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From Fossil Fuels to Renewables: The Role of Electricity Storage

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From Fossil Fuels to Renewables: The Role of Electricity Storage*

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Abstract

We analyze the role of electricity storage for technological innovations in electricity generation. We propose a directed technological change model of the electricity sector, where innovative firms develop better electricity storage solutions, which affect not only the relative competitiveness between renewable and nonrenewable electricity sources but also the ease with which they can be substituted. Using a global firm-level data set of electricity patents from 1963 to 2011, we empirically analyze the determinants of innovation in electricity generation, and the role of storage in directing innovation. Our results show that electricity storage increases innovation not only in renewables but also in conventional technologies. This implies that efforts to increase innovation in storage can benefit conventional, fossil fuel-fired electricity plants as well as increasing the use of renewable electricity.

Keywords: Innovation; Directed technical change; Electricity storage; Electricity markets; Power generation

JEL Classification Codes: O3, O4, O5, Q2, Q3, Q4, Q5

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1 Introduction

Concerns over climate change have led society to seek alternatives to reduce carbon emissions. To that end, many call for a shift in energy production from fossil fuels toward renewables. Although renewable energy can provide a clean source of electricity, fossil fuels still account for the vast majority of the world's electricity generation.[1] As a consequence, electricity generation is currently the single largest carbon emitter globally, and with energy demands continuing to grow rapidly, innovation in the electricity sector is an important channel for curbing carbon emissions. Although innovation has already resulted in new and improved renewable technologies, efficient electricity storage is often considered to be a key innovation challenge for meeting renewable goals because cheap, large-scale storage solutions can boost the use of intermittent renewable energy in the grid mix.

Our main goal is to study the role of electricity storage in the electricity sector. Specifically, we ask three questions. First, how do better storage technologies affect innovation in electricity generation? Second, how does innovation in electricity generation affect technological advancements in storage? Finally, what is the impact of fossil-fuel prices on innovation? To answer these questions, we develop a stylized theoretical model of directed technological change, where innovation in electricity storage improves the elasticity of substitution between conventional and renewable electricity production. Then, we test our theoretical predictions using a global firm-level database of patents related to electricity generation and storage from 1963 to 2011.

The most widely used form of electricity storage is pumped hydro, which accounts for over 90% of the current global storage capacity and has been used commercially since the 1890s. However, current innovation efforts mainly target other technologies, including batteries or compressed air storage, because the potential to expand the use of traditional pumped-hydro storage is limited by the availability of suitable sites. Many of these initiatives seek a breakthrough in batteries, but governments and private companies also direct innovation efforts to a multitude of other possible solutions.[2] These include ways to use cheap and

[1] According to the International Energy Agency, in 2013, 67.2% of world electricity production came from conventional fossil fuel-powered plants. Hydroelectric plants provided 16.6%, nuclear plants 10.6%, biofuels and waste 2.0%, and the rest came from geothermal, solar, wind, and other sources (IEA, 2015).

[2] Indeed, the media describe the occurrence of a technology race in electricity storage, with scientists searching for game-changing solutions to the challenge of efficiently storing electricity. See, for example, "How energy storage can change everything" by Daniel Burrus (`http://www.huffingtonpost.com/daniel-burrus/how-energy-storage-can-ch_b_8010258.html`) or "Innovation sputters in battle against climate change" by Eduardo Porter (`http://www.nytimes.com/2015/07/22/business/energy-environment/innovation-to-stanch-climate-change-sputters.html`).

easily available materials, including air and water, as the storage media (e.g., compressed air, flywheels, and pumped hydro), hydrogen-based technologies, and electrical and thermal storage.

One important feature of electricity markets is the requirement to maintain grid balance at all times. Unfortunately, conventional and renewable electricity sources are not perfect substitutes in ensuring grid balance because of the intermittency of renewable energy. However, once electricity generating firms have access to affordable, large-scale storage solutions, intermittent renewable energy can become as flexible as conventional (fossil-fuel based) energy in balancing the grid. Indeed, the capacity to store electricity is the key component that links electricity generation to its delivery. Hence, electricity storage mitigates another key challenge in electricity markets: balancing the grid when there are large fluctuations in consumption across the day and the week.

As storage provides greater flexibility to meet variable demands, regardless of the energy source, it can provide benefits to both conventional and renewable electricity producers. Storing electricity efficiently can enable full exploitation of the energy potential in intermittent renewables, as producers can simply produce as much electricity as the sun and the wind offer at all times, store it, and dispatch it to the grid when needed. In addition, efficient storage technologies can create new arbitrage possibilities for conventional electricity producers, because storage enables them to produce at a fairly constant rate, thereby minimizing ramping and other costs, to store the electricity, and to dispatch it during peak periods. Thus, both renewable and conventional electricity producers can profit from electricity storage solutions. Given this, we study the incentives to develop better storage solutions and their role in fostering innovation in renewable and conventional generation.

We start by theoretically analyzing the drivers of innovation in the electricity sector. Our innovation model builds on the directed technological change framework used by Acemoglu et al. (2012) and Aghion et al. (2016). Specifically, we model three types of innovation: innovation in renewable electricity generation, innovation in conventional electricity generation, and innovation in electricity storage. Innovation in electricity generation increases efficiency and results in cost savings, whereas innovation in storage improves the elasticity of substitution between renewable and conventional electricity production. The theoretical contribution of our paper is to propose an endogenous process to improve the elasticity of substitution in a directed technological change model.

We find that better storage solutions promote innovation in both renewable and conventional electricity when the two production processes are substitutes. Hence, better electricity storage technologies not only benefit renewable energy production but also benefit conventional production, by creating incentives to develop better fossil-fuel technologies. In addition, we show how better electricity generation technologies affect the incentives to innovate in the electricity sector. Then, we empirically evaluate our theoretical predictions and quantify the effect of storage on innovation.

To conduct our empirical analysis, we first build a global firm-level data set of electricity patents. We focus on Triadic patents, which are patents filed in all of the three major patent offices: the European Patent Office (EPO), the US Patent and Trademark Office (USPTO), and the Japanese Patent Office (JPO). In total, we identify 19,232 unique Triadic patent applications for electricity storage, 154,041 for conventional technologies, and 178,841 for renewable technologies. In addition to the patent data, we use data on energy prices and macroeconomic variables. Altogether, our data set covers 13,877 firms, across 79 countries, for a period from 1963 to 2011. Guided by the theoretical analysis, we use the data set to estimate the probability of innovation in the three technologies using information on the firms' past innovations, knowledge spillovers from other firms, energy prices, and macroeconomic indicators as explanatory variables.

Our empirical results confirm that the development of new storage technologies promotes innovations in both conventional and renewable technologies. Hence, electricity storage not only benefits renewables, by mitigating the intermittency problem, but also encourages the development of efficiency-improving fossil-fuel technologies; for example, by allowing conventional power plants to reduce ramping costs. In addition, we find evidence for a positive feedback effect between innovation in storage and in renewable generation. Our results imply that the development of large-scale electricity storage, by increasing the flexibility to meet demand at all times, improves efficiency in electricity generation. Although it has been widely argued that electricity storage is a key solution to reducing carbon emissions in the electricity sector, this is the first paper to provide evidence that better storage not only will improve the potential for renewable technologies but also will boost the efficiency of the entire electricity sector.

Our study contributes to the literature studying energy prices, induced innovation, and economic growth (see e.g. Popp, 2002, 2004, 2006b; Acemoglu et al., 2012, 2013; Aghion et al., 2016).[3] In particular, our work has several similarities with Acemoglu et al. (2012),

[3] Acemoglu et al. (2012); Bovenberg and Smulders (1995, 1996); Goulder and Schneider (1999) theoretically analyze directed technological change and the environment. In addition, there is an extensive empirical literature studying the incentives to innovate in the energy sector; see, for example, Buonanno et al. (2003); Popp (2002, 2005); Calel and Dechezleprêtre (2012); Dechezleprêtre and Glachant (2014); Gans (2012), and

who present a theoretical framework for studying induced innovation in the energy sector. We contribute to this theoretical literature by proposing an endogenous mechanism for improving the substitutability between conventional and renewable technologies through innovation using the directed technological change framework. Our empirical analysis is related most closely to the studies by Aghion et al. (2016) and Noailly and Smeets (2015), which quantify firm-level incentives to direct technological innovations toward renewable technologies in different sectors. Whereas Aghion et al. (2016) focus on innovation in the automobile industry, Noailly and Smeets (2015) analyze the electricity sector. Our paper differs from the latter study in that we explicitly analyze the role of electricity storage in this sector and examine how better storage affects innovation in electricity generation.

