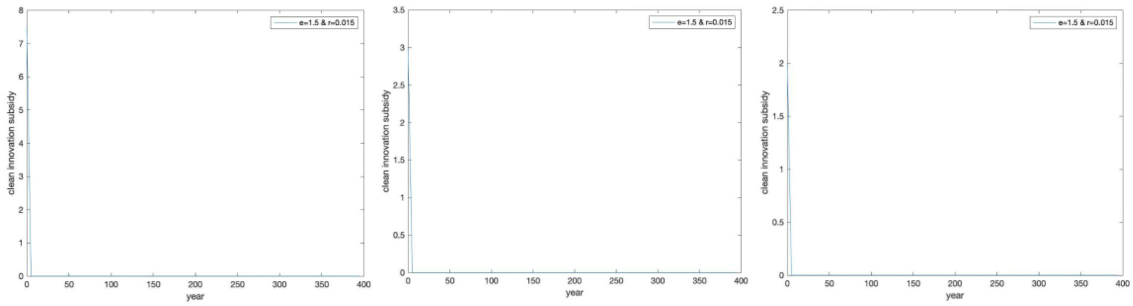


Figure 3.3: Optimal environmental policy for $\epsilon = 1.5$.

3.4 Conclusion

Energy storage technologies can boost renewable energy use while also improving the efficiency of conventional power plants. While many focus on energy storage as the solution to the intermittency problem of renewable resources, its benefits to conventional technologies receives far less attention. By introducing a research subsidy to energy



(a) $q^s = 0.5q_t$ (b) $q^s = q_t$ (c) $q^s = 1.5q_t$

Figure 3.4: Subsidy to clean sector in the optimal allocation with a subsidy to energy storage when $\epsilon = 1.5$.

storage contributing to both clean and dirty sectors, we modify the theoretical model of directed technical change, and present energy storage as a mechanism that can promote innovation in both sectors and influence the optimal allocation. We then report the results of the same quantitative example as Acemoglu et al. (2012). We find that in other conditions unchanged, a storage subsidy changes the optimal subsidy to clean innovation, particularly when the elasticity of substitution between two sectors are low. And different levels of storage subsidies would postpone the timing of its adoption, shorten its duration, or lower the optimal level. However, they cannot guarantee the avoidance of natural disasters. In line with Acemoglu et al. (2012), a sufficiently high elasticity is more reliable to get rid of the environmental threaten and go back to the preindustrial level. Therefore, energy storage might play a more important role in energy transitions by improving the substitution between clean and dirty inputs than encouraging innovation directly, as solving the intermittency problem will increase the ability of renewables to substitute dirty energy inputs.

References

Acemoglu, D. (2002, 8). Directed technical change. *The Review of Economic Studies 69*(4), 781–809.

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

Acemoglu, D., P. Aghion, and D. Hémous (2014). The environment and directed technical change in a north-south model. *Oxford Review of Economic Policy 30*(3), 513–530.

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

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

Allison, P. D. and R. P. Waterman (2002). Fixed-effects negative binomial regression models. *Sociological Methodology 32*, 247–265.

Asheim, B. and M. Gertler (2009). The geography of innovation: Regional innovation systems. *The Geography of Innovation: Regional Innovation Systems*.

Audretsch, D. B. and M. P. Feldman (2004a). Chapter 61 - knowledge spillovers and the geography of innovation. In J. V. Henderson and J.-F. Thisse (Eds.), *Cities and Geography*, Volume 4 of *Handbook of Regional and Urban Economics*, pp. 2713–2739. Elsevier.

Audretsch, D. B. and M. P. Feldman (2004b). Chapter 61 - knowledge spillovers and the geography of innovation. In J. V. Henderson and J.-F. Thisse (Eds.), *Cities and Geography*, Volume 4 of *Handbook of Regional and Urban Economics*, pp. 2713–2739. Elsevier.

Barradale, M. J. (2010). Impact of public policy uncertainty on renewable energy investment: Wind power and the production tax credit. *Energy Policy 38*(12), 7698–7709. Special Section: Carbon Reduction at Community Scale.

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

Blundell, R., R. Griffith, and J. Van Reenen (1995). Dynamic count data models of technological innovation. *The Economic Journal*, 333–344.

Böhringer, C., A. Cuntz, D. Harhoff, and E. Asane-Otoo (2017). The impact of the German feed-in tariff scheme on innovation: Evidence based on patent filings in renewable energy technologies. *Energy Economics 67*, 545–553.

Borghesi, S., G. Cainelli, and M. Mazzanti (2015). Linking emission trading to environmental innovation: Evidence from the italian manufacturing industry. *Research Policy 44*(3), 669–683.

Botta, E. and T. Koźluk (2014). Measuring environmental policy stringency in OECD countries. In *OECD Economics Department Working Papers*, Number No.1177. OECD Publishing, Paris.

Brunnermeier, S. B. and M. A. Cohen (2003). Determinants of environmental innovation in us manufacturing industries. *Journal of environmental economics and management 45*(2), 278–293.

Caballero, R. and A. Jaffe (1993). How high are the giants' shoulders: An empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. In *NBER Macroeconomics Annual 1993, Volume 8*, pp. 15–86. National Bureau of Economic Research, Inc.

Carley, S. (2009). State renewable energy electricity policies: An empirical evaluation of effectiveness. *Energy Policy 37*(8), 3071–3081.

Costantini, V., F. Crespi, and A. Palma (2017). Characterizing the policy mix and its impact on eco-innovation: A patent analysis of energy-efficient technologies. *Research policy 46*(4), 799–819.

Crabb, J. M. and D. K. Johnson (2010). Fueling Innovation: The Impact of Oil Prices and CAFE Standards on Energy-Efficient Automotive Technology. *The Energy Journal 0*(Number 1), 199–216.

Cui, J., J. Zhang, and Y. Zheng (2018). Carbon pricing induces innovation: Evidence from China's regional carbon market pilots. *AEA Papers and Proceedings 108*, 453–57.

de Serres, A., F. Murtin, and G. Nicoletti (2010). A framework for assessing green growth policies. *OECD Economics Department Working Papers*.

Fabrizio, K. R., S. Poczter, and B. A. Zelner (2017). Does innovation policy attract international competition? evidence from energy storage. *Research Policy 46*(6), 1106–1117.

Feng, S. and I. Lazkano (2022). Innovation trends in electricity storage: What drives global innovation? *Energy Policy 167*, 113084.

Girod, B., T. Stucki, and M. Woerter (2017). How do policies for efficient energy use in the household sector induce energy-efficiency innovation? an evaluation of european countries. *Energy Policy 103*, 223–237.

Goulder, L. H. and S. H. Schneider (1999). Induced technological change and the attractiveness of CO_2 abatement policies. *Resource and Energy Economics 21*(3), 211–253.

Grossman, G. M. and E. Helpman (1991). Trade, knowledge spillovers, and growth. *European Economic Review 35*(2), 517–526.

Hall, B., A. Jaffe, and M. Trajtenberg (2005). Market value and patent citations. *RAND Journal of Economics 36*, 16–38.

Hall, B., J. Mairesse, and P. Mohnen (2010). Measuring the returns to R&D. Volume 2, Chapter Chapter 24, pp. 1033–1082. Elsevier.

Hall, P. and E. Bain (2008). Energy-storage technologies and electricity generation. *Energy Policy 36*(12), 4352–4355.

Hausman, J., B. H. Hall, and Z. Griliches (1984, July). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica 52*(4), 909–38.

Hollingsworth, A. and I. Rudik (2019). External impacts of local energy policy: The case of renewable portfolio standards. *Journal of the Association of Environmental and Resource Economists 6*(1), 187–213.

Hu, X., Y. Liu, L. Yang, Q. Shi, W. Zhang, and C. Zhong (2018). SO_2 emission reduction decomposition of environmental tax based on different consumption tax refunds. *Journal of Cleaner Production 186*, 997–1010.

IEA (2021a). Achieving net zero electricity sectors in G7 members. Report, International Energy Agency. Paris.

IEA (2021b). The role of critical minerals in clean energy transitions. Report, International Energy Agency, Paris.

IEA (2022a). A 10-point plan to reduce the European Unions reliance on Russian natural gas. Report, International Energy Agency. Paris.

IEA (2022b). Renewable electricity. Report, International Energy Agency. Paris.

International Energy Agency (2020). World energy balances: Overview. Technical report, International Energy Agency.

International Energy Agency (2021). End-use prices: Energy prices in us dollars (edition 2020).

IRENA, IEA and REN21 (2018). Renewable energy policies in a time of transition. Report, International Renewable Energy Agency, International Energy Agency, Renewable Energy Policy Network for the 21st Century.

Isaksen, A. and M. Trippl (2017, 02). Innovation in space: the mosaic of regional innovation patterns. *Oxford Review of Economic Policy 33*(1), 122–140.

Jaffe, A. B. (1986). Technological opportunity and spillovers of r & d: Evidence from firms' patents, profits, and market value. *The American Economic Review*, 984–1001.

Jaffe, A. B. (1989). Real effects of academic research. *The American Economic Review 79*(5), 957–970.

Jaffe, A. B. and M. Trajtenberg (1996). Flows of knowledge from universities and federal laboratories: Modeling the flow of patent citations over time and across institutional and geographic boundaries. *Proceedings of the National Academy of Sciences 93*(23), 12671–12677.

Jaffe, A. B., M. Trajtenberg, and R. Henderson (1993, 08). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations*. *The Quarterly Journal of Economics 108*(3), 577–598.

Johnstone, N., I. Haščič, and D. Popp (2009, 11). Renewable energy policies and technological innovation: Evidence based on patent counts. *Environmental and Resource Economics 45*, 133–155.

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

Kete, N. (1994). Environmental policy instruments for market and mixed-market economies. *Utilities Policy 4*(1), 5–18.

Kim, J. E. (2014). Energy security and climate change: How oil endowment influences alternative vehicle innovation. *Energy Policy 66*, 400–410.

Knittel, C. R. (2011). Automobiles on steroids: Product attribute trade-offs and technological progress in the automobile sector. *American Economic Review 101*(7), 3368–99.

Kruse, T., A. Dechezleprêtre, R. Saffar, and L. Robert (2022). Measuring environmental policy stringency in OECD countries. In *OECD Economics Department Working Papers*, Number 1703. OECD Publishing, Paris.

Lanjouw, J. O. and A. Mody (1996). Innovation and the international diffusion of environmentally responsive technology. *Research policy 25*(4), 549–571.

Lanzi, E. and I. Sue Wing (2010). Capital malleability and the macroeconomic costs of climate policy. Sustainable Development Papers 59476, Fondazione Eni Enrico Mattei (FEEM).

Lanzi, E., E. Verdolini, and I. Haščič (2011). Efficiency-improving fossil fuel technologies for electricity generation: Data selection and trends. *Energy Policy 39*(11), 7000–7014.

Lazkano, I., L. Nøstbakken, and M. Pelli (2017a). From fossil fuels to renewables: The role of electricity storage. *European Economic Review 99*(C), 113–129.

Lazkano, I., L. Nøstbakken, and M. Pelli (2017b). From fossil fuels to renewables: The role of electricity storage. *European Economic Review 99*, 113–129.

Lazkano, I. and L. Pham (2021). Which fossil fuel prices promote innovation in electricity generation? evidence before and after the shale gas revolution. Working paper.

Lemoine, D. (2017). Innovation-led transitions in energy supply. Working Paper 23420, National Bureau of Economic Research.

Ley, M., T. Stucki, and M. Woerter (2016). The impact of energy prices on green innovation. *The Energy Journal 37*(1).

Linn, J. (2008). Energy prices and the adoption of energy-saving technology. *Economic Journal 118*(533), 1986–2012.

Newell, R. G., A. B. Jaffe, and R. N. Stavins (1999). The induced innovation hypothesis and energy-saving technological change. *The Quarterly Journal of Economics 114*(3), 941–975.

Noailly, J. (2012). Improving the energy efficiency of buildings: The impact of environmental policy on technological innovation. *Energy Economics 34*(3), 795–806.

Noailly, J. and R. Smeets (2015). Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level patent data. *Journal of Environmental Economics and Management 72*, 15–37.

OECD (2015). *The Innovation Imperative.*

OECD (2016). Environmental policy: Environmental policy stringency index.

Papageorgiou, C., M. Saam, and P. Schulte (2017). Substitution between clean and dirty energy inputs: A macroeconomic perspective. *The Review of Economics and Statistics 99*(2), 281–290.