The remainder of the paper is organized as follows. In section 2, we present our theoretical model. In section 3, we explain how we build our unique data set and present descriptive statistics. Section 4 describes our empirical strategy, and section 5 discusses our estimation results. Finally, section 6 concludes the paper.

2 Theoretical framework

In this section, we develop and analyze a directed technological change model of the electricity sector, where innovation in electricity storage improves the substitutability of renewable and conventional technologies. The directed technological change framework, first introduced by Acemoglu (2002), and later applied to the environment by Acemoglu et al. (2012), analyzes how renewable and conventional technologies evolve over time. Aghion et al. (2016) use this framework to study brown versus green innovation in the automobile industry. We build on this approach to explain innovation in the electricity sector. The novelty of our model is that we endogenize the elasticity of substitution between renewable and conventional technologies. To the best of our knowledge, this is the first paper to study an endogenous process for improving the substitutability between two types of production using the directed technological change framework.

Without storage solutions, it is not feasible for intermittent renewable energy to contribute a large share of electricity to the grid, as this would require a large overcapacity of renewables to ensure grid balance and, thus, energy security, at all times. For this reason, intermittent renewable electricity production relies on a buffer of conventional generation to balance the grid. In this setting, limited storage solutions imply that conventional electricity

Hassler et al. (2012).

generation is a complement to intermittent renewable energy. Fortunately, the development of better storage offers a solution to this issue by improving the substitutability between renewable and conventional electricity generation by decoupling the production of energy from its consumption. Hence, with storage solutions, renewable electricity production can overcome the intermittency problem and become a substitute for, rather than a complement to, conventional production. This is our motivation for modeling innovation in electricity storage as an endogenous mechanism that improves the elasticity of substitution between renewable and conventional electricity generation. In addition, we model innovation that yields efficiency gains and, thus, lower production costs, in renewable and conventional electricity generation.

We develop a one-period model, where consumers obtain utility from electricity and an aggregate outside good. Firms that are price and technology taking produce electricity from renewable and conventional sources.[4] We make two distinctions between renewable and conventional electricity. First, all renewable resources, unlike nonrenewables, are intermittent (e.g., wind and solar). Second, energy inputs into renewable production are free (wind and sun), whereas conventional electricity generation uses costly fossil fuels.

With this model, we show that the development of better electricity storage technologies provides two benefits to the electricity sector. First, it boosts renewable electricity generation because decoupling electricity production from consumption alleviates the intermittency issue.[5] Second, electricity storage makes the electricity market more flexible, which benefits conventional producers who can exploit arbitrage possibilities and reduce their ramping costs. This leads to more innovation in efficiency-improving conventional technologies and greater flexibility to meet demand at all times. Thus, the development of better electricity storage technologies promotes greater efficiency in the entire electricity sector, as we show analytically in the following sections.

[4]This implies deregulated electricity markets, which have been seen to yield close to perfect competition as long as there are two or more competing electricity retailers.

[5]Note that hydropower is a significant exception to our framework because we assume that renewable electricity generation comes only from intermittent resources. In reality, hydropower producers have the ability to store energy for later dispatch. For example, Danish wind power production relies on Norwegian hydropower as a buffer. However, owing to the high utilization of available hydropower resources, little room is left for expansion, and consequently, further growth in renewable energy must come from other sources that are likely to be intermittent. For this reason, we exclude hydropower from our theoretical analysis.

2.1 The model

Consider an economy with a continuum of consumers who spend their fixed income on electricity and an aggregate outside good c_0 (the *numeraire*) to maximize utility.[6] The utility function is quasi-linear with respect to c_0 and takes the following form:

$$U = c_0 + \frac{\beta}{\beta - 1} Y^{\frac{\beta-1}{\beta}}, \tag{1}$$

where $Y = \int Y_i di$ is aggregate electricity consumption, with i representing a continuum of consumers, and β is the elasticity of substitution between electricity and the aggregate consumption good.

Innovation affects both the efficiency of electricity generation and the ease of substitution between renewable and conventional electricity. Firms invest in technological innovation at the beginning of the period, before they produce with the improved technologies at the end of the period.[7] Firms take the initial state of technologies as given, and decide how much to invest in R&D to maximize their profits. The firms' innovations lead to cost savings from more efficient technologies in the end-of-period production stage. Given price and technology taking firms (perfect markets), we can derive the equilibrium levels of innovation and production.

The cost of innovation effort x_j is $\frac{1}{2}\psi_j x_j^2$, for technology type $j = s, c, r$, where ψ is a positive constant and subscripts s, c, and r denote electricity storage, conventional (fossil fuel), and renewable electricity generation, whereas the cost is measured in terms of the aggregate consumption good. The impact of innovation in a given technology is:

$$A_j = (1 + x_j) A_{j0}, \quad \text{for } j = s, c, r, \tag{2}$$

where $A_{j0} \geq 0$ denotes the initial efficiency of the technology, and A_j is the technology after innovation.

The costs of conventional and renewable electricity generation depend on available technologies, as follows: $\frac{\phi_j g_j Y_j}{A_j}$, for $j = c, r$, with $g_c = f \geq 1$ and $g_r = 1$, where Y_c and Y_r are conventional and renewable electricity production, ϕ_j, $j = c, d$ are positive constants, and f is the fossil fuel price. The parameter g_j indicates electricity generation that relies on costly

[6]On the demand side, we assume that consumers consider electricity to be a homogenous product. Hence, we abstract from any consumer preferences for renewable over nonrenewable electricity.

[7]Within our static framework, there are no spillover effects of R&D activities. We relax this assumption in the empirical section, where we account for knowledge spillovers.

fossil fuel inputs, in contrast to renewable sources.

Before dispatching electricity to consumers, retailers (or utilities) aggregate electricity from conventional and renewable sources according to the following production function:

$$Y = \left(Y_r^{\frac{\epsilon(A_s)-1}{\epsilon(A_s)}} + Y_c^{\frac{\epsilon(A_s)-1}{\epsilon(A_s)}} \right)^{\frac{\epsilon(A_s)}{\epsilon(A_s)-1}}, \tag{3}$$

where $\epsilon = \epsilon(A_s) \in [0, +\infty\rangle$ is the elasticity of substitution between renewable and conventional electricity. We assume that the elasticity of substitution depends linearly on the efficiency of the storage technology: $\epsilon(A_s) = \epsilon_0 A_s$, where ϵ_0 is a positive constant. The inputs are complements when $\epsilon(A_s) < 1$ and substitutes when $\epsilon(A_s) > 1$. Thus, innovation in renewable and conventional technologies lowers the cost of generating electricity, whereas innovation in storage technologies improves the substitutability between electricity produced by renewable and conventional generators.

2.2 Equilibrium

To solve for the model's equilibrium, we first derive the demand for electricity from the consumers' problem.[8] Using this demand function, we solve the electricity production problem, which occurs at the end of the period. Finally, we calculate the industry's equilibrium investment in research by solving the innovation problem at the beginning of the period, given the solution of the production problem. Our goal is to analyze the drivers of innovation in electricity storage and in conventional and renewable generation.

Consumers maximize utility with respect to their use of electricity, Y:

$$\max_{Y} \; c_0 + \frac{\beta}{\beta - 1} Y^{\frac{\beta-1}{\beta}}, \tag{4}$$

subject to $m = c_0 + PY$, where m is the available budget and P is the electricity price. The optimality condition of the problem simplifies to the following demand function:

$$Y = P^{-\beta}. \tag{5}$$

[8]This equilibrium represents a social planner's solution as well as the market outcome, as we abstract from externalities.

2.2.1 End-of-period production problem

To determine how much to invest in innovation at the beginning of the period, firms consider the value of having better technologies in the production stage, which takes place at the end of the period. Therefore, we begin by solving the electricity production problem:

$$\max_{Y_r,Y_c} P\left(Y_r^{\frac{\epsilon(A_s)-1}{\epsilon(A_s)}} + Y_c^{\frac{\epsilon(A_s)-1}{\epsilon(A_s)}}\right)^{\frac{\epsilon(A_s)}{\epsilon(A_s)-1}} - \frac{\phi_r}{A_r}Y_r - \frac{\phi_c f}{A_c}Y_c, \tag{6}$$

where P is given because firms take prices as given. Note that, at this stage, all technologies are fixed (A_j, $j = s, c, r$).

After some manipulation of the first-order conditions, we obtain the optimal production level of renewable and conventional electricity:

$$Y_j = Y\left(\frac{\phi_j g_j}{A_j}\right)^{-\epsilon(A_s)} P^{\epsilon(A_s)},\ j = c, r. \tag{7}$$

Using the electricity demand function (5), the optimal production of electricity from fossil fuels and renewables (7) becomes:

$$Y_j = \left(\frac{\phi_j g_j}{A_j}\right)^{-\epsilon(A_s)} P^{\epsilon(A_s)-\beta},\ j = c, r, \tag{8}$$

which is identical to the market equilibrium.

2.2.2 Beginning-of-period innovation problem

To solve the beginning-of-period innovation problem, we substitute the optimal electricity production for a given technology level into the aggregate profit function. This yields the following objective function for the innovation problem:

$$\begin{aligned}\Pi =& P\left(F_c^{(1-\epsilon)}P^{\frac{(\epsilon-\beta)(\epsilon-1)}{\epsilon}} + F_r^{(1-\epsilon)}P^{\frac{(\epsilon-\beta)(\epsilon-1)}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}} \\ & - F_c^{1-\epsilon}P^{\epsilon-\beta} - F_r^{1-\epsilon}P^{\epsilon-\beta} - \frac{1}{2}\sum_{j=s,c,r}\psi_j x_j^2,\end{aligned}$$

where Π is aggregate industry profits, $F_j \equiv \frac{\phi_j g_j}{A_j}$ for $j = c, r$, $F \equiv F_r^{1-\epsilon(A_s)} + F_c^{1-\epsilon(A_s)}$, and where we have dropped the argument A_s from the ϵ function to simplify notation. This expression simplifies to:

$$\Pi = P^{\epsilon-\beta}\left[PF^{\frac{\epsilon}{\epsilon-1}}\right] - \frac{1}{2}\sum_{j=s,c,r}\psi_j x_j^2. \tag{9}$$

To find the equilibrium level of innovation in renewable, conventional, and storage technologies, we maximize equation (9) subject to each technology's innovation constraint (2). Doing this, we can express the optimality condition for innovation in storage, x_s, as:

$$\begin{aligned}\frac{\psi_s x_s P^{\beta-\epsilon}}{\epsilon_0 A_{s0}} =& \ln P\left(PF^{\frac{\epsilon}{\epsilon-1}} - F\right) + F_c^{1-\epsilon}\ln F_c + F_r^{1-\epsilon}\ln F_r \\ &+ PF^{\frac{\epsilon}{\epsilon-1}}\left\{\left(\frac{\epsilon}{\epsilon-1}\right)\frac{F_r^\epsilon F_c \ln F_c + F_r F_c^\epsilon \ln F_r}{F_r F_c^\epsilon + F_r^\epsilon F_c} + \frac{\ln F}{(\epsilon-1)^2}\right\},\end{aligned} \tag{10}$$

where we have used the definition of $\epsilon(A_s)$ and equation (2) to substitute for $\frac{\partial\epsilon}{\partial x_s} = \epsilon_0 A_{s0}$.

Similarly, we can express the optimality condition for innovation in electricity generation as:

$$\psi_j x_j P^{\beta-\epsilon} = \left(\epsilon PF^{\frac{1}{\epsilon-1}} + 1 - \epsilon\right)F_j^{1-\epsilon}\left(\frac{A_{j0}}{A_j}\right), \quad j = c, r. \tag{11}$$

Note that ϵ, A_j, and F_j in the equation system (10) and (11) are functions of innovation, x_j, and that we cannot solve explicitly for the equilibrium values of innovation. Instead, the highly nonlinear equation system (10) and (11) implicitly defines the equilibrium levels of innovation in the three technologies. These equations show that innovation in equilibrium depends on past innovation, the elasticity of substitution between conventional and renewable electricity, and energy prices. Next, we carry out comparative statics to analyze the drivers of innovation in more detail.

2.3 Determinants of innovation in equilibrium

As the equilibrium is given by the highly nonlinear and implicit equation system (10) and (11), we numerically analyze the comparative statics for innovation. We focus on three key variables that affect innovation: the elasticity of substitution, which is equivalent to past innovation in electricity storage technologies (ϵ_0 and A_{s0}); past innovation in generation ($A_{j0},\ j = r, c$); and the fuel price (f). Table 1 below and Figure A.1 in the appendix summarize how each of these factors affects innovation in renewable, conventional, and storage technologies, when conventional and renewable production are complements and substitutes, respectively.

Table 1: Comparative statics: Innovation drivers.

Innovation in	Renewable		Conventional		Storage	
Initial elasticity of subst., $A_{s0}\epsilon_0$	Compl.	Subs.	Compl.	Subs.	Compl.	Subs.
Initial storage technology, A_{s0}	$-$	$+$	$-$	$+$	$-$	$-$
Initial renewable technology, A_{r0}	$-$	$+ \rightarrow -$	$+$	$-$	$+$	$+ \rightarrow -$
Initial conventional technology, A_{c0}	$+$	$-$	$-$	$+ \rightarrow -$	$+$	$+ \rightarrow -$
Fuel price, f	$-$	$+$	$+$	$+ \rightarrow -$	$-$	$+ \rightarrow -$

We are primarily interested in three relationships: first, how the current electricity storage technology affects innovation in conventional and renewable generation; second, the feedback effect of improved generation technologies on innovation in both storage and generation; and, finally, how the fossil-fuel price affects innovation. In the following, we discuss what our theoretical analysis predicts for each of these relationships.

The first row of Table 1 shows the impact of better initial storage technologies on innovation.[9] We find that innovation in storage, which improves the substitutability between conventional and renewable electricity production, can promote innovation in the two generation technologies. Specifically, if conventional and renewable electricity (initially) are substitutes ($\epsilon_0 A_{s0} > 1$), which recent empirical work suggests is most plausible,[10] then innovation in these technologies increases with the ability to store electricity. This happens because improved storage technologies enhance the flexibility of the electricity market, and a more flexible market increases the potential payoff from developing better generation technologies, both conventional and renewable. This implies that better storage technologies promote innovation in both types of generation technologies, not just in renewables, by mitigating the intermittency problem.

The second effect that we focus on is the impact of better electricity generation technologies on the incentives to innovate in storage. Innovation in storage is extensive when renewable and conventional production are close to perfect complements and when they are perfect substitutes (see Figure A.1(a)). Moreover, when conventional and renewable production are not sufficiently close substitutes, better generation technologies lead to stronger

[9]Note that the initial level of the storage technology, A_{s0}, and the elasticity parameter, ϵ_0, have the same impact on innovation. This is because the elasticity of substitution in the production stage is given by both parameters. As the comparative statics for a change in ϵ_0 are the same as for A_{s0}, we only report the latter in Table 1.

[10]See, for example, Gerlagh and van der Zwaan (2004); Popp (2006a); Papageorgiou et al. (2016). Whereas these and other studies estimate a constant elasticity of substitution, see Lazkano and Pham (2016) for the estimate of a variable elasticity of substitution (VES).

incentives to innovate in storage. In contrast, as the two types of production become closer substitutes, the marginal value of better storage technologies becomes lower (because of higher substitution), and the incentives to innovate in storage become weaker. Thus, for a sufficiently high initial elasticity of substitution, better generating technologies have a negative impact on innovation in storage. Finally, a higher initial elasticity of substitution leads to a larger payoff from further innovation in electricity generation. This implies that, as the storage technology (A_{s0}) improves, innovation efforts shift from storage toward generation. This result suggests that innovation in storage and innovation in generation are substitutes in this case (Figure A.1(a)).