Parrilli, M. D., M. Balavac, and D. Radicic (2020). Business innovation modes and their impact on innovation outputs: Regional variations and the nature of innovation across eu regions. *Research Policy 49*(8), 104047.

Perdana, S., G. Xexakis, K. Koasidis, M. Vielle, A. Nikas, H. Doukas, A. Gambhir, A. Anger-Kraavi, E. May, B. McWilliams, and B. Boitier (2023). Expert perceptions of game-changing innovations towards net zero. *Energy Strategy Reviews 45*, 101022.

Pizer, W. A. (1997). Prices vs. quantities revisited: The case of climate change. Discussion Papers 10498, Resources for the Future.

Pizer, W. A. and B. C. Prest (2020). Prices versus quantities with policy updating. *Journal of the Association of Environmental and Resource Economists 7*(3), 483–518.

Popp, D. (2002). Induced innovation and energy prices. *American Economic Review 92*(1), 160–180.

Popp, D. (2004). Entice: endogenous technological change in the dice model of global warming. *Journal of Environmental Economics and Management 48*(1), 742–768.

Popp, D. (2010). Innovation and climate policy. *Annual Review of Resource Economics 2*(1), 275–298.

Popp, D. (2019). Environmental policy and innovation: A decade of research. Working Paper 25631, National Bureau of Economic Research.

Price, A. (2011). 12 - energy storage for small and micro combined heat and power (chp) systems. In R. Beith (Ed.), *Small and Micro Combined Heat and Power (CHP) Systems*, Woodhead Publishing Series in Energy, pp. 307 – 322. Woodhead Publishing.

Rogge, K. S. and V. H. Hoffmann (2010). The impact of the EU ETS on the sectoral innovation system for power generation technologies - Findings for Germany. *Energy Policy 38*(12), 7639–7652. Special Section: Carbon Reduction at Community Scale.

Rozendaal, R. and H. R. Vollebergh (2021). Policy-induced innovation in clean technologies: Evidence from the car market.

Schmidt, T. S., M. Schneider, K. S. Rogge, M. J. Schuetz, and V. H. Hoffmann (2012). The effects of climate policy on the rate and direction of innovation: A survey of the eu ets and the electricity sector. *Environmental Innovation and Societal Transitions 2*, 23–48.

Shrimali, G. and J. Kniefel (2011). Are government policies effective in promoting deployment of renewable electricity resources? *Energy Policy 39*(9), 4726–4741.

Stevens, K. and A. Rouhollahi (2021, January). Side effects: How renewable energy policies drive innovation in complementary grid technologies. Report, Information Technology and Innovation Foundation.

Stevens, K. A. and T. Tang (2021, 11). Renewable energy policies and innovation of complementary technology. 38th USAEE/IAEE North American Virtual Conference, Innovation in Storage Technology Session.

Valero, A. and J. Van Reenen (2019). The economic impact of universities: Evidence from across the globe. *Economics of Education Review 68*(C), 53–67.

Verdolini, E. and M. Galeotti (2011a). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of Environmental Economics and Management 61*(2), 119–134.

Verdolini, E. and M. Galeotti (2011b). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of Environmental Economics and Management 61*(2), 119–134.

Weidner, M. and T. Zylkin (2021). Bias and consistency in three-way gravity models. *Journal of International Economics 132*, 103513.

Weitzman, M. L. (1974). Prices vs. quantities. *The Review of Economic Studies 41*(4), 477–491.

Wiskich, A. (2021). A comment on innovation with multiple equilibria and "the environment and directed technical change". *Energy Economics 94*, 105077.

World Bank (2022). State and trends of carbon pricing 2022. State and Trends of Carbon Pricing;. Washington, DC: World Bank.

Xin-gang, Z. and W. Wei (2020). Driving force for China's photovoltaic industry output growth: Factor-driven or technological innovation-driven? *Journal of Cleaner Production 274*, 122848.

Ziegler, M. S., J. M. Mueller, G. D. Pereira, J. Song, M. Ferrara, Y.-M. Chiang, and J. E. Trancik (2019). Storage requirements and costs of shaping renewable energy toward grid decarbonization. *Joule 3*(9), 2134 – 2153.

Appendix A

Appendix to Chapter 1

A.1 Technology Descriptions: Energy Storage Systems

There are multiple types of energy conversion used for either short-term or long-term storage. For short-term storage, electrochemical devices convert electrical energy to chemical energy for storage. The most common technologies are batteries, which have been used since the 19th century and currently have uses in everyday technology such as phones and in small-scale energy storage.[1] Research in batteries is extensive and installations plans are on the rise. For example, South Australia is able to power over 30,000 homes with a 100MW-capacity battery built in 2017. Batteries are expected to be the largest commercial-level form of energy storage. Instead, long-term storage, such as days to weeks or even months, relies on mechanical methods that convert electrical

[1] Normally when chemicals mix they release energy in the form of thermal energy. A battery is able to control the output of these reactions so that it yields electrical energy. Typical batteries consists of two electrodes. One controls the release of ions and the other the release of electrons. An electrolyte between the electrodes will allow ions to flow from one electrode to the other while keeping the electrons in place. The electrolyte is what allows the battery to produce power. There are two main types of batteries available: primary cell and secondary cell batteries. Primary cells cannot be recharged while secondary cells are able to reproduce the reactants which makes these favorable for the energy industry. One type of secondary cell is a standard secondary cell. A standard secondary cell carries all of its reactants within the cell. Lead-acid batteries fall in this category. A second type of secondary cell is flow batteries. Compared to standard secondary cells, flow batteries carry the reactants on the outside of the cell which can be made larger or smaller based on capacity needs. These could be economically beneficial for large-scale uses.

energy into two types of mechanical energy: kinetic and potential energy. For example, flywheels employ kinetic energy conversion whereas compressed air energy storage (CAES) systems and pumped storage hydropower (PSH) rely on potential energy.

In the following, we describe the specific technologies associated with each type of energy conversion, durability, and cost.

A.1.1 Long-term storage: flywheels, pumped storage hydropower, and compressed air energy storage

Flywheels use kinetic energy and they consist of a wheel on top of an axle layered with bearings, a rotor, and an electric motor generator. Electrical energy is delivered to the flywheel through a reversible motor generator, which causes the rotor to spin and in turn the flywheel also spins.[2] The general principle is that the more rotations the device is capable of, the more kinetic energy storage potential there is. However, along with high energy storage potential, faster rotations can also lead to energy loss to friction. Although bearings are used to reduce these losses some loss of energy is inevitable. Their commercial cost ranges from \$500 to \$2000 per kilowatt. Larger flywheels are expected to be less expensive than smaller ones. Commercial flywheels have the potential to store between 1-100 kWh with 80% of efficiency. The technology has a high round-trip efficiency because mechanical energy is the only energy flowing into, through, and out of the technology until it must be converted for usage. Other benefits include very little machinery upkeep and a quick 25 msec response time. Full power can be reached in 15 seconds or less. Examples of current uses include New York City's power network and Japan's installations used for research.

Another form of long-term storage technology is pumped storage hydropower (PSH) plants. They stem from typical hydropower plants where water is stored in a reservoir

[2] As the wheel moves, kinetic energy is stored in the rotating rotor. When electricity is required back out of the system, energy stops feeding through the motor. The motor begins to go in the opposite direction and the flywheel's rotation speed decreases as energy exits the system. Light materials such as carbon and glass fiber have been engineered to work at the utility-level to exploit flywheel rotations since a heavy material will increase friction and reduce rotation speed.

and released when energy is needed.[3] There are 130 GW of capacity in use of this technology and since long-term energy losses are low, this technology is beneficial for seasonal storage purposes. PSH plants usually have a roundtrip efficiency of 75-80%. A disadvantage of this technology is the varied response times, between 10 seconds and 15 minutes to provide power. Another well-known limitation is site availability.[4] Regarding costs, pumped hydropower plants are costly to build. In the U.S., a 500MW-capable plant could cost as much as $1.1 billion while a more capable (1800MW) plant would cost the same amount in Zhejiang, China. Despite these challenges, PSH is the most common large-scale energy storage system used today.[5] They are used in China, Australia, Japan, the United States, Russia, and in parts of Europe.

Finally, compressed-air energy storage (CAES) also makes use of mechanical energy. CAES is used in textile, industrial motor, and printing industries since the 19th century. It stores potential energy in the form of pressurized air.[6] An advantage of compressed air systems is that they can provide power in as little as 2-3 minutes. However, the amount it takes to compress air into storage usually exceeds the amount of the time that the system can supply energy. The larger the compressor is relative to the turbines, the faster it generates one hour of electricity. Ultimately it generates between 25-60% more energy than is required to compress the air during the first stages of the process. The overall roundtrip efficiency is 65%. Another benefit of CAES is cost. Limited large-scale usage of CAES only provides provisional expected costs but low ones compared to other technologies. Unfortunately, a main limitation of CAES is location. There must be

[3]PSH technology involves a second reservoir that stores the water that was released from the first repository. Water is relocated to the first reservoir by the use of pumps when excess energy is available. The reservoirs must be at different heights for this process to be carried out. A larger height difference and bigger set of reservoirs will yield higher capabilities to store and supply energy.

[4]There must be a natural height difference or space to engineer the two reservoirs used in the process. Usually, a natural lake is used as one source and another is built into the site. Another option is creating two man-made reservoirs. This option makes the overall cost of constructing a PSH plant more expensive than the combination of using a natural body of water and a man-made one.

[5]Installments of these technologies were established in the 1970s. Pumped hydropower storage is often used to store base-load energy from nuclear power plants when it is not needed.

[6]Off-peak energy is delivered to a motor that supplies it to a compressor. The compressed air is then stored in a storage chamber and later used by a recuperator that extracts the energy from this vessel when needed. Following the recuperator step, compressed air is mixed with fuel and used in the turbines which will ultimately deliver energy to the last step which is the generator. Like PSH, excess energy supplies the compressor the potential to compress the air as well as store energy in the storage reservoir.

space to build a compressed air reservoir. Small-scale installations can use above-ground chambers but commercial and utility-level facilities require underground caverns. The demand for caverns is high by other industries like natural gas.[7]

A.1.2 Short-term storage: lead-acid and flow batteries

Batteries store electrical energy from sources such as wind and solar installments as chemical energy. Lead-acid batteries (LAB), based on the reaction between lead acid and sulfuric acid, are a popular option for a variety of storage needs. The cost ranges from $400 to $2300 per kWh. Lead-acid batteries can supply power in 5 msec and have a slightly larger roundtrip efficiency than normal batteries at 75-85%. The durability of these cells at the utility level is almost 20 years when cycled effectively. Another advantage of lead-acid batteries is the ease at which they can be translated into large-scale installations because there is little limitation on location. Currently, the most used secondary cell is lead-acid batteries, making up over half of global secondary cell purchases. On the other hand, a disadvantage is that, like many batteries, lead-acid cells can leak over time and discharge themselves completely. In fact, the large-scale installations of this type of battery have been short lived due to cell degradation. For this reason, LAB are used in smaller scale wind and solar farms to store daily power. Another disadvantage of LAB is their temperature dependance because they have water-based electrolytes.

In addition, flow batteries store chemicals combining batteries and fuel cells. Their roundtrip efficiency is about 90% because the separation of the cell and the reactants. They have several main advantages. Their storage depleting capacity is slow, they can provide power within 100 msec, and they are cheaper than other batteries with a range of $150-800 per kWh. Note, however, that there are no utility level flow battery installations, but once built, the most cost-effective installations would be at the large-scale. The flow

[7]The options for chamber/cavern sites depend on the geology of the area. Hard-rock can be cleared out to create a cavern. This choice is one of the most expensive options however. Another alternative are salt caverns which can be created by dissolving salt domes available in many areas of the world. Aquifers and old oil extraction sites can also be used for cavern-purposes and are the least expensive alternative. Potential sites were found across 80% of the U.S. so locations worldwide are available, but they may be limited by the demand from other industries.There is currently only one commercial CAES plant in function today. It is located in Alabama, U.S. and has been used for over 30 years.

batteries currently in use are zinc-bromide battery, polysulfide-bromide battery, and the vanadium redox flow battery.

A.1.3 Superconductors

A technology type that uses electromagnetic conversion is superconducting magnetic energy storage (SMES).[8] The most important advantage over other technologies described above is that power is available almost immediately. This technology is particularly useful when demand is immediate. Indeed, superconductors have storage and supply potentials of up to 100MW. The largest capacity known today is 10 MW. Superconductors can convert energy in 5 ms. Daily cycling using superconductors can yield an efficiency of 90%. This number will decrease as the technology is used for more long-term purposes. A limitation of superconductors is that the system must be kept cold.[9]

A.2 IPC Codes for Electricity Technologies

The complete list of the selected IPC classes used to extract patents for this study is provided in table A.2.1. There are some electricity patents that are defined as *environmentally friendly*. We follow the definition developed by the IPC Committee of Experts in the *IPC Green Inventory* for Environmentally Sound Technologies (ESTs). From this list, we summarize the main EST categories related to our electricity patents in table A.2.2.

[8]Superconductors involve a DC current flowing through a storage ring known as the superconducting loop, creating a magnetic field. The device can store this magnetic field for months if temperature conditions are adequate. Temperatures must be low enough to surpass the transition temperature. This temperature indicates the point where the superconducting material's physical properties change and current is able to flow without energy loss.

[9]There is abundant research in finding superconducting material that can work equally as effective as current materials but at relatively higher temperatures. The most modern superconducting materials must be kept at around -253 degrees Celsius to function. Liquid hydrogen or liquid helium are used to keep the coil material cool but this can be an expensive process.

Table A.2.1: Selected IPC codes for electricity technologies.

Storage	
General	
H01M002/06-40	Details, processes of manufacture of the non-active parts for batteries.
H01M004	Electrodes
H01M006	Primary cells.
H01M010	Secondary cells.
H01M014	Electrochemical current or voltage generators.
H01M016	Combinations of different types of electrochemical generators.
Fuel Cells	
H01M002/00-04	Details, processes of manufacture of the non-active parts for batteries: cases, jackets or wrappings; lids or covers.
H01M004/86-98	Electrodes for fuel cells.
H01M008	Fuel cells.
H01M012	Hybrid cells.
WIPO	
B60K006/28	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. hybrid propulsion systems comprising electric motors and internal combustion engines.
B60W010/26	Conjoint control of vehicle sub-units of different type or different function.
H01G009/155	Electrolytic capacitors, rectifiers, detectors, switching devices, light-sensitive or temperature-sensitive devices; processes of their manufacture.
H01M010/44-46	Secondary cells; methods for charging or discharging; accumulators structurally combined with charging apparatus.
H02J003/28	Arrangements for balancing the load in a network by storage of energy.
H02J007/00	Circuit arrangements for charging or depolarising batteries or for supplying loads from batteries.
H02J015/00	Systems for storing electric energy.
Hydro	
B63H019/02-04	Marine propulsion not otherwise provided for, by using energy derived from movement of ambient water, e.g. from rolling or pitching of vessels; propelled by water current.
E02B009	Water-power plants; Layout, construction or equipment, methods of, or apparatus for.
F03B	Machines or engines for liquids.
F03C	Positive-displacement engines driven by liquids.
Generation, conversion and distribution	
H01B/C/F/G/H/J/K/L/P/Q/R/S/T	Basic electric elements (except processes or means for the direct conversion of chemical energy into electrical energy).
H02B/G/H/J/K/M/N/P/S	Generation, conversion or distributionof electric power.
H03B/C/D/F/G/H/J/K/L/M	Basic electronic circuitry.
H04B/H/J/K/L/M/N/Q/R/S/W	Electric communication technique.
H05B/C/F/G/H/K	Electric techniques not otherwise provided for.
H99Z99/00	Subject matter not otherwise provided for in this section.

Table A.2.2: IPC list of electricity patents in IPC Green Inventory .

Topic	**IPC codes**
Storage of electrical energy	H01M 10/44-10/46; H01G 11/00; H02J 3/28, 7/00, 15/00
Power supply circuitry	H02J
Fuel cells	H01M 4/86-4/98, 8/00-8/24, 12/00-12/08
Solar energy	H02S

A.3 Additional Figures

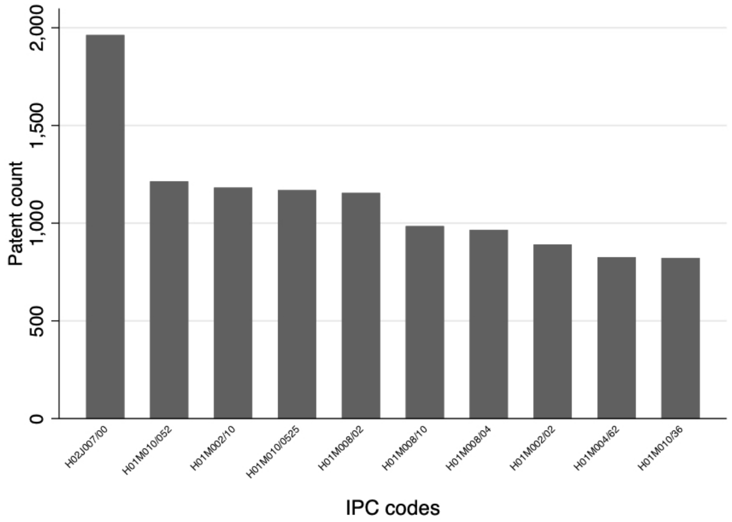


Figure A.3.1: Patenting in top ten IPC codes of electricity storage technologies, 1978-2017.

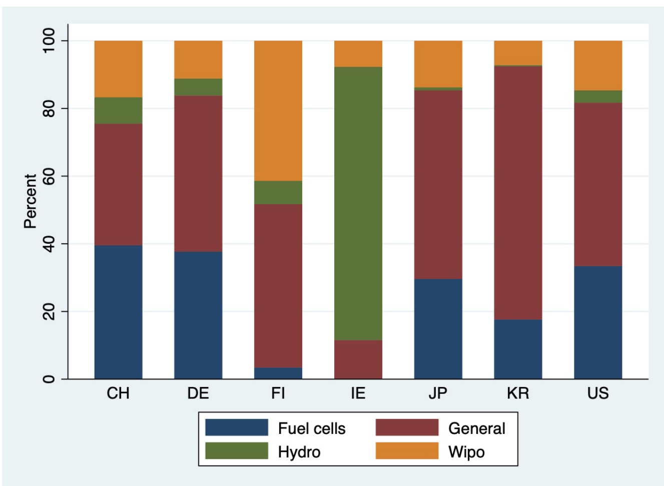
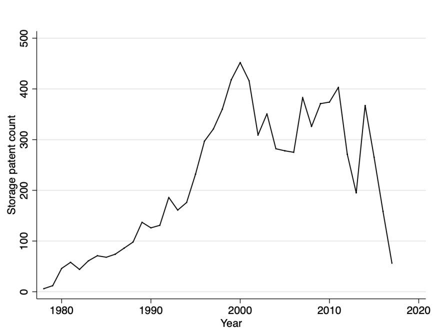
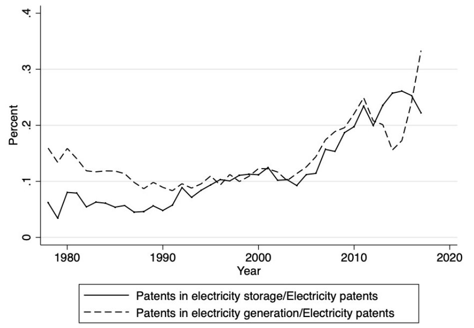


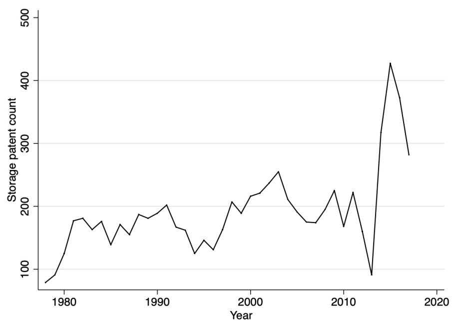
Figure A.3.2: Distribution of patenting by technology type in selected countries, 1978-2017.



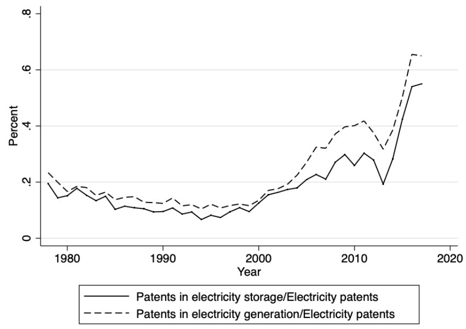
(a) Japan.



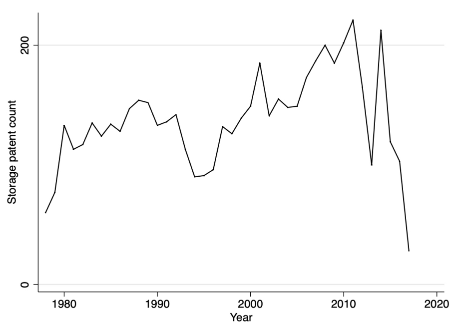
(b) Japan.



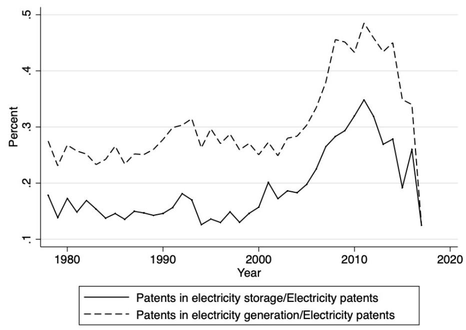
(c) U.S.



(d) U.S.



(e) Germany.



(f) Germany.

Figure A.3.3: Distribution of patenting in electricity storage, most innovative countries, 1978-2017.

A.4 Constructing the Knowledge Stocks

When a patent is granted, the applicant and the examiner will list all related previous patents. Therefore, we assume citations indicate a flow of knowledge and use citations to an earlier patent as the previous technological knowledge upon which the current inventor could build. In our dataset, every patent application contains information about which application it has cited and which application has cited it. Following Popp (2002), we look at the probability of citation and use an exponential distribution to model flows of knowledge (Caballero and Jaffe, 1993; Jaffe and Trajtenberg, 1996).

First, we group citations by the year cited, which is denoted CTD, and the year citing which is CTG for each region. For example, in region US40147, citations of storage patents granted in 1978 made by storage patents granted in 1995. Denoting citations in each region as $\mathrm{C}_{iCTD,CTG}$, the number of potentially cited patents granted for in year CTD as n_{iCTD} and the number of potentially citing patents granted in year CTG as $\mathrm{n}_{i,CTG}$, the probability of citation for patents within each group, p, is shown as A.1.

$$P_{i,CTD,CTG} = \frac{c_{i,CTD,CTG}}{(n_{i,CTD})\,(n_{i,CTG})}. \tag{A.1}$$

We then estimate the probability that a patent would be cited by subsequent patents using A.2. β_1 stands for the rate of decay of knowledge, and β_2 represents the rate of diffusion at which newly patented innovation occurs. As an example of it, a patent in battery technology granted in 1978 might inspire a lot of innovation in 1980 but little in 2019.

$$P_{i,CTD,CTG} = \alpha_{i,CTD,CTG} exp[-\beta_1\,(CTD - CTG)] * [1 - exp\,(-\beta_2\,(CTD - CTG))] + \varepsilon_{\,i,CTD,CTG}\,. \tag{A.2}$$

With the rate of decay and diffusion estimated above, we construct two stocks of knowledge for each region:

(1) A simple stock of accumulated previous granted patents:

$$K_{i,t} = \sum_{s=1978}^{t} PAT_{i,s}. \tag{A.3}$$

(2) A citation-adjusted stock of previous granted patents:

$$K_{i,t} = \sum_{s=1978}^{t} PAT_{i,s} exp[-\beta_1\,(t - s)] * [1 - exp\,(-\beta_2\,(t - s))]. \tag{A.4}$$

A.5 Country-level Analysis

Table A.5.3: Baseline specification using country-level data for all countries.