Next, we consider the impact of better generation technologies on the equilibrium level of innovation in conventional and renewable technologies. When renewable and conventional production are substitutes, we find an ambiguous response in innovation to changes in the initial efficiency of each electricity generation technology. Indeed, the impact of more knowledge (higher efficiency) on current innovation depends on the size of the knowledge stock.[11] As the initial generation technology improves, the marginal value of further innovation in the technology falls, and eventually, the effect of more existing knowledge on innovation becomes negative. In addition, as the knowledge stock in renewable generation expands, innovation in conventional technologies shrinks and *vice versa* (see Figures A.1(c) and A.1(d)). The reason is that innovation in a generation technology reduces its cost of production, which makes the technology more competitive relative to the alternative technology, which then attracts less innovation.

Finally, we study the effect of the fuel price on innovation. As the only difference between renewable and conventional production in our model is the fossil fuel input, the fuel price affects conventional and renewable innovation in different ways. We find that the response to higher fuel prices depends on the elasticity of substitution between renewable and conventional production (see Table 1, last row, and Figure A.1(b)). When the two are complements, firms innovate more in conventional technologies while reducing their innovation in renewable generation and storage. In contrast, when renewable and conventional production are substitutes, the innovation response to higher fuel prices depends on the level of the fuel price. At a low fuel price, an increase in the price strengthens innovation in all three technologies. However, at a higher fuel price, an increase in the price reduces innovation in conventional technologies but boosts innovation in renewable generation and storage. Note,

[11] When renewable and conventional production are complements, more past innovation in renewable (conventional) technologies yields more innovation in storage and conventional (renewable) technologies but less innovation in renewable (conventional) technologies.

however, that for sufficiently high fuel prices, innovation in storage falls in response to more expensive fuel.[12] These findings imply that energy taxes can induce innovation in electricity storage technologies, provided that they do not drive up the post-tax fuel price too much (see Figure A.1(b)).

To summarize, our theoretical analysis shows that the development of better electricity storage solutions can potentially promote technological advancements in both renewable and conventional electricity generation. As our theoretical predictions depend on the elasticity of substitution between conventional and renewable production, we turn to empirical analysis to investigate further how different factors affect innovation in storage and generation technologies.

First and foremost, our goal is to identify whether storage promotes innovation in renewable and conventional electricity generation. We investigate both the direct effect of better storage solutions on innovation in generation and the effect of improved generation technologies on innovation in storage and generation. In addition, we analyze the firm-level innovation response to higher fuel prices. To accomplish this, we estimate a reduced form of the equilibrium innovation level given by equations (10) and (11), using a global panel of firm-level patent data. In the next section, we describe the data set, before presenting the empirical strategy and analysis in sections 4 and 5.

3 Data

Estimating the reduced form of innovation equations (10) and (11) requires firm-level data on research, past innovations, and energy prices. Our data set, which spans 49 years (1963–2011) and 79 countries, comes primarily from two sources: the OECD's patent database and the International Energy Agency (IEA). We start by describing the selection of data before presenting descriptive statistics.

We use patent data to measure research effort and to construct our unique patent data set following Popp (2005) and Aghion et al. (2016). There are several advantages of using

[12] To understand the shift in firms' responses for conventional and storage innovations, note that a higher fuel price affects conventional electricity generation in two ways. On the one hand, it makes conventional electricity more costly and, hence, less competitive relative to the renewable substitute, thereby reducing the incentives to innovate in conventional technologies. On the other hand, a higher fossil fuel price increases the gains from developing more efficient conventional generation technologies, thereby strengthening the incentives to innovate. At low fuel prices, the latter effect on innovation is stronger, whereas at high fuel prices, the first effect is stronger. This mechanism also affects innovation in storage because the more expensive is the conventional electricity (high fuel price), the lower is its share in the grid mix, and the lower is the gain from higher substitutability (better storage).

patents as a measure of innovation. First, patents measure innovation output close to the actual time of invention (Popp, 2005). In addition, each patent contains detailed information about its applicants and inventors, which is helpful in identifying who owns each patent. Following Aghion et al. (2016), we consider patent families from the OECD's Triadic Patent Database to account for the vast value differences in patents across firms and countries.[13] A Triadic patent application involves an applicant filing for an invention at each of the three most important patent offices: the EPO, the USPTO, and the JPO. Triadic patents form a special type of patent family that protect the same idea across different countries.[14] This implies that each patent application has an equivalent application at the EPO, the JPO, and the USPTO. Because Triadic patents are filed in all three of the main patent offices, they include only the highest valued patents. The Triadic patent families database provides a common worldwide measure of innovation that avoids the heterogeneity of individual patent office administrations (Popp, 2005).[15]

A disadvantage of Triadic patent families is the lag associated with the USPTO, with legal delays between the priority date and the publication date varying from 18 months to five years (Dernis and Khan, 2004). A patent shows up in the database, under its filing date, only after it has been granted. As a consequence, US patent grants may delay the completion of data on Triadic patent families.

At the time of filing, each patent is assigned one or more IPC codes, which describe the technology area that a patent aims to protect.[16] We use these IPC codes to identify technologies related to electricity generation and storage.

For conventional electricity generation technologies, we use the patent classification list

[13]Patent families correct for *home bias*, which occurs because domestic firms tend to register more patents than do international competitors. A direct implication of this bias is that patents filed domestically only may have a lower value than patents registered both domestically and internationally. Also, because the same invention registered in a different country will receive a different application number and may be classified under additional International Patent Classification (IPC) codes, the risk of counting the same invention more than once is high. We avoid such problems by using Triadic patents.

[14]A patent family consists of patents in multiple countries designed to protect one invention by the same inventor. Furthermore, the OECD uses the concept of "extended families", which are designed to identify any possible links between patent documents (Martinez, 2010). This is advantageous because it provides the most comprehensive method of consolidating patents into distinct families, allowing us to include an extensive number of patented ideas and to minimize omissions.

[15]A disadvantage of Triadic patent families is the lag associated with the USPTO, with legal delays between the priority date and the publication date varying from 18 months to five years (Dernis and Khan, 2004). A patent shows up in the database, under its filing date, only after it has been granted. As a consequence, US patent grants may delay the completion of data on Triadic patent families. In the last two years of our data set, this delay is evident as the number of patents almost drops to zero (see Figure 1).

[16]Patent classification codes are developed by the World Intellectual Property Organization (WIPO) and provided by the IPO.

compiled by Lanzi et al. (2011). In the appendix, Table B.3 presents IPC codes for efficiency-improving fossil-fuel technologies, whereas Table B.4 lists general fossil-fuel based IPC codes. For renewable electricity generation technologies, we compile the list of classification codes directly from WIPO's Green IPC Inventory (see Table B.5 in the appendix).[17] This list is more comprehensive than others previously used in the literature, and thus, our patent database covers a significantly broader range of technologies. The most widely used list is perhaps the one compiled by Johnstone et al. (2010), which contains a subset of the IPC codes from WIPO's Green Technology inventory. Although we employ WIPO's complete list in our baseline estimations, we evaluate the robustness of our results using the classification codes by Johnstone et al. (2010). We present a comparison of these two classifications in Table B.7 in the appendix. Finally, we select electricity storage technologies using WIPO's Green Technology inventory (Table B.6). In total, our baseline data set includes 392,445 patent applications. Of these, 154,041 relate to conventional fossil-fuel technologies,[18] 178,841 are for renewables, and 19,232 are for storage technologies.

Figure 1 shows the evolution of patent applications in the three technologies from 1963 to 2011. In the mid 1970s, we observe a sharp increase in electricity generation patenting. The evolution of conventional and renewable patents is correlated, but a strong increase in renewable patent applications occurred at the end of the 1990s, such that they surpassed conventional patents, until the early 2000s, when a sharp decline occurred.[19] The large drop in patents at the end of the period is due to the aforementioned legal delays of patents registered with the USPTO. This means that appearing in the Triadic patent database can take up to five years from the time a patent is filed in all three patent offices.