	Dependent variable: Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	0.0445	-0.2308	-2.491***	-0.3585	-0.6379	-0.2735	-2.72†	-0.5827
	(1.033)	(0.7621)	(0.9473)	(0.654)	(1.187)	(1.347)	(1.684)	(1.015)
Electricity price	-0.1387	-0.0064	0.4725	-0.0813	-0.0339	-0.0586	0.1617	-0.0444
	(0.1995)	(0.3467)	(0.5493)	(0.2999)	(0.2986)	(0.4201)	(0.5475)	(0.6202)
K^S_{t-1}	-0.0493	0.0575†	-0.0284	0.0624	-0.4653	0.0786	0.6459	0.0807
	(0.1056)	(0.0394)	(0.1865)	(0.0437)	(0.4433)	(0.0824)	(3.216)	(0.1591)
K^R_{t-1}					0.1458	0.4079	-0.7715	0.0297
					(0.3898)	(0.9119)	(1.68)	(1.571)
K^{FF}_{t-1}					.3241	-.473	.1253	-.139
					(.468)	(.9516)	(1.665)	(1.673)
Total R&D	-0.0523	-0.0225	-0.0040	-0.2245	-0.0258	-0.0288	0.1474	-0.1354
	(0.1598)	(0.1256)	(0.1709)	(0.1795)	(0.1652)	(0.1831)	(0.2136)	(0.2365)
Time trend	-0.0087	-0.0097	0.0365	0.0151	-0.0227	-0.0056	-0.0075	0.0083
	(0.0168)	(0.0100)	(0.0416)	(0.0241)	(0.0216)	(0.0173)	(0.0323)	(0.0350)
λ	-0.0534	-0.3363	-0.0442	0.2298	0.2067	-0.1609	-0.7339	0.0602
	(0.2187)	(0.3454)	(0.2842)	(0.3456)	(0.4306)	(0.3809)	(3.506)	(0.3858)
N	536	543	547	558	534	543	544	558
chi2	2	13	3	43	5	41	2	86

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

A.6 Firm-level Analysis

We create a firm-level database to estimate our baseline specification. This specification includes a variable to control for firm-level heterogeneity in addition to a time trend. This dataset includes 7443 firms; 3665 of those firms have applied for at least one storage patent. In our firm-level estimations, we have considered three different sub-samples: (1) the full sample with 3665 firms having one or more storage patent; (2) 690 firms with at least three storage patents accounting for 73% of total storage patents; (3) 301 firms with at least five storage patents accounting for 64% of all storage patents.

In the first estimation, using the full sample, the estimation results are consistent with our baseline estimates using regional-level data in table 1.1, however, they show a lower significance. We use a large number of dummies to control for firm-specific heterogeneity, which could explain the lower significance of this analysis. The second estimation, using a sub-sample that includes 73% of total storage patents, also shows results consistent with our baseline estimates. In this case, the firm-level analysis finds an even stronger significance than our baseline regional analysis. Finally, the third estimation, based on the most innovative firms, shows little statistical significance. This sample only covers 64% of all storage patents and the majority of these firms are located in Japan, the U.S. and Germany. The lack of variation in this sub-sample, which relies on explanatory variables such as electricity price and total R&D that are unavailable at the firm level, may drive the lack of significance in our results. Out of these three estimations, we report the estimation results of sub-sample (2) in table A.6.4.

Notice that our firm-level estimations rely on a small number of observations. The reason is that firms with storage patents often have 0 electricity generation and electricity patents. Since generation and electricity patents are used in the denominator to calculate our dependent variable, many firms/observations drop from the estimation. The sub-sample used in table A.6.4 includes 690 firms that apply for 3 or more storage patents, however, only 112 of these firms have a dependent variable bigger or equal to zero. Given this limitation, we estimate our baseline model with an alternative dependent variable: the total number of storage patents using firm-level data. The results in table A.6.5 show that the number of observations is much larger than in table A.6.4. Furthermore, the results in table A.6.5 confirm our main results in table 1.1. Since our explanatory variables are unavailable at the firm level, we keep the regional-level analysis as our baseline analysis.

Table A.6.4: Baseline specification using firm-level data for all countries.

	Dependent variable:							
	Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-0.2738***	-0.1504†	-0.6661**	-0.8359†	-0.2023	-0.1978**	-0.4876	-0.8904*
	(0.0737)	(0.0975)	(0.2909)	(0.5105)	(0.1637)	(0.0956)	(0.5692)	(0.4617)
Electricity price	-0.0591*	-0.0426*	-0.0327	-0.1524†	-0.0515	-0.0368	-0.0650	-0.1955
	(0.0346)	(0.0254)	(0.0988)	(0.0994)	(0.0403)	(0.0332)	(0.1311)	(0.1466)
K^{S}_{t-1}	-0.0292**	0.0130	-0.0576	-0.1259**	-0.0345	0.0056	-0.0513	-0.0039
	(0.0120)	(0.0129)	(0.0549)	(0.0525)	(0.0243)	(0.0297)	(0.1406)	(0.0795)
K^{Ren}_{t-1}					0.0314*	0.02324**	0.0144	-0.0182
					(0.0171)	(0.0116)	(0.0556)	(0.0358)
K^{FF}_{t-1}					-0.0123	-0.0210	0.0114	-0.0793
					(0.0242)	(0.0209)	(0.1187)	(0.0920)
Total R&D	0.0356***	0.0208*	0.021	0.0673	0.0354**	0.0355***	0.0080	0.0672
	(0.0095)	(0.0114)	(0.0533)	(0.0879)	(0.0163)	(0.0119)	(0.0751)	(0.1127)
Time trend	0.0013	-0.0012	0.0062	0.0083	-0.0009	-0.0023	0.0038	0.0080
	(0.0013)	(0.0017)	(0.0110)	(0.0065)	(0.0029)	(0.0020)	(0.0114)	(0.0147)
Firm ID	9.0e-06	6.3e-07	7.7e-05***	8.6e-05***	5.9e-06	3.0e-06	6.1e-05	7.6e-05***
	(8.3e-06)	(1.4e-05)	(1.2e-05)	(3.0e-05)	(1.7e-05)	(8.6e-06)	(4.9e-05)	(3.0e-05)
λ	0.2485***	0.2449***	0.2958***	0.2091***	0.2373***	0.2368***	0.2507***	0.1622†
	(0.0803)	(0.0852)	(0.0710)	(0.0738)	(0.0764)	(0.0823)	(0.0809)	(0.1087)
N	347	347	423	423	306	347	382	423
chi2	89	108	89	114	68	117	85	272

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

Note: We use a sub-sample of firms with three or more storage patents. Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Table A.6.5: Baseline specification using firm-level data and the number of storage patents as a dependent variable.

	Dependent variable: the number of storage patents.			
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-252.4**	-285**	-219.8***	-263.1**
	(104.8)	(127.1)	(79.39)	(110.1)
Electricity price	-100.6*	-81.38†	-88.11†	-72.83†
	(60.68)	(52.7)	(55.82)	(47.57)
K^{S}_{t-1}	10.3	17.15**	10.56	29.47***
	(7.352)	(6.944)	(12.07)	(10.01)
K^{Ren}_{t-1}			-35.15***	-30.24***
			(11)	(9.975)
K^{FF}_{t-1}			26.51***	16.17
			(8.642)	(11.32)
Total R&D	23.77**	21.53*	22.3**	20.45*
	(11)	(11.47)	(9.831)	(11.25)
Time trend	5.916**	6*	5.762**	5.785*
	(2.958)	(3.4)	(2.737)	(3.319)
Firm ID	0.0068	0.0102**	0.0003	0.0044
	(0.0053)	(0.0049)	(0.0089)	(0.0072)
λ	0.2419***	0.2527***	0.2434***	0.2346***
	(0.0495)	(0.0578)	(0.0510)	(0.0595)
N	4769	4769	4769	4769
chi2	90	81	124	125

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

Note: We use a sub-sample of firms with three or more storage patents. Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

A.7 Exponential Feedback Model

We estimate a dynamic feedback model using a fixed-effect Poisson estimator, which is robust to different variance-mean relationship (Hausman et al., 1984; Blundell et al., 1995). We do not estimate a zero-inflated Poisson estimator because we lack region-level variables that would allow us to estimate the two margins. Another option is a negative binomial estimator, which is appropriate with patent data that exhibits over-dispersion. Note, however, that even with over-dispersion, the negative binomial is not necessarily an appropriate estimator for our main specification due to the large number of regional and time fixed effects that we would need to incorporate. The estimation results in table A.7.6 confirm the importance of technological opportunity as a determinant of innovation in energy storage. This specification is more in line with the one used by Lazkano et al. (2017a), but it fails to address exogenous shocks to the electricity sector in different regions. Moreover, it is less instructive for the transition within the industry since we need to explore the interaction between electricity generation and storage. For these reasons, we prefer the log-log estimation.

Table A.7.6: Fixed-effect Poisson estimation of the exponential model (dependent variable: the number of patent applications).

	Dependent variable: Storage Patents		Generation Patents		Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Electricity price	-0.0136	0.2228	-0.1417	0.0131	-0.0693	0.0365
	(0.1680)	(0.1997)	(0.1673)	(0.1806)	(0.1238)	(0.1317)
K^{S}_{t-1}	0.0116***	0.0057**	0.0071**	0.0029	0.0003	-0.0008
	(0.0028)	(0.0025)	(0.0031)	(0.0028)	(0.0011)	(0.0009)
K^{Ren}_{t-1}	-0.0013	-0.0265***	-0.0024	-0.0231***	-0.0001	0.0016
	(0.0021)	(0.0047)	(0.0022)	(0.0054)	(0.0037)	(0.0119)
K^{FF}_{t-1}	0.0012	0.0260***	0.0026	0.0231***	0.0011	0.0007
	(0.0021)	(0.0047)	(0.0022)	(0.0053)	(0.0037)	(0.0115)
Total R&D	5.6e-05**	7.7e-05***	5.9e-05**	7.5e-05***	1.1e-05	2.3e-05
	(2.6e-05)	(2.2e-05)	(2.4e-05)	(2.4e-05)	(3.3e-05)	(3.3e-05)
N	11126	11102	11318	11296	11564	11538
chi2	4193	1971	2238	1036	2893	3053

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

Note: Year dummies control for year fixed effects. Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

A.8 Pooled-OLS Model

Table A.8.7: Pooled-OLS model with time and regional controls.

	Dependent variable:							
	Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-0.6435***	-0.434***	-2.424***	-2.277***	-0.5671**	-0.306*	-1.979***	-1.903***
	(0.1884)	(0.1579)	(0.2316)	(0.198)	(0.2211)	(0.1628)	(0.2559)	(0.1962)
Electricity price	-0.0389	-0.0556	-0.2752***	-0.2085***	-0.0200	-0.0369	-0.2732***	-0.1739***
	(0.0675)	(0.0550)	(0.0810)	(0.0674)	(0.0757)	(0.0557)	(0.0862)	(0.0661)
K_{t-1}^{S}	0.0199***	0.0489***	-0.0240***	0.0213**	0.0455***	0.0757***	0.0727***	0.1108***
	(0.0063)	(0.0089)	(0.0075)	(0.0106)	(0.0090)	(0.0101)	(0.0103)	(0.0117)
K_{t-1}^{Ren}					-0.0214**	-0.0040	-0.0986***	-0.0456***
					(0.0094)	(0.0114)	(0.0108)	(0.0139)
K_{t-1}^{FF}					-0.0185*	-0.0597***	-0.0581***	-0.1794***
					(0.0095)	(0.0149)	(0.0109)	(0.0180)
Total R&D	-0.119	-0.0477	-0.5941*	-0.7736**	-0.1231	-0.1509	-0.8382**	-1.248***
	(0.2942)	(0.2653)	(0.3553)	(0.3294)	(0.3288)	(0.2801)	(0.3779)	(0.3372)
Region FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	3179	4298	3482	4774	2732	4225	3013	4699
chi2	575	957	14134	18083	573	995	15740	19634

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

Note: The table shows our regression results from a pooled-OLS model with IVs. Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

A.9 Construction of the Fixed-weight Price Index

We build on Linn (2008) and create a fixed-weight price index as instrumental variable for energy prices. Because the lack of data, we can only build a country-level fixed-weight price index.

As shown in equation A.5, the price index of country c in year t is obtained from the average of the share of electricity production from the energy input f in country c over the sample period, and the price of energy input f in country c at time t:

$$PI_{c,t} = \frac{1}{t - 1978 + 1} \sum_{s=1978}^{t} (w_{c,f} * price_{c,f,s}). \tag{A.5}$$

A.10 Spillover Effects

We adopt the NUT3 definition of region in our empirical analysis. In addition, we consider three geographic definitions to examine spillover effects by other inventors. Table A.10.8 presents the complete list of countries, GEO subregions, and GEO regions used to calculate spillover effects. We construct these measures by adding all patent applications by other regions in a country/GEO subregion/GEO region minus the number of patents in NUT3 region i. We only report country-level spillover effects in table A.10.9 since other definitions provide statistically insignificant results.

Following Jaffe (1986), we measure spillover effects by accounting for technology relatedness in a region. For each pair of regions (i, j) in a country and year t, we calculate weights based on their patent shares in storage, renewable and fossil fuel technologies, which are then used to construct a regional spillover measure. Specifically, h technology spillover in region i is $S_{i,ht} = \sum_{i \neq j} P_{ij} Pat_{jh}$ where weights $P_{ij} = \frac{F_i F_j'}{((F_i F_j) F_{ji})^{1/2}}$ are calculated with F_i being a vector with the fraction of the region i's patents devoted to technology h (s, ren or ff), and Pat_{jh} is the number of total patents in region j and technology h. Within each country, we calculate all region-pairs to construct the spillover measure. On average, each region has none-zero technology relatedness with 87% of other regions in the same country. Therefore, each region receives a large percentage of the innovation effort made by a peer region. In figure A.10.4, we plot the frequency distribution of technology relatedness, and table A.10.10 present the empirical results.

Table A.10.8: List of countries, GEO subregions and GEO regions.

Spillover levels	
Country	Argentina; Aruba; Australia; Austria; Azerbaijan; Bahamas; Barbados; Belarus; Belgium; Bermuda; Brazil; British Virgin Islands; Brunei Darussalam; Bulgaria; Burundi; Canada; Cayman Islands; Chile; China; Colombia; Croatia; Cyprus; Czech Republic; Denmark; Dominica; Ecuador; Egypt; Estonia; Finland; France; Gabon; Germany; Greece; Hong Kong, Special Administrative Region of China; Hungary; India; Indonesia; Iran; Islamic, Republic of; Ireland; Israel; Italy; Japan; Kazakhstan; Korea, Republic of; Kuwait; Latvia; Lebanon; Liechtenstein; Lithuania; Luxembourg; Macao, Special Administrative Region of China; Malaysia; Malta; Mauritius; Mexico; Monaco; Netherlands; Netherlands Antilles; New Zealand; Norway; Panama; Philippines; Poland; Portugal; Puerto Rico; Romania; Russian Federation; Samoa; San Marino; Saudi Arabia; Sierra Leone; Singapore; Slovakia; Slovenia; South Africa; Spain; Sweden; Switzerland; Taiwan, Republic of China; Thailand; Turkey; Turks and Caicos Islands; Ukraine; United Arab Emirates; United Kingdom; United States of America; Uruguay; Venezuela, Bolivarian Republic of.
GEO Subregion	Arabian Peninsula, Australia and New Zealand, Caribbean, Central Africa, Central Asia, Central Europe, Eastern Africa, Eastern Europe, Mashriq, Meso America, North America, North East Asia, Northern Africa, South America, South Asia, South East Asia, South Pacific, Southern Africa, Western Africa, Western Europe,Western Indian Ocean.
GEO Region	Africa, Asia and Pacific, Europe, Latin America and Caribbean, North America, West Asia.

Table A.10.9: Country-level spillover effects.

	Dependent variable:							
	Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-0.3815**	-0.4647**	-0.4863*	-0.6123**	-0.4218**	-0.5252***	-0.5326*	-0.8272***
	(0.1786)	(0.1905)	(0.2573)	(0.2817)	(0.2105)	(0.1853)	(0.3002)	(0.2132)
Electricity Price	-0.1174†	-0.1569**	-0.1039	-0.0168	-0.1243†	-0.1495**	-0.1199	-0.1415†
	(0.0719)	(0.0707)	(0.0949)	(0.0959)	(0.0826)	(0.0702)	(0.1085)	(0.0968)
K^S_{t-1}	-0.0317***	0.0235	-0.0924***	0.0083	-0.0336**	0.0473†	-0.1127***	0.0957**
	(0.0090)	(0.0268)	(0.0126)	(0.0328)	(0.0131)	(0.0319)	(0.0164)	(0.0376)
$\text{Spillovers}^S_{t-1}$	0.0034	0.0105	-0.0068	0.0498*	0.0016	0.0122	-0.0041	0.1715***
	(0.0087)	(0.0168)	(0.0112)	(0.0275)	(0.0116)	(0.0435)	(0.0132)	(0.0634)
K^{Ren}_{t-1}					-0.0032	-0.0108	0.0313**	-0.1223***
					(0.0119)	(0.0292)	(0.0139)	(0.0457)
$\text{Spillovers}^{Ren}_{t-1}$					0.0120	0.0326	-0.0147	-0.0482
					(0.0110)	(0.1377)	(0.0122)	(0.1264)
K^{FF}_{t-1}					0.0039	-0.0497*	-0.0060	-0.1193***
					(0.0118)	(0.0298)	(0.0144)	(0.0425)
$\text{Spillovers}^{FF}_{t-1}$					-0.0046	-0.0243	-0.0005	-0.1012
					(0.0134)	(0.1484)	(0.0145)	(0.1225)
Total R&D	0.0375†	0.0135	0.0022	-0.0967**	0.0330	0.0219	0.0147	-0.0105
	(0.0242)	(0.0251)	(0.0362)	(0.0406)	(0.0295)	(0.0254)	(0.0405)	(0.0341)
Time Trend	0.0069*	0.0057†	0.0099**	0.0047	0.0072**	0.0063†	0.0113**	0.0070†
	(0.0035)	(0.0040)	(0.0051)	(0.0056)	(0.0036)	(0.0040)	(0.0052)	(0.0045)
λ	0.1452***	0.1190***	0.2944***	0.2611***	0.1442***	0.1168***	0.2729***	0.2615***
	(0.0327)	(0.0326)	(0.0384)	(0.0398)	(0.0336)	(0.0348)	(0.0487)	(0.0369)
N	2218	2635	2495	2997	2006	2608	2274	2970
chi2	28	17	120	80	39	23	100	145

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

Note: Spillovers are from all regions except own in the same country. Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

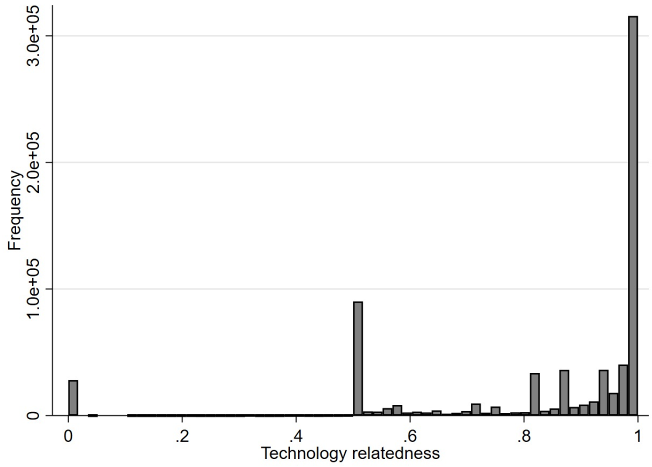


Figure A.10.4: Frequency distribution of technology relatedness.

Table A.10.10: Country-level spillover measure accounting for technology relatedness in each region-pair and year.

	Dependent variable: Storage Patents/Generation Patents	Storage Patents/Electricity Patents	Storage Patents/Generation Patents	Storage Patents/Electricity Patents
Constant	-0.5307***	-0.4584†	-0.564***	-0.6202**
	(0.1997)	(0.3113)	(0.2012)	(0.246)
Electricity Price	-0.1268*	-0.0111	-0.1442*	-0.1243
	(0.0750)	(0.0940)	(0.0753)	(0.0887)
K^S_{t-1}	0.0415	0.0355	0.0512†	0.0904**
	(0.0307)	(0.0364)	(0.0322)	(0.0391)
$\text{Spillovers}^S_{t-1}$	0.0390†	0.0249	0.0518†	0.0780**
	(0.0268)	(0.0323)	(0.0359)	(0.0367)
K^{Ren}_{t-1}			-0.0088	-0.0388
			(0.0288)	(0.0413)
$\text{Spillovers}^{Ren}_{t-1}$			0.0168	0.1316
			(0.0573)	(0.1029)
K^{FF}_{t-1}			-0.0266	-0.1723***
			(0.0305)	(0.0489)
$\text{Spillovers}^{FF}_{t-1}$			-0.0326	-0.217*
			(0.0560)	(0.1147)
Total R&D	0.0055	-0.1088**	0.0177	-0.0342
	(0.0287)	(0.044)	(0.0280)	(0.0338)
Time Trend	0.0075**	0.0045	0.0081**	0.0083*
	(0.0036)	(0.0055)	(0.0034)	(0.0045)
λ	0.1122***	0.2221***	0.1131***	0.2358***
	(0.0413)	(0.0417)	(0.0420)	(0.0374)
N	2475	2824	2457	2806
chi2	26	50	33	104

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

Note: All internal knowledge stocks are citation adjusted. The spillover effects are based on the spillover measure of Jaffe (1986). Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

A.11 Alternative Proxies for the Electricity Demand

While we use knowledge stocks of renewable and fossil fuel technologies in table 1.1, and shares of electricity generated from renewables and fossil fuels in 1.3 as channels incorporating electricity demand, table A.11.11 uses proxies in a macroeconomic way: using generation, capacity and consumption, respectively, in different panels.

Table A.11.12 examines different R&D policies instead of a total R&D spending in our baseline table. Panel A controls for R&D spending in storage, renewable-energy generation and fossil-fuel generation. Note that not all regions have detailed R&D information in our sample time period. That explains the drop of observations and might lead to the poor performance. Panel B takes GDP for the size of each economy and GDP per capita for its productivity level as macroeconomic controls.

Table A.11.11: Estimates with electricity generation, capacity and consumption.

	Dependent variable: Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Panel A: with electricity generation				
Constant	-0.5484***	-0.6909***	-0.5021*	-0.6907**
	(0.1815)	(0.1667)	(0.3052)	(0.3448)
Electricity price	-0.1417**	-0.1609***	-0.0865	-0.0292
	(0.0658)	(0.0617)	(0.0970)	(0.0985)
K^S_{t-1}	-0.0311***	0.0423*	-0.1028***	0.0198
	(0.0079)	(0.0238)	(0.0124)	(0.0344)
Total R&D	-0.0257	-0.0613*	-0.0489	-0.1545***
	(0.0389)	(0.0350)	(0.0530)	(0.0598)
Electricity generation	0.0963**	0.1190***	0.0507	0.0987
	(0.0397)	(0.0380)	(0.0696)	(0.0809)
Time trend	0.0091***	0.0069**	0.0093†	0.0049
	(0.0032)	(0.0031)	(0.0056)	(0.0057)
λ	0.1362***	0.1178***	0.2611***	0.2126***
	(0.0364)	(0.0295)	(0.0431)	(0.0440)
N	2204	2609	2491	2986
chi2	55	47	111	43
Panel B: with electricity capacity				
Constant	-0.4064**	-0.5136***	-0.4260†	-0.5354*
	(0.1976)	(0.1953)	(0.2723)	(0.3042)
Electricity price	-0.1582**	-0.1790***	-0.0970	-0.0431
	(0.0664)	(0.0691)	(0.0943)	(0.0939)
K^S_{t-1}	-0.0310***	0.0409†	-0.1023***	0.0196
	(0.0091)	(0.0276)	(0.0124)	(0.0346)
Total R&D	-0.0351	-0.0725*	-0.0774	-0.1874***
	(0.0461)	(0.0439)	(0.0561)	(0.0646)
Electricity capacity	0.1081**	0.1335***	0.0906	0.1432†
	(0.0491)	(0.0494)	(0.0780)	(0.0924)
Time trend	0.0087**	0.0065*	0.0086†	0.0041
	(0.0036)	(0.0036)	(0.0055)	(0.0057)
λ	0.1371***	0.1189***	0.2594***	0.2110***
	(0.0374)	(0.0392)	(0.0420)	(0.0439)
N	2204	2609	2491	2986
chi2	44	37	113	46
Panel C: with electricity consumption				
Constant	-.5458***	-.6916***	-.4962†	-.6824**
	(.1745)	(.1953)	(.306)	(.3478)
Electricity price	-.1417**	-.1603**	-.08698	-.03001
	(.06243)	(.06897)	(.09764)	(.09761)
K^S_{t-1}	-.03106***	.04194*	-.1028***	.01998
	(.00803)	(.02549)	(.01229)	(.03436)
Total R&D	-.02451	-.05969†	-.04591	-.1541**
	(.03508)	(.03881)	(.0522)	(.06015)
Electricity consumption	.09548***	.1183***	.04688	.09786
	(.03448)	(.04295)	(.06928)	(.08204)
Time trend	.00905***	.00697**	.00933*	.0049
	(.00304)	(.00335)	(.00552)	(.00575)
λ	.1361***	.1176***	.2615***	.2122***
	(.03189)	(.03487)	(.04243)	(.04401)
N	2204	2609	2491	2986
chi2	57	42	115	43

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Table A.11.12: Estimates with R&D spending in storage, renewable and fossil fuel policies, and controls for GDP and GDP per capita.