Having defined and selected patents for all three types of technologies, we assign each patent to its owner. As the Triadic database contains detailed information only for some applicants, we draw more comprehensive information from the OECD Harmonized Applicants Names (HAN) database, which matches applicants with company names from business registry data. With this, we are able to link patents to firms and individuals. Fortunately, the HAN database contains firm information for many patent applications in our sample. We synchronize the remaining applications using applicant information contained in the Triadic Patent Families database. This procedure allows us to match every patent with an applicant.

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

[18]Of these, 130,587 are general fossil-fuel technologies and 23,184 are efficiency-improving fossil-fuel technologies.

[19]This trend is consistent with Noailly and Smeets (2015) and Nesta et al. (2014).

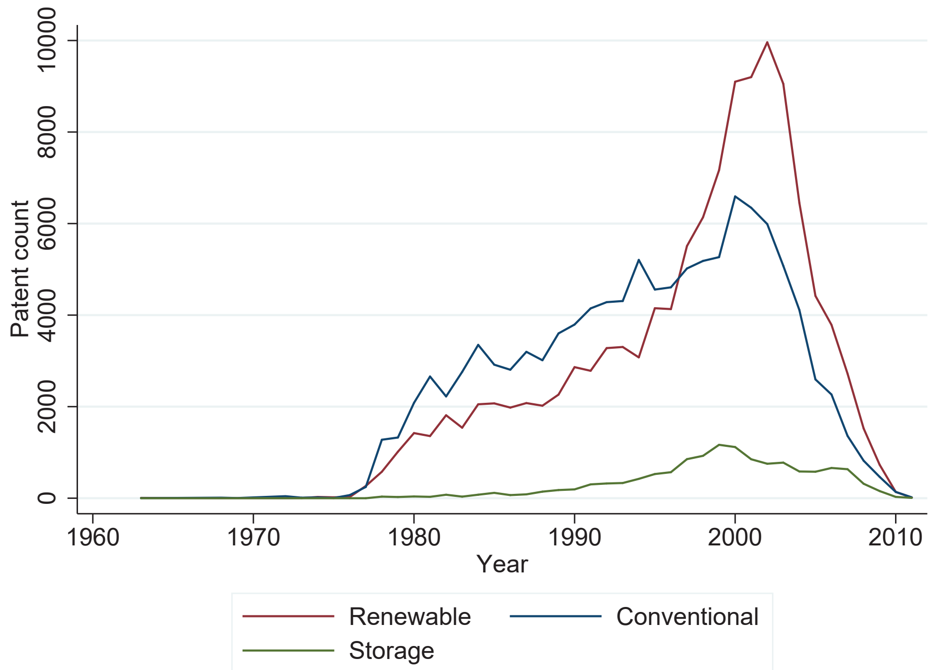

Figure 1: Global patenting over time.

However, it poses two difficulties.

First, applicant names in the Triadic Patent database contain a number of spelling, character, and name variations. For example, "3M Innovative Properties" and "3M Innovative Properties Co" would be incorrectly treated as separate firms in the absence of name harmonization. We harmonize firm names using algorithms and manual corrections to capture variations in spelling and to match firms correctly with their patents. A second harmonization challenge is that some patent applications have multiple inventors and applicants. In these cases, we accurately represent the ownership of each patent by assigning the ownership share of each patent to its corresponding firm.

Overall, our database contains 13,877 firms that claim residence in 79 countries. Of these firms, 4.54% are devoted exclusively to the advancement of storage technologies, whereas 26.94% and 51.44% focus only on conventional and renewable innovation, respectively. In addition, 11.27% of our sample firms innovate in both conventional and renewable electricity generation, whereas only 2.21% innovate in all types of technologies. The share of firms that innovate in renewable and storage technologies is 3.34%, while the share that innovates in conventional and storage is 0.25%.[20] Figure B.1 reports the number of firms per country, with

[20]Because there are more firms that innovate in renewable technologies than in conventional, our data do

more detail provided in the appendix, whereas Table B.2 lists all countries. Most patenting firms are based in a few countries, and the biggest countries in terms of innovating firms are the US, Japan, Germany, France, and Great Britain. In addition to conducting a global analysis using the full sample of 79 countries, we estimate our model using a subsample of data on these five countries that account for the majority of innovating firms.

We combine the data into a firm-level panel containing the number of patent applications for each technology type and year between 1963 and 2011. As Figure 1 shows, patenting activity increases in the mid 1970s. For this reason, we use data from 1963 to 2011 to calculate variables that explain past innovation, while we use data only for the period 1978-2009 in the estimations. As only a small number of firms apply for patents every year, we utilize an unbalanced panel to account for firms entering and exiting the market. We assume that a firm is active, and therefore included in our unbalanced panel, from the first year that it applies for a patent until the last year that it does so.[21] For example, if a firm files for its first patent in 1981 and its last patent in 1995, we assume that this firm is active at least between 1981 and 1995.

Once we identify the number of patents that a firm applies for in each technology type in a given year, we create two variables to describe the extent of their past innovations. Following Aghion et al. (2016), we define a firm's existing knowledge stock in terms of internal and external past innovations. The internal knowledge stock captures a firm's past innovations in a specific technology, which we calculate by accumulating the total number of patents in each technology type until year t. On the other hand, the external knowledge stock captures spillover effects, which are represented by past innovations in a given technology by all other firms in the relevant region. For each firm, we calculate this by adding the total number of patents in a region by all the other companies in that region in year t. We classify a firm's external knowledge stocks (spillovers) into eleven geographical regions based on the World Bank's income classification. Our geographical regions are: Caucasian and Central Asia, Eastern Asia, Eastern Europe, Europe, Latin America and the Caribbean, Northern America, Oceania, South Eastern Asia, Southern Asia, Sub-Saharan Africa, and Western Asia.[22]

Our theory predicts that energy prices affect innovation in the electricity sector. We

not suggest that there are more synergies between storage and renewable technologies, than between storage and conventional technologies.

[21] We extend this period by including additional years at the beginning of the active period when considering different lag structures in our estimations. We return to this issue when we present our empirical analysis below.

[22] In our robustness analysis, we explore alternative definitions of spillover regions.

include data on electricity input and output prices. We proxy input prices with coal, natural gas, and oil prices, and we use electricity retail prices as proxies for the output price. We draw country-level data from the IEA's database of energy prices and taxes (IEA, 2014). All prices are in US dollars per ton of oil equivalent net calorific value (USD/toe NCV). Unfortunately, complete energy price series are only available for 33 out of the 79 countries in our patent data set.[23] Below, we explain how we address this issue.

Fuel and electricity prices in different countries behave similarly over time, even though there are level differences. In addition, incomplete time series tend to have missing data at the beginning and/or end of the series. Given this, we fill the gaps in the energy price series by imposing the same annual growth over the missing range of the price series, as exhibited by a relevant reference price index. This addresses the issue of level differences between the reference price indices and the country-specific price series. In the case of non-OECD countries for which we do not have any energy price data, we simply impose the most relevant price index.

We choose the reference price for each country and energy type based on the characteristics of the different energy markets. As there are global markets for *oil and coal*, we use the respective global OECD price indices as reference prices. There is extensive international trade in oil, and international trade in coal currently accounts for about 25% of the total coal consumed (World Coal Association, 2015). Both oil and coal can travel large distances by ship in relatively little time. However, because transportation costs account for a significant share of the price of coal, international trade in this commodity generally occurs within two main regional markets: the Atlantic market, driven by importing countries in Western Europe, and the Pacific market, driven by imports to China, Japan, and Korea. Nonetheless, prices in these markets are closely related, justifying the use of a global price index.

Unlike oil and coal prices, our *natural gas* price data suggest some differences across regions. Being more difficult to move than coal or oil, natural gas has traditionally been more of a regional commodity, traded in three main markets: North America, Europe, and Asia. For this reason, we use regional prices as reference prices for natural gas. For Europe, we use the OECD Europe price index, whereas for Asia and the Middle East, we use the

[23]Note that the IEA data set contains both industry and household prices for the different commodities and, in some cases, prices for use in electricity generation. In addition, the data set reports prices on different types of coal and oil. As the different price series for each commodity are highly correlated, we select, for each country, the price series with the lowest number of missing values. Given this, we impose the following order of priority for uses: electricity generation, industry, and households. In addition, we impose the following order of priority for types of oil: high sulfur, low sulfur, and light oil; and the following order of priority for types of coal: steam coal and coking coal.