	Dependent variable:			
	Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Panel A: with different R&D spendings				
Constant	-0.3955**	-0.3114†	-1.0150***	-1.3860***
	(0.1857)	(0.2038)	(0.3701)	(0.4944)
Electricity price	-0.2060	-0.1738	-0.1702	-0.0381
	(0.1445)	(0.1302)	(0.2060)	(0.1736)
K^S_{t-1}	-0.0108	0.0380	-0.1180***	0.0535
	(0.0187)	(0.0367)	(0.0295)	(0.0565)
R&D in storage	0.0004	-0.0208	0.0239	0.0164
	(0.0521)	(0.0505)	(0.0949)	(0.0946)
R&D in renewables	0.1430***	0.1203**	0.1629**	0.1246
	(0.0533)	(0.0522)	(0.0760)	(0.0870)
R&D in fossil fuels	-0.0481	-0.0328	-0.0744	-0.1005
	(0.0497)	(0.0502)	(0.0934)	(0.0853)
Time trend	-0.0080	-0.0122	0.0057	0.0073
	(0.0090)	(0.0094)	(0.0137)	(0.0140)
λ	0.0525	0.0389	0.2452**	0.2052†
	(0.0568)	(0.0521)	(0.1050)	(0.1248)
N	663	800	756	934
chi2	9	14	65	18
Panel B: with GDP and GDP per capita				
Constant	-1.9910	-1.0560	0.2790	-0.0353
	(1.9740)	(1.8750)	(3.5750)	(3.7140)
Electricity price	-0.1310*	-0.1489**	-0.0373	0.0110
	(0.0723)	(0.0690)	(0.0980)	(0.0990)
K^S_{t-1}	-0.0324***	0.0281	-0.1002***	0.0114
	(0.0098)	(0.0252)	(0.0115)	(0.0325)
Total R&D	-0.0295	-0.0425	-0.0913*	-0.1699***
	(0.0423)	(0.0369)	(0.0500)	(0.0542)
GDP	0.1103**	0.1079**	0.1117†	0.1366*
	(0.0532)	(0.0493)	(0.0702)	(0.0803)
GDP per capita	0.0504	-0.0540	-0.1711	-0.1802
	(0.2076)	(0.2026)	(0.3415)	(0.3502)
Time trend	0.0056	0.0060	0.0063	0.0029
	(0.0058)	(0.0053)	(0.0082)	(0.0093)
λ	0.1459***	0.1289***	0.2542***	0.2060***
	(0.0427)	(0.0410)	(0.0426)	(0.0428)
N	2168	2573	2449	2942
chi2	41	29	119	44

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

Note: Government R&D spending in storage, renewable-energy generation and fossil-fuel generation are used as R&D policy proxies. GDP stands for the size of the economy while GDP per capita refer to the productivity level. Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

A.12 Robustness Tests

Table A.12.13: Baseline estimates with a price-square term using data from 1978 to 2019.

	Dependent variable:							
	Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	0.0322	0.4498	-0.7389	0.2568	-0.1335	0.1792	-0.7264	-0.5467
	(1.2450)	(1.0520)	(1.3050)	(1.448)	(1.144)	(1.058)	(1.327)	(1.126)
Electricity price	-0.0385	-0.0137	-0.1073	0.11	-0.0679	-0.0543	-0.0899	-0.0030
	(0.1563)	(0.1379)	(0.2009)	(0.2067)	(0.1451)	(0.1338)	(0.2134)	(0.1645)
Electricity $price^2$	-0.0291	-0.0686	0.0169	-0.0592	-0.0199	-0.0521	0.0064	-0.0125
	(0.0825)	(0.0711)	(0.0960)	(0.1033)	(0.0772)	(0.07)	(0.0988)	(0.0808)
K^S_{t-1}	-0.0429***	0.0307	-0.1013***	0.0245	-0.0477***	0.0578*	-0.1293***	0.0885**
	(0.0092)	(0.0262)	(0.0114)	(0.0301)	(0.0111)	(0.0309)	(0.0156)	(0.0363)
K^{Ren}_{t-1}					0.0130	0.0062	0.0171	-0.0634†
					(0.0124)	(0.0286)	(0.0140)	(0.0401)
K^{FF}_{t-1}					-0.0096	-0.0724**	0.0159	-0.1035**
					(0.0130)	(0.0358)	(0.0137)	(0.0436)
Total R&D	0.0453†	0.0143	0.0030	-0.0809**	0.0522†	0.0305	0.0053	-0.0356
	(0.0314)	(0.0276)	(0.0311)	(0.0363)	(0.0328)	(0.0292)	(0.0340)	(0.0308)
Time trend	0.0098***	0.0085**	0.0087†	0.0058	0.0103***	0.0090***	0.0098*	0.0074†
	(0.0036)	(0.0038)	(0.0053)	(0.0055)	(0.0036)	(0.0035)	(0.0055)	(0.0045)
λ	0.1422***	0.112***	0.2837***	0.2445***	0.1453***	0.1141***	0.2614***	0.2673***
	(0.0371)	(0.0379)	(0.0399)	(0.0429)	(0.0373)	(0.0382)	(0.047)	(0.0395)
N	2215	2629	2490	2984	2010	2612	2275	2967
chi2	38	19	140	58	44	25	118	93

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Table A.12.14: Heterogeneous impact of energy prices.

	Dependent variable: Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-.5067**	-.668***	-.4446	-.6613*
	(.2336)	(.2404)	(.3537)	(.3807)
Electricity price	-.4314**	-.4438**	-.3877	.02639
	(.1966)	(.1867)	(.2974)	(.3057)
K_{t-1}^{S}	-.04188***	.02439	-.1012***	.0154
	(.00807)	(.02499)	(.01185)	(.03078)
Share of renewables	.00033	.00109	.0051	.00763
	(.0099)	(.00873)	(.01498)	(.01374)
Share fossil-fuels	.00214	.00218	.00174	.004
	(.00218)	(.00211)	(.00258)	(.00292)
Total R&D	.03991	.02155	-.02091	-.1**
	(.02791)	(.02558)	(.04219)	(.04756)
Time trend	0.0120***	0.0097**	0.0034	-0.0002
	(0.0039)	(0.0040)	(0.0063)	(0.0059)
Price×Ren share	-.00847	-.00616	.02027	.02145
	(.01749)	(.0149)	(.02613)	(.02425)
Price×FF share	.00567*	.005*	.00425	-.00298
	(.00312)	(.00302)	(.00472)	(.00489)
λ	.1577***	.1293***	.2461***	.2033***
	(.04352)	(.03869)	(.04487)	(.04581)
N	2168	2573	2449	2942
chi2	45	26	132	54

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Table A.12.15: Baseline estimates using early-period and later-period subsamples for all regions.

	Dependent variable: Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Panel A: Sample 1978-1989:								
Constant	-0.4474	-0.5011	0.1935	0.3564	-0.2535	-0.3626	0.0916	0.12
	(0.4713)	(0.4384)	(0.7008)	(0.7078)	(0.4467)	(0.447)	(0.6114)	(0.5816)
Electricity price	-0.1357	-0.02577	-0.1583	0.0033	-0.1646	-0.1027	-0.0880	0.0004
	(0.1586)	(0.1532)	(0.1905)	(0.2193)	(0.1447)	(0.1445)	(0.2165)	(0.2279)
K^S_{t-1}	-0.0340*	-0.0023	-0.1141***	0.1129†	-0.0283*	0.0231	-0.1002***	.03316***
	(0.0180)	(0.0508)	(0.0206)	(0.0694)	(0.0165)	(0.0598)	(0.0285)	(0.0900)
K^{Ren}_{t-1}					0.0170	-0.0414	0.0189	-0.0585
					(0.0178)	(0.0533)	(0.0279)	(0.1121)
K^{FF}_{t-1}					-0.0290	-0.0230	-0.0245	-0.2256*
					(0.0240)	(0.0731)	(0.0242)	(0.1327)
Total R&D	0.0529	0.0451	-0.0660	-0.177*	0.0221	0.0327	-0.0803	-0.1127*
	(0.0492)	(0.0434)	(0.0847)	(0.0923)	(0.0506)	(0.0491)	(0.0750)	(0.0682)
Time trend	-0.0019	-0.0084	-0.0225	-0.0353	0.0095	-0.0138	-0.0136	-0.0210
	(0.0151)	(0.0211)	(0.0193)	(0.0249)	(0.0129)	(0.0162)	(0.0170)	(0.0235)
λ	0.0730	0.0657	0.2229***	0.1818**	0.1307**	0.1238**	0.2018**	0.2915***
	(0.0616)	(0.0572)	(0.0773)	(0.0902)	(0.0651)	(0.0617)	(0.0971)	(0.0685)
N	619	660	675	726	569	644	627	711
chi2	9	5	51	14	11	13	33	49
Panel B: Sample 1990-2019:								
Constant	-0.4658**	-0.6132***	-0.4858*	-0.6351**	-0.4759*	-0.5546***	-0.4554	-0.7222***
	(0.1966)	(0.2082)	(0.2722)	(0.2781)	(0.2625)	(0.2021)	(0.32)	(0.2246)
Electricity price	-0.193**	-0.2097**	-0.1469	-0.0683	-0.3141***	-0.275***	-0.1697	-0.1003
	(0.0859)	(0.0927)	(0.1214)	(0.1095)	(0.1069)	(0.0857)	(0.1212)	(0.0941)
K^S_{t-1}	-0.0523***	0.0449	-0.0967***	0.0149	-0.0407**	0.0264	-0.1006***	0.0565†
	(0.0120)	(0.0383)	(0.0147)	(0.0372)	(0.0162)	(0.0335)	(0.0181)	(0.0363)
K^{Ren}_{t-1}					0.0197	-0.0057	0.0019	-0.1164**
					(0.0152)	(0.0351)	(0.0196)	(0.0506)
K^{FF}_{t-1}					-0.0105	-0.0519	-0.0121	-0.0765†
					(0.0156)	(0.0362)	(0.0183)	(0.05)
Total R&D	0.0849***	0.0452†	0.0024	-0.0586	0.06754*	0.0436	-0.0055	-0.0209
	(0.0271)	(0.0297)	(0.0442)	(0.0454)	(0.0371)	(0.0317)	(0.0503)	(0.0412)
Time trend	0.0111*	0.0105†	0.0122†	0.0102	0.0147***	0.0092*	0.0181**	0.0080
	(0.0063)	(0.0065)	(0.0081)	(0.0090)	(0.0055)	(0.0054)	(0.0083)	(0.0076)
λ	0.1306**	0.1131*	0.264***	0.2504***	0.0323	0.0349	0.2419***	0.2621***
	(0.0570)	(0.0641)	(0.0555)	(0.0612)	(0.0503)	(0.0514)	(0.0652)	(0.0558)
N	1427	1772	1629	2056	1294	1780	1511	2078
chi2	33	17	74	35	27	14	84	46

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Table A.12.16: Baseline specification excluding data from the U.S..

	Dependent variable:							
	Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-0.0274	-0.1377	-0.1661	-0.1659	-0.0308	-0.1367	-0.2809	-0.5524^{**}
	(0.2083)	(0.2044)	(0.2385)	(0.2715)	(0.2298)	(0.2133)	(0.2554)	(0.2262)
Electricity price	-0.1373^{*}	-0.162^{**}	0.0135	0.0412	-0.1698^{*}	-0.1921^{**}	0.0066	-0.0123
	(0.0813)	(0.0744)	(0.0907)	(0.0893)	(0.0893)	(0.0765)	(0.0888)	(0.0837)
K^{S}_{t-1}	-0.0175^{*}	0.0214	-0.0892^{***}	0.0350	-0.0126	0.0292	-0.0980^{***}	0.1101^{**}
	(0.0096)	(0.0295)	(0.0130)	(0.0362)	(0.0148)	(0.0338)	(0.0198)	(0.0456)
K^{Ren}_{t-1}					0.0119	0.0609^{**}	0.0184	-0.0555
					(0.0158)	(0.0280)	(0.0171)	(0.0530)
K^{FF}_{t-1}					$-0.0196^{\dagger}$	-0.0754^{*}	-0.0234	-0.1779^{***}
					(0.0128)	(0.0394)	(0.0168)	(0.0622)
Total R&D	-0.0335	-0.0388	-0.0561	-0.1365^{***}	-0.0345	-0.0353	-0.0450	$-0.0557^{\dagger}$
	(0.0330)	(0.0322)	(0.0413)	(0.0453)	(0.0354)	(0.0332)	(0.0427)	(0.0378)
Time trend	0.0070^{*}	0.0087^{**}	0.0045	0.0015	0.0074^{*}	0.0088^{**}	0.0068	0.0060
	(0.0041)	(0.0040)	(0.0050)	(0.0054)	(0.0038)	(0.0042)	(0.0057)	(0.0048)
λ	0.1096^{***}	0.0970^{**}	0.2041^{***}	0.2283^{***}	0.1066^{***}	0.0948^{**}	0.1635^{***}	0.2324^{***}
	(0.0375)	(0.0404)	(0.0478)	(0.056)	(0.0389)	(0.0405)	(0.0624)	(0.0519)
N	1651	1999	1845	2256	1486	1985	1673	2242
chi2	16	13	94	46	21	20	85	80

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Table A.12.17: Baseline specification using data from the three most innovative countries – Japan, the U.S. and Germany.