Japanese price series, as Japan is a key natural gas player in Asia. For the American continent, we use the Mexican natural gas price as the reference, as Mexico is geographically closer to the countries with missing data, and the Mexican price series is very similar to the US and Canadian prices. Finally, because we have no natural gas prices for Africa, we use the global OECD price index for gas in this region, which is our best measure of an average world price.

Finally, our data set reveals relatively large differences in *electricity* prices across countries and regions. Whereas fossil fuels used in electricity production can be shipped over large distances, it is harder to sell electricity in markets (grids) other than the market in which the electricity is produced. In addition, national and local regulations can have a big impact on electricity prices. This makes it more challenging to identify the appropriate reference price to fill in the missing data. For the American continent, where we lack information on countries in Central and South America, we use the Mexican electricity price as a reference.[24] For Asia, the Middle East, and Africa, we use the global OECD price index.[25]

As we rely on price indices to complete our energy price data set, it could be argued that our approach reduces the variation in our data set. Note, however, that the largest countries in terms of electricity-related patents are all part of the OECD, which means that we have a complete or nearly complete set of energy price series for the most innovative countries. Similarly, countries for which we make the strongest assumptions about energy prices (e.g., countries in Africa) are countries in which little patenting takes place. Therefore, we have accurate energy prices for the vast majority of innovating firms in our data set and for all firms in the five-country subsample.

Finally, we control for cross-country differences in the size of an economy and its wealth by using real GDP and real GDP per capita, respectively. We draw these data from the Penn World Tables (Feenstra et al., 2013).

Based on the patent data, we can identify the countries in which each firm in our data set is active. Some companies are active in more than one country and are thus affected by the regulations, taxes, and macroeconomic indicators of several countries. To account for this,

[24]We have complete price series for the US, Canada, Mexico, and Chile. We choose the Mexican price because it is less volatile than the Chilean price and because, in terms of levels, it is located between the Chilean and the North American prices. For Europe, we use the OECD Europe price index, as the price differences among European countries are small.

[25]In Asia and the Middle East, electricity prices vary considerably across the relatively few countries for which we have data. We choose a reference price based on the global OECD price index, which is close to the average price over the countries for which we have data and does not exhibit extreme variation over time, which could have affected our results. For Africa, we have no electricity prices and resort to using the OECD (global) average as a best guess.

we construct firm-specific variables for energy prices and economic indicators by calculating the averages for these variables across all countries in which a firm is present. For firms that are only active in one country, firm prices and economic variables are identical to the respective country-level variables. Firm-level variation in energy prices and macroeconomic indicators is useful, as it allows us to use country fixed effects to control for country-level variation.[26]

As noted, altogether, the data set comprises 13,877 firms in 79 countries from 1963 to 2011. The data set accounts for the most valuable electricity-related patents, and these patents capture the global trends in innovation in the electricity sector.

4 Empirical framework and identification

This section describes the econometric approach that we use to identify the role of electricity storage for firm-level innovation in electricity generation technologies. Our estimation strategy is based on the theoretical analysis in section 2 and, particularly, the firm-level innovation in equilibrium (equations (10) and (11)). Following Aghion et al. (2016), we use a fixed-effects Poisson estimator to estimate a reduced-form specification of the nonlinear equation system given by equations (10) and (11). In particular, for firm i's innovation in technology j in year t, we estimate:

$$x_{j,it} = \exp\left(A_{j,it-2} + \boldsymbol{\alpha_j} \ln \mathbf{P}_{it-1} + \boldsymbol{\gamma_j} \ln \mathbf{Z}_{it-1}\right) + \delta_{j,i} + \delta_{j,n} + \delta_{j,t} + \delta_{j,nt} + u_{j,it}, \; j = s, c, r, \quad (12)$$

where j denotes the type of technology (s storage, c conventional, and r renewable) and where i, n, and t represent firm, country, and year. $x_{j,it}$ is the number of patents in technology j that firm i applies for in year t. $A_{j,it}$ is the firm's existing knowledge stock, which we define in terms of internal and external past innovations, following Aghion et al. (2016).

As our theoretical analysis predicts a nonlinear relationship between innovation and existing knowledge, we specify past innovation as:

$$A_{j,it} = \boldsymbol{\beta_{1j}} \mathbf{E}_{mit} + \boldsymbol{\beta_{2j}} \mathbf{I}_{it} + \boldsymbol{\beta_{3j}} \mathbf{I}_{it}^2, \quad (13)$$

where the external knowledge vector $\mathbf{E}_{mit}$ represents for each technology, the total number of patents across all firms minus firm i in firm i's region m at time t, whereas the internal

[26] As each firm can be active in several countries, we can include both country and firm fixed effects.

knowledge vector $\mathbf{I}_{it}$ is firm i's stock of patents of the different technology types in year t.[27]

Another main determinant of innovation is energy prices. $\mathbf{P}_{it}$ indicates a firm's exposure to energy prices in year t. We take into account the prices of both inputs and outputs in the electricity sector. Our baseline specification uses the coal price as the proxy for input prices in conventional electricity generation, and electricity prices as the proxy for output prices. Our empirical model accounts for other factors that may affect innovation, including the economic environment of the countries in which the firm is located. Specifically, $\mathbf{Z}_{it}$ is a vector that captures the firm-specific exposure to the economic environment, which we characterize by the economy's size (proxied by GDP) and wealth (proxied by GDP per capita). As explained in section 3, we calculate $\mathbf{P}_{it}$ and $\mathbf{Z}_{it}$ for each firm by taking the average of all the energy prices and economic indicators across all countries in which firm i is located. This captures multinational firms' exposure to energy prices and macroeconomic conditions in all countries in which they operate.

Our identification strategy, based on equation (12), attributes any differences in a firm's patent applications in a specific technology to be caused by differences in internal and external knowledge stocks and energy prices, after controlling for macroeconomic, country, and firm-specific time-varying heterogeneity.

To account for the possibility of firms entering and exiting the research sector, we only include data for years in which firms are defined as active, as explained in section 3. We control for time-varying, firm- and country-specific differences using a set of fixed effects.[28] Specifically, $\delta_{j,i}$, $\delta_{j,n}$, and $\delta_{j,t}$ denote firm, country, and time fixed effects, whereas $\delta_{j,nt}$ controls for the country–year fixed effect. As all country-level variables, including energy prices and macroeconomic variables, are firm specific by construction, we include country and time fixed effects to control for other unobserved variation. Finally, $u_{j,it}$ denotes the error term.

As seen in Figure B.1, many countries in our sample host a small number of firms with relatively few patents. This implies that there are too few observations to estimate the full set of fixed effects (firm, country, year, and country-by-year) when using the full global

[27]Robustness analysis shows that squared terms of external knowledge stocks are not significant, and therefore, we exclude them from the baseline specification.

[28]These fixed effects control for differences in electricity markets and innovation and energy policies across countries, differences in firm sizes, industry focus, and many other characteristics. Both innovation efforts and the number of patent applications may change over time in response to both the firms' and the relevant country's idiosyncrasies, and the volatile nature of the industries. Finally, the country–year fixed effects control for all time-varying country-specific factors, including environmental policies, innovation incentives, or changes in the way that patents are granted.

sample. We deal with this by estimating our main specification for a subsample of the data that includes firms from the five most innovative countries. The subset of countries with the highest number of innovations comprises the US, Japan, Germany, France, and Great Britain. Therefore, we include firm, country, and year fixed effects in the full-sample estimations, whereas the subsample estimations for the five-country subsample include a full set of fixed effects.

We estimate the count data model in equation (12) using a fixed-effects Poisson estimator, which assumes equality between the mean and the variance.[29] Patent data often presents a high degree of over-dispersion, for which the negative binomial distribution is more appropriate. We investigate this issue by estimating our main specification assuming both Poisson and negative binomial distributions. As our results show that over-dispersion is not a problem in our data, we present the Poisson results as our baseline estimates. Finally, to reflect adequately the delayed patenting response of firms to changes in innovation drivers, and to reduce contemporaneous feedback effects, we lag the knowledge stock variables by two periods and the rest of the explanatory variables by one period in our baseline model.[30]

Using the above econometric model, we empirically study the firm-level determinants of innovation in the electricity sector and the role of electricity storage in innovation. We discuss the main empirical results in the next section.

5 Empirical results

In this section, we present our main estimation results, followed by multiple robustness tests to validate our results. We test three hypotheses: (1) How do better storage technologies affect innovation in electricity generation? (2) How does innovation in electricity generation affect innovation in storage? and (3) What is the impact of fossil-fuel prices on innovation? To answer these questions, we estimate equation (12), which is a reduced form of the innovation equilibrium that we derived in the theory section.

We present our baseline estimates in Tables 2 and 3. Table 2 reports the marginal effects of our Poisson estimates of the baseline specification, equation (12), using data from 1978 to

[29]Hausman et al. (1984) and Blundell et al. (1995, 2002) extensively study the challenges of estimating dynamic count data models with patent data and propose a generalized Poisson estimator that includes fixed effects, which allows for feedback effects from past innovation activity. In addition, our Poisson specification has the advantage that, despite having relatively few annual observations per firm, the introduction of firm-level fixed effects does not cause an incidental parameters problem (Cameron and Trivedi, 2013).

[30]As seen below, our robustness analysis shows that the lag specification does not significantly alter our results.

2009.[31] Columns (1)–(3) use data from the full sample of 79 countries, controlling for firm and year fixed effects, whereas columns (4)–(6) report the results for the five most innovative countries and control for firm, year, and country fixed effects. As we have few observations for many of the countries (recall Figure B.1), the full-sample estimations cannot converge to a maximum likelihood if we include country fixed effects. Instead, we estimate the model with the complete fixed-effects specification for the subsample of firms in the five most innovative countries. Table 3 presents the results. Note that the fixed-effects specification in column (2) of Table 3 is identical to that reported for the five-country sample in Table 2.

There are no statistically significant differences in key coefficients across the three fixed-effects specifications reported in Table 3 for the five-country subsample. This suggests that our full-sample estimates, which only control for firm and year fixed effects, are reliable. Adding country fixed effects to the basic specification with only firm and year fixed effects has little or no effect on the coefficient estimates and their standard errors. Adding year-by-country fixed effects tend to increase the absolute value of the coefficient estimates slightly, but it also increases the standard errors.

In the appendix, we present multiple robustness checks to validate our results. First, in the baseline specification, conventional technologies include only efficiency-improving fossil-fuel technologies. In Appendix C.1, we estimate our main specification using data on both general and efficiency-improving fossil-fuel technologies. Second, the main estimates include two-year lags on past innovations relative to the dependent variable, whereas prices and macroeconomic indicators are lagged by one year. In Appendix C.2, we consider alternate lag structures. Third, Appendix C.3 reports the results of using the definition of Johnstone et al. (2010) instead of WIPO when selecting electricity patents. Next, Appendix C.4 estimates the baseline specification including only the 20% most innovative firms, and Appendix C.5 considers alternative definitions of regions in which knowledge spillovers occur. Finally, whereas the baseline specification uses coal prices as a proxy for fuel prices in conventional production, Appendix C.6 reports the results from using natural gas and oil prices to measure fuel prices. We also consider the potential endogeneity of coal and electricity prices in our model, but we return to this and other potential caveats in section 5.5.

Overall, our robustness results show that the marginal effects reported in Tables 2 and 3 are highly robust to a variety of different specifications. We consistently find that past innovation in electricity storage promotes innovation in both renewable and conventional electricity generation technologies. This implies that storage is critical, not only to solve the

[31] We evaluate marginal effects at mean levels of the variables.

intermittency problem of renewable electricity generation but also to increase the flexibility of conventional generation. We discuss our baseline results in more detail below.

Table 2: Baseline estimates for all countries and top-five innovative countries (marginal effects).

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01108**	.00661*	-.0072*	.01105**	.00748*	-.00631*
	(.00376)	(.00312)	(.00293)	(.00401)	(.00332)	(.00265)
L2.Renewable	-.00188*	-.0002	.00182**	-.0017*	-.00023	.00172**
	(.00076)	(.00176)	(.00052)	(.00078)	(.00172)	(.00056)
L2.Conventional	-.00374	.0004	-.00038	-.00389	.00175	-.00012
	(.00253)	(.00216)	(.00571)	(.00265)	(.00284)	(.00563)
External knowledge:						
L2.Storage	.00023†	-8.2e-05	.00026†	.00013	-.00013	5.3e-05
	(.00013)	(.0002)	(.00015)	(.00015)	(.00021)	(.00016)
L2.Renewable	-6.8e-05**	-2.1e-05	-7.2e-05*	-5.8e-05*	-1.1e-05	-3.2e-05
	(2.2e-05)	(4.7e-05)	(3.4e-05)	(2.5e-05)	(4.8e-05)	(4.0e-05)
L2.Conventional	-2.8e-05	-8.3e-05	8.9e-06	-6.5e-05	-1.3e-05	-7.7e-05
	(5.4e-05)	(1.0e-04)	(9.0e-05)	(6.2e-05)	(.00013)	(9.6e-05)
Energy prices (firm level):						
L1.Coal	-.3175*	-.683**	-.2066	-.4625*	-.7042**	-.4092
	(.1359)	(.2506)	(.2321)	(.1899)	(.2343)	(.3393)
L1.Electricity	.1645	-.04924	.08163	.1903	.2113	.188
	(.1937)	(.2813)	(.2431)	(.2361)	(.3411)	(.3322)
Economic controls (firm level):						
L1.GDP	-.1408	-.318**	.2058	-.2362*	-.3057**	.00381
	(.08626)	(.08135)	(.1441)	(.1033)	(.1184)	(.2124)
L1.GDPcap	1.276†	.7467	.896	.4583	1.284	-.3656
	(.68)	(.6163)	(.8632)	(.7552)	(1.112)	(1.382)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51245	13058	12059	40976	10490	10343

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

Note: The top five countries are the US, Japan, Germany, France, and Great Britain.

Table 3: Baseline estimates for top-five innovative countries with different fixed-effects specifications (marginal effects).

	Dependent variable: firm-level patents								
	Renewable			Conventional			Storage		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Internal knowledge (marginal effects):									
L2.Storage	.01105**	.01105**	.01063*	.00753*	.00748*	.00907*	-.00634*	-.00631*	-.00791**
	(.00401)	(.00401)	(.00413)	(.00331)	(.00332)	(.00425)	(.00266)	(.00265)	(.00231)
L2.Renewable	-.0017*	-.0017*	-.00169*	-.00028	-.00023	-1.2e-05	.00173**	.00172**	.00166**
	(.00078)	(.00078)	(.00076)	(.00173)	(.00172)	(.00122)	(.00056)	(.00056)	(.0006)
L2.Conventional	-.00387	-.00389	-.00333	.00185	.00175	.00164	-.00012	-.00012	9.0e-05
	(.00265)	(.00265)	(.00285)	(.00287)	(.00284)	(.00195)	(.00563)	(.00563)	(.0047)
External knowledge:									
L2.Storage	.00013	.00013	-.00016	-.00013	-.00013	.00125**	5.8e-05	5.3e-05	-.00023
	(.00015)	(.00015)	(.00016)	(.0002)	(.00021)	(.00045)	(.00016)	(.00016)	(.00051)
L2.Renewable	-5.8e-05*	-5.8e-05*	1.4e-05	-8.3e-06	-1.1e-05	-3.2e-05	-3.3e-05	-3.2e-05	-2.4e-05
	(2.5e-05)	(2.5e-05)	(2.5e-05)	(4.7e-05)	(4.8e-05)	(6.8e-05)	(3.9e-05)	(4.0e-05)	(7.3e-05)
L2.Conventional	-6.2e-05	-6.5e-05	1.7e-05	-1.4e-05	-1.3e-05	.00078**	-8.2e-05	-7.7e-05	-1.7e-05
	(6.1e-05)	(6.2e-05)	(8.5e-05)	(.00013)	(.00013)	(.00019)	(9.6e-05)	(9.6e-05)	(.00023)
Energy prices (firm level):									
L1.Coal	-.4532*	-.4625*	-.4063†	-.7304**	-.7042**	.09741	-.4136	-.4092	-.9126*
	(.1888)	(.1899)	(.245)	(.2427)	(.2343)	(.5085)	(.3364)	(.3393)	(.4136)
L1.Electricity	.1969	.1903	.2597	.2073	.2113	-1.411	.1768	.188	-.8005
	(.2356)	(.2361)	(.2646)	(.3412)	(.3411)	(.998)	(.3298)	(.3322)	(.5587)
Economic controls (firm level):									
L1.GDP	-.2391*	-.2362*	-.1392	-.3163**	-.3057**	-.5555**	.03565	.00381	-.4393†
	(.1046)	(.1033)	(.0872)	(.115)	(.1184)	(.1699)	(.2451)	(.2124)	(.2297)
L1.GDPcap	.4943	.4583	-.5858	1.461	1.284	2.318†	-.316	-.3656	1.135
	(.741)	(.7552)	(.5053)	(1.08)	(1.112)	(1.277)	(1.432)	(1.382)	(1.117)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year x Country FE	No	No	Yes	No	No	Yes	No	No	Yes
Number of observations	40976	40976	40976	10490	10490	10490	10343	10343	10343

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

Our theoretical results show that the level of substitutability between renewable and conventional electricity is a key determinant in understanding the role of storage in innovation. Table 4 compares the main empirical results with our theoretical predictions in section 2.3. Most estimated effects are in line with the theoretical results for the case where renewable and conventional production are substitutes. Combining the effects of internal and external knowledge stocks on innovation in renewable, conventional, and storage, we find that with one exception, all estimated effects, whether statistically significant or not, correspond with the theoretical predictions when renewable and conventional production are substitutes. The exception is the effect of the fuel price on innovation in renewable technologies, which consistently and significantly, at the 5% level, violates our theoretical predictions across model specifications. Indeed, the estimated effect of the fuel price on renewable innovation indicates that conventional and renewable production are complements, not substitutes. We nonetheless conclude that conventional and renewable electricity production are substitutes, which is in line with the empirical literature that estimates the elasticity of substitution in electricity generation (Popp, 2006a; Gerlagh and van der Zwaan, 2004; Papageorgiou et al., 2016, among others). We further discuss the effect of the fuel price on innovation in section 5.3.

Table 4: Theoretical predictions compared with empirical results.

Innovation in	*Renewable*		*Conventional*		*Storage*	
Initial elasticity of subst., $A_{s0}\epsilon_0$	Compl.	Subs.	Compl.	Subs.	Compl.	Subs.
Initial storage technology, A_{s0}	$-$	$+$	$-$	$+$	$-$	$-$
Initial renewable technology, A_{c0}	$-$	$+ \rightarrow -$	$+$	$-$	$+$	$+ \rightarrow -$
Initial conventional technology, A_{d0}	$+$	$-$	$-$	$+ \rightarrow -$	$+$	$+ \rightarrow -$
Fuel price, f	$-$	$+$	$+$	$+ \rightarrow -$	$-$	$+ \rightarrow -$

Note: Green (red) indicates that our empirical results support (violate) the theoretical predictions of our model that conventional and renewable production are substitutes. Dark and light colors denote significant and nonsignificant results at the 5% level, respectively.

5.1 How do better storage technologies affect innovation in electricity generation?

To investigate the role of storage in electricity generation, we analyze the impact of internal and external storage knowledge stocks on the firm-level probability of applying for a new patent in electricity generation. In this case, we are interested in the coefficient estimates for the internal and external *L2.Storage* variables.[32]

As seen in the first rows of Tables 2 and 3, one additional internal storage patent increases the firm-level probability of applying for a new patent in electricity generation. Specifically, the coefficient estimate for the internal storage variable in the all countries, 0.0111, is statistically significant at the 1% level (renewable column of Table 2). The estimate indicates that if the average firm had an additional storage patent two years ago, the probability that the firm files for a renewable patent today increases with 1.11%. We obtain exactly the same point estimate if we instead use data on the five most innovative countries. This positive effect of storage on innovation in renewables is expected, as storing electricity is considered to be the key to mitigating the intermittency problem of renewable electricity generation.

Similarly, the coefficient estimate for the internal storage knowledge stock variable in the all countries, 0.0066, is statistically significant at the 5% level, and indicates that having one more storage patent increases the probability that the average firm applies for a conventional patent by 0.66% (conventional column of Table 2). The corresponding marginal effect of an additional storage patent for the five-country sample is 0.75%, also statistically significant at the 5% level. Hence, our results suggest that more internal storage knowledge increases innovation in both renewable and conventional technologies. The positive impact of storage technologies on conventional technologies is perhaps less obvious at first but even more striking. In addition, Table C.1 in the appendix shows that more past innovation in storage no longer has a statistically significant effect on innovation in conventional technologies if we include both general fossil-fuel technologies and efficiency-improving technologies. This suggests that better storage solutions primarily benefit efficiency-improving technologies and that more innovation in storage can steer innovation in conventional generation toward improved efficiency. One reason for this is that electricity storage allows thermal power plants to reduce their ramping costs, which enhances the importance of efficiency in production.

Having looked at the effects of internal knowledge in storage technologies, we consider the external knowledge (spillover) effects. We find that more external storage knowledge has a positive effect on innovation in renewable generation. This finding is statistically significant at the 10% level for the full sample but is not significant for the five-country subsample, regardless of the fixed-effects specification.[33] The corresponding estimates for

[32]Note that *L2* refers to the number of lags of the variable, which in the case of knowledge stocks is two.

[33]The small standard errors on the coefficient estimates for the external knowledge stocks in our estimation tables could be caused by multicolinearity. Since 82.94% of firms exclusively patent in one technology type, this is likely the result of the large number of firms that in any given year do not file for any patents in the other two technologies.

conventional generation are negative but not significant. Our baseline estimation includes eleven regions for knowledge spillovers, based on the World Bank's income classification. Appendix C.5 reports three alternative definitions of regions that define spillovers occurring: (i) at the country level (Table C.6); (ii) within five world regions, as defined by the Fédération International de Football Association (FIFA), (Table C.7);[34] and (iii) at the global level, so that all countries are subject to the same knowledge spillovers (Table C.8). Alternative definitions of spillover regions do not qualitatively change the results regarding how external knowledge in storage affects innovation in generating technologies.[35]

To conclude, our empirical results show that the development of storage technologies promotes innovation in both renewable and efficiency-improving fossil fuel technologies. These results are in line with our theoretical predictions, as summarized in Table 4, and they are robust to a variety of different specifications, including alternative lag structures and firm sizes (refer to Appendix C.2 and C.4). These results imply that innovation efforts directed at the development of better storage technologies can give renewable electricity a boost by mitigating the intermittency problem. However, whether in fact storage will increase the share of renewable electricity depends on its competitiveness in comparison with more efficient conventional electricity production, which gains from efficiency-improving innovations and lower ramping costs with storage.

5.2 How does innovation in electricity generation affect technological advancements in storage?

Next, we analyze the feedback effect of better electricity generation technologies on innovation in storage. Tables 2 and 3 show that having an additional renewable energy patent promotes new innovation in storage technologies, although it may have a negative effect on innovation in storage in other firms in the region (negative spillovers). This result holds for the full sample and across the different fixed-effects specifications for the five-country sample. However, the coefficient capturing the external effect becomes smaller, and its standard error increases, as we control for more fixed effects. Therefore, we conclude that a greater level of innovation in the past in renewable generation has a positive effect on innovation in storage overall.

[34]The five FIFA regions are Africa, Asia and the Pacific, Europe, Latin America and the Caribbean, and North America.

[35]Estimating the baseline model without R&D spillovers also yields estimates that are consistent with our baseline results.

Although we find a positive feedback effect between innovation in storage and innovation in renewable generation, we find no evidence for such feedback between innovation in storage and innovation