	Dependent variable:							
	Storage Patents/Generation Patents		Storage Patents/Electricity Patents		Storage Patents/Generation Patents		Storage Patents/Electricity Patents	
	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock	simple stock	citation-adjusted stock
Constant	-0.3939	-0.5455*	-0.5053†	-0.2823	-0.3452	-0.4741†	-0.5937†	-0.6702**
	(0.2915)	(0.3037)	(0.337)	(0.4501)	(0.3416)	(0.3053)	(0.3683)	(0.314)
Electricity price	-0.0630	-0.1413*	-0.0089	0.0548	-0.0202	-0.1346†	0.0111	0.0081
	(0.0807)	(0.0804)	(0.0920)	(0.1002)	(0.0801)	(0.0856)	(0.107)	(0.0717)
K^{S}_{t-1}	-0.0055	0.0831**	-0.0678***	-0.0988***	-0.0247*	-0.0746**	-0.0704***	-0.0571*
	(0.011)	(0.0320)	(0.0120)	(0.0325)	(0.0150)	(0.0333)	(0.0202)	(0.0318)
K^{Ren}_{t-1}					0.0359**	0.0271	0.0048	-0.0968**
					(0.0167)	(0.0326)	(0.0195)	(0.0469)
K^{FF}_{t-1}					0.0003	-0.0107	-0.0072	-0.1032**
					(0.0132)	(0.0220)	(0.0183)	(0.0447)
Total R&D	0.0172	0.0280	-0.0280	-0.116**	-0.0026	0.0186	-0.0339	-0.0498
	(0.0349)	(0.0353)	(0.0416)	(0.0542)	(0.0415)	(0.0357)	(0.0441)	(0.0428)
Time trend	0.0042	0.005	0.0102**	0.0107*	0.0033	0.0045	0.0109**	0.0135***
	(0.003)	(0.0035)	(0.0044)	(0.0059)	(0.0030)	(0.0036)	(0.005)	(0.0045)
λ	0.0788**	0.0573	0.2445***	0.2512***	0.0876**	0.0553†	0.1902***	0.2512***
	(0.0402)	(0.0413)	(0.0376)	(0.0489)	(0.0402)	(0.0366)	(0.0606)	(0.0494)
N	1380	1595	1555	1824	1259	1585	1429	1814
chi2	7	13	126	72	11	14	90	146

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

Note: Total R&D stands for total government R&D spending, which is lagged to instrument for R&D spending. Numbers in parentheses are standard errors.

Appendix B

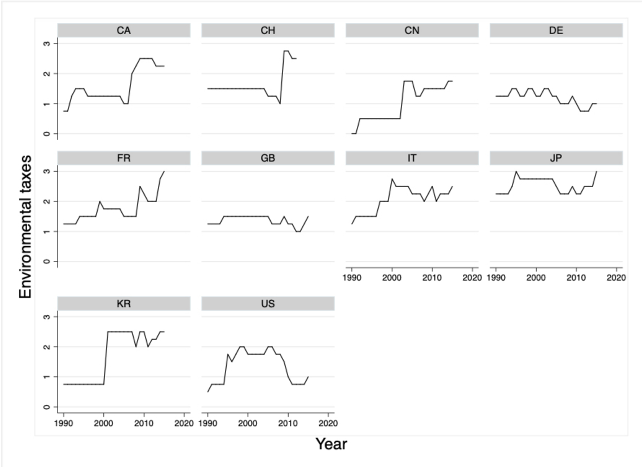
Appendix to Chapter 2

B.1 IPC Codes for Storage Technologies

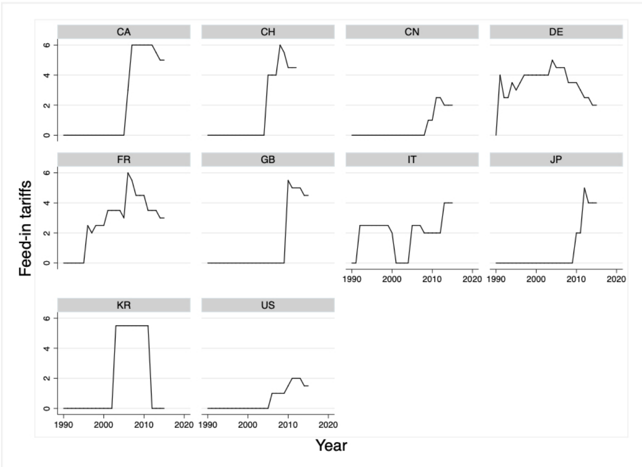
Table B.1.1: Selected IPC codes for battery and fuel cell technologies.

Batteries	
H01M002/06-40	Details, processes of manufacture of the non-active parts for batteries.
H01M004	Electrodes
H01M006	Primary cells.
H01M010	Secondary cells.
H01M014	Electrochemical current or voltage generators.
H01M016	Combinations of different types of electrochemical generators.
Fuel Cells	
H01M002/00-04	Details, processes of manufacture of the non-active parts for batteries: cases, jackets or wrappings; lids or covers.
H01M004/86-98	Electrodes for fuel cells.
H01M008	Fuel cells.
H01M012	Hybrid cells.

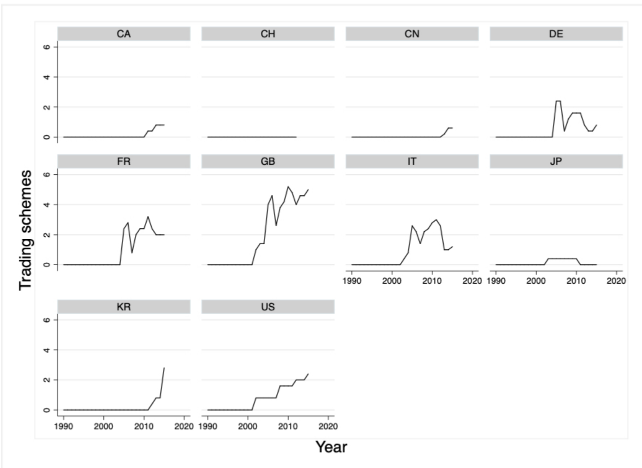
B.2 Additional Figures



(a) Environmental taxes.



(b) FITs.



(c) Trading schemes.

Figure B.2.1: The stringency of three policy types for the top ten countries, 1990-2015.

B.3 Baseline estimates using non-university patents

Table B.3.2: Firm-level baseline estimates using non-university patents.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	-1.839*** (0.2264)		-2.602*** (0.2658)		-2.741*** (0.2715)	
Energy price index$_{t-1}$	2.1e-08** (9.3e-09)	0%**	2.4e-08** (9.4e-09)	0%**	3.0e-08*** (1.0e-08)	0%***
K$_{t-1}$	0.292*** (0.0235)	33.9%***	0.2801*** (0.0231)	32.3%***	0.2735*** (0.0227)	31.5%***
Spillovers$_{t-1}$	0.0042*** (0.0005)	0.4%***	0.0012* (0.0008)	0.1%*	0.0009 (0.0008)	0.1%
Market EPS$_{t-1}$	0.4694*** (0.1448)	59.9%***				
Environmental Taxes$_{t-1}$			0.7175*** (0.1108)	104.9%***	0.7683*** (0.1115)	115.6%***
Feed-in Tariffs$_{t-1}$			0.0953* (0.0504)	10%*		
FIT Solar$_{t-1}$					0.1128† (0.0749)	11.9%†
FIT Wind$_{t-1}$					-0.0372 (0.0545)	-3.65%
Trading Scheme$_{t-1}$			.04671 (0.1737)	4.8%		
Certificates: CO$_{2t-1}$					0.1555* (0.0895)	16.8%*
Certificates: Green$_{t-1}$					-0.3349** (0.1598)	-28.46%**
Certificates: White$_{t-1}$					-1.283** (0.5541)	-72.27%**
Pre-sample Firm	-0.0467 (0.0486)	-4.57%	-0.0150 (0.0487)	-1.49%	-0.0037 (0.0478)	-0.37%
Pre-sample Zero	-1.149*** (0.0978)	-68.3%***	-1.142*** (0.0979)	-68.1%***	-1.11*** (0.0976)	-67.05%***
Year	YES		YES		YES	
N	3894		3894		3894	
chi2	949		982		1009	

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

Note: The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

B.4 Baseline estimates with a country fixed effect

Table B.4.3: Firm-level baseline estimates with country fixed effects.

	Dependent variable: the number of storage patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	-1.58		-1.623		$-1.736^{\dagger}$	
	(1.148)		(1.165)		(1.167)	
Energy price index$_{t-1}$	$-4.0e\text{-}08^{\dagger}$	$0\%^{\dagger}$	$-4.1e\text{-}08^{\dagger}$	$0\%^{\dagger}$	-1.3e-08	0%
	(2.5e-08)		(2.7e-08)		(3.3e-08)	
K$_{t-1}$	0.2908^{***}	$33.8\%^{***}$	0.2727^{***}	$31.3\%^{***}$	0.288^{***}	$33.4\%^{***}$
	(0.0235)		(0.0230)		(0.0233)	
Spillovers$_{t-1}$	-0.0021^{**}	$-0.21\%^{***}$	-0.0021^{**}	$-0.21\%^{**}$	-0.0020^{**}	$-0.2\%^{***}$
	(0.0009)		(0.0010)		(0.0010)	
Market EPS$_{t-1}$	-0.2081	-18.78%				
	(0.2121)					
Environmental Taxes$_{t-1}$			-0.0322	-3.17%	0.0402	4.1%
			(0.2783)		(0.2965)	
Feed-in Tariffs$_{t-1}$			-0.0591	-5.74%		
			(0.0743)			
FIT Solar$_{t-1}$					0.0137	1.4%
					(0.0968)	
FIT Wind$_{t-1}$					-0.0703	-6.79%
					(0.0631)	
Trading Scheme$_{t-1}$			-0.1709	-15.71%		
			(0.1881)			
Certificates: CO_{2t-1}					0.0376	3.8%
					(0.0956)	
Certificates: Green$_{t-1}$					-0.3581^{**}	$-30.1\%^{**}$
					(0.1812)	
Certificates: White$_{t-1}$					-1.153	-68.42%
					(0.8436)	
Pre-sample Firm	-0.0508	-4.86%	-0.0142	-1.41%	-0.0410	-4.02%
	(0.0483)		(0.0476)		(0.0483)	
Pre-sample Zero	-1.134^{***}	$-67.83\%^{***}$	-1.114^{***}	$-67.18\%^{***}$	-1.118^{***}	$-67.31\%^{***}$
	(0.1048)		(0.0985)		(0.1053)	
Country	YES		YES		YES	
Year	YES		YES		YES	
N	3894		3894		3894	
chi2	1013		1023		1026	

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

Note: The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

B.5 Baseline estimates on generation patents

Table B.5.4: Firm-level estimates on total generation patent.

	Dependent variable: the number of total generation patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	-0.292		-0.0356		-0.0602	
	(0.1305)		(0.143)		(0.1438)	
Energy price index$_{t-1}$	-2.7e-08***	0%***	-2.8e-08***	0%***	-3.0e-08***	0%***
	(5.6e-09)		(6.5e-09)		(6.7e-09)	
K_{t-1}	0.124***	13.2%***	0.126***	13.4%***	0.126***	13.4%***
	(0.0081)		(0.0083)		(0.0082)	
Spillovers$_{t-1}$	0.0025***	0.2%***	0.0030***	0.3%***	0.0035***	0.4%***
	(0.0009)		(0.0011)		(0.0012)	
Market EPS$_{t-1}$	-0.2042**	-18.47%**				
	(0.0830)					
Environmental Taxes$_{t-1}$			-0.0965†	-9.2%†	-0.912	-8.72%
			(0.0661)		(0.0664)	
Feed-in Tariffs$_{t-1}$			-0.0693**	-6.7%**		
			(0.0298)			
FIT Solar$_{t-1}$					-0.1669***	-15.38%***
					(0.0487)	
FIT Wind$_{t-1}$					0.0468†	4.8%†
					(0.0295)	
Trading Scheme$_{t-1}$			-0.1016	-9.66%		
			(0.1106)			
Certificates: CO_{2t-1}					0.0238**	2.4%
					(0.0635)	
Certificates: Green$_{t-1}$					0.0947	9.9%
					(0.0907)	
Certificates: White$_{t-1}$					-0.2588†	-22.8%†
					(0.1626)	
Pre-sample Firm	-0.0118	-1.17%	-0.0139*	-1.38%*	-0.0121†	-1.2%†
	(0.0083)		(0.0083)		(0.0082)	
Pre-sample Zero	-0.8492***	-57.22%***	-0.8948***	-59.13%***	-0.8476***	-57.15%***
	(0.0648)		(0.0654)		(0.065)	
Year	YES		YES		YES	
N	3894		3894		3894	
chi2	1705		1708		1720	

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

Note: The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

Table B.5.5: Firm-level estimates on fossil-fuel generation technologies

	Dependent variable: the number of fossil-fuel generation patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	0.0449		0.1032		0.1631	
	(0.136)		(0.1556)		(0.1563)	
Energy price index$_{t-1}$	7.7e-09	0%	2.6e-09	0%	-4.5e-09	-0%
	(5.7e-09)		(6.8e-09)		(7.4e-09)	
K$_{t-1}$	0.0134***	1.3%***	0.0140***	1.4%***	0.0135***	1.4%***
	(0.0010)		(0.0011)		(0.0011)	
Spillovers$_{t-1}$	-0.0006***	-0.6%***	-0.0005***	-0.5%***	-0.0003**	-0.3%**
	(8.7e-05)		(0.0001)		(0.0002)	
Market EPS$_{t-s}$	-0.2119**	-19.09%**				
	(0.0925)					
Environmental Taxes$_{t-1}$			-0.1501*	-13.94%*	-0.1797**	-16.45%**
			(0.0899)		(0.0909)	
Feed-in Tariffs$_{t-1}$			-0.0740**	-7.13%**		
			(0.0323)			
FIT Solar$_{t-1}$					-0.1152**	-10.88%**
					(0.0512)	
FIT Wind$_{t-1}$					0.0248	2.5%
					(0.0335)	
Trading Scheme$_{t-1}$			0.0690	7.1%		
			(0.1231)			
Certificates: CO$_{2t-1}$					0.0773	8%
					(0.0659)	
Certificates: Green$_{t-1}$					0.2624***	30.3%***
					(0.0996)	
Certificates: White$_{t-1}$					-0.5796***	-43.99%***
					(0.2084)	
Presample Firm	0.0012†	0.1%†	0.0008	0.1%	0.0012†	0.1%†
	(0.0008)		(0.0008)		(0.0008)	
Presample Zero	-0.3679***	-30.78%***	-0.4616***	-36.97%***	-0.3854***	-31.98%***
	(0.1306)		(0.1333)		(0.1311)	
Year	YES		YES		YES	
N	3894		3894		3894	
chi2	1054		1054		1076	

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

Note: Data from 1990 to 2015 for all firms in top 10 countries is used. The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

Table B.5.6: Firm-level estimates on renewable generation technologies

	Dependent variable: the number of renewable generation patents					
	(1) Coeff.	(2) %Change	(3) Coeff.	(4) %Change	(5) Coeff.	(6) %Change
Constant	-0.0468		-0.1442		-0.0551	
	(0.1404)		(0.1594)		(0.1601)	
Energy price index$_{t-1}$	3.1e-08***	0%***	3.1e-08***	0%***	2.1e-08***	0%***
	(5.4e-09)		(6.4e-09)		(7.0e-09)	
K$_{t-1}$	0.0560***	5.8%***	0.0574***	5.9%***	0.0542***	5.6%***
	(0.0057)		(0.0058)		(0.0056)	
Spillovers$_{t-1}$	-0.0007***	-0.7%***	-0.0008***	-0.8%***	-0.0007***	-0.7%***
	(7.7e-05)		(0.0001)		(0.0001)	
Market EPS$_{t-s}$	-0.2107**	-19%**				
	(0.0958)					
Environmental Taxes$_{t-1}$			0.0216	2.2%	-0.0188	-1.87%
			(0.0902)		(0.0912)	
Feed-in Tariffs$_{t-1}$			-0.0886***	-8.48%***		
			(0.0332)			
FIT Solar$_{t-1}$					-0.0901*	-9.66%*
					(0.0531)	
FIT Wind$_{t-1}$					0.0044	0.4%
					(0.0347)	
Trading Scheme$_{t-1}$			0.103	10.9%		
			(0.1296)			
Certificates: CO$_{2t-1}$					0.0704	7.3%
					(0.0674)	
Certificates: Green$_{t-1}$					0.3307***	39.2%***
					(0.1038)	
Certificates: White$_{t-1}$					-0.6055***	-49.11%***
					(0.2361)	
Presample Firm	0.0203***	2.1%***	0.0196***	2%***	0.0213***	2.1%***
	(0.0041)		(0.0042)		(0.0042)	
Presample Zero	-0.119	-11.22%	-0.1469	-13.66%	-0.127	-11.93%
	(0.1266)		(0.1278)		(0.1266)	
Year	YES		YES		YES	
N	3894		3894		3894	
chi2	941		939		966	

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

Note: Data from 1990 to 2015 for all firms in top 10 countries is used. The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

B.6 Complete tables of heterogenous policy effects

Table B.6.7: Heterogenous policy effects in the share of renewable patents.

	Dependent variable: the number of storage patents					
	(1)	(2)	(3)	(4)	(5)	(6)
	Coeff.	%Change	Coeff.	%Change	Coeff.	%Change
Constant	-1.988***		-3.302***		-3.66***	
	(0.3339)		(0.4094)		(0.4186)	
Energy price index$_{t-1}$	4.1e-08***	0%***	4.5e-08***	0%***	6.2e-08***	0%***
	(1.3e-08)		(1.4e-08)		(1.6e-08)	
K$_{t-1}$	0.1866***	20.5%***	0.158***	17.1%***	0.1617***	17.6%***
	(0.0227)		(0.0223)		(0.0212)	
Spillover$_{t-1}$	0.0042***	0.4%***	-0.0004	-0.4%	-0.0002	-0.02%
	(0.0006)		(0.0010)		(0.0010)	
Specialty$_{t-1}$	0.0229**	2.3%**	0.0271**	2.7%**	0.0332***	3.4%***
	(0.0111)		(0.0115)		(0.0119)	
Market EPS$_{t-1}$	0.7284***	107.2%***				
	(0.2067)					
Environmental Taxes$_{t-1}$			1.188***	227.9%***	1.294***	264.7%***
			(0.1722)		(0.1704)	
Feed-in Tariffs$_{t-1}$			0.2249***	25.2%***		
			(0.0795)			
FIT Solar$_{t-1}$					0.3063**	35.8%**
					(0.1216)	
FIT Wind$_{t-1}$					-0.0682	-6.59%
					(0.0885)	
Trading Scheme$_{t-1}$			0.2956	34.4%		
			(0.2451)			
Certificates: CO_{2t-1}					-0.1117	-10.58%
					(0.1646)	
Certificates: Green$_{t-1}$					-0.2831	-24.65%
					(0.2037)	

(Continued on next page)

(Continued from previous page)

Certificates: White$_{t-1}$					5.1	16310%
					(8.374)	
Interaction with Specialty$_{t-1}$						
xMarket EPS$_{t-1}$	-0.0159	-1.58%				
	(0.0138)					
xEnvironmental Taxes$_{t-1}$			-0.0076†	-0.76%†	-0.0111**	-1.1%**
			(0.0051)		(0.0050)	
xFeed-in Tariffs$_{t-1}$			-0.0135	-1.34%		
			(0.0129)			
xFIT Solar$_{t-1}$					-0.0034	-0.34%
					(0.0160)	
xFIT Wind$_{t-1}$					-0.0079	-0.78%
					(0.0118)	
xTrading Scheme$_{t-1}$			-0.0054	-0.54%		
			(0.0199)			
xCertificates: CO_{2t-1}					0.1119**	11.8%**
					(0.0465)	
xCertificates: Green$_{t-1}$					-0.0045	-0.45%
					(0.0103)	
xCertificates: White$_{t-1}$					-20.26	-100%
					(52.63)	
Pre-sample Firm	-0.0638	-6.18%	-0.0121	-1.2%	-0.0520	-5.07%
	(0.0607)		(0.0584)		(0.0588)	
Pre-sample Zero	-0.9861***	-62.7%***	-1.025***	-64.14%***	-0.9719***	-62.16%***
	(0.144)		(0.1352)		(0.1439)	
Year	YES		YES		YES	
N	1549		1550		1549	
chi2	477		512		558	

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

Note: Data from 1990 to 2015 in top 10 countries. The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.

Table B.6.8: Heterogenous policy effects in the time length of renewable innovation.

	Dependent variable: the number of storage patents					
	(1)	(2)	(3)	(4)	(5)	(6)
	Coeff.	%Change	Coeff.	%Change	Coeff.	%Change
Constant	-1.791***		-2.568***		-2.731***	
	(0.3134)		(0.4855)		(0.482)	
Energy price index$_{t-1}$	2.6e-08***	0%***	2.4e-08**	0%**	3.7e-08***	0%***
	(9.5e-09)		(9.6e-09)		(1.1e-08)	
K_{t-1}	0.3171***	37.3%***	0.2857***	33.1%***	0.2968***	34.6%***
	(0.0243)		(0.0237)		(0.0236)	
Spillover$_{t-1}$	0.0042***	0.4%***	0.0011†	0.1%†	0.0010	0.1%
	(0.0005)		(0.0008)		(0.0008)	
Timing$_{t-1}$	-0.0048	-0.48%	-0.0034	-0.34%	-0.0047	-0.47%
	(0.0223)		(0.0415)		(0.0407)	
Market EPS$_{t-1}$	0.4613**	58.6%**				
	(0.2323)					
Environmental Taxes$_{t-1}$			0.7438***	110.4%***	0.7829***	118.8%***
			(0.2117)		(0.2098)	
Feed-in Tariffs$_{t-1}$			-0.0261	-2.58%		
			(0.1039)			
FIT Solar$_{t-1}$					0.1466	15.8%
					(0.1307)	
FIT Wind$_{t-1}$					-0.0911	-8.71%
					(0.1087)	
Trading Scheme$_{t-1}$			0.1033	10.9%		
			(0.3853)			
Certificates: CO_{2t-1}					0.2157	24.1%
					(0.1659)	
Certificates: Green$_{t-1}$					-0.3603	30.25%
					(0.3767)	
Certificates: White$_{t-1}$					49.61	3.5e+21
					(1935)	
Interaction with Timing$_{t-1}$						

(Continued on next page)

(Continued from previous page)

xMarket EPS_{t-1}	0.0048	0.5%				
	(0.0185)					
xEnvironmental $Taxes_{t-1}$			-0.0025	-0.25%	0.0015	0.2%
			(0.0176)		(0.0175)	
xFeed-in $Tariffs_{t-1}$			$0.0128^{\dagger}$	$1.3\%^{\dagger}$		
			(0.0087)			
xFIT $Solar_{t-1}$					-0.0027	-0.27%
					(0.0120)	
xFIT $Wind_{t-1}$					0.0056	0.6%
					(0.0100)	
xTrading $Scheme_{t-1}$			-0.0020	-0.2%		
			(0.0296)			
xCertificates: CO_{2t-1}					-0.0024	-0.24%
					(0.0132)	
xCertificates: $Green_{t-1}$					-0.0013	-0.13%
					(0.0253)	
xCertificates: $White_{t-1}$					-15.7	-100%
					(644.9)	
Pre-sample Firm	-0.0919^{*}	$-8.78\%^{*}$	-0.0210	-2.08%	-0.0496	4.84%
	(0.0507)		(0.0504)		(0.0496)	
Pre-sample Zero	-1.143^{***}	$-68.12\%^{***}$	-1.125^{***}	$-67.54\%^{***}$	-1.124^{***}	$-67.52\%^{***}$
	(0.1146)		(0.1094)		(0.1148)	
Year	YES		YES		YES	
N	3882		3880		3882	
chi2	922		955		994	

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

Note: Data from 1990 to 2015 in top 10 countries. The citation-adjusted knowledge in the last pre-sample year (t = 1989) is used as the firm fixed effect. The last-two-year data was weighted with application granted distribution to address truncation problem. The 1st lag of all explanatory variables is used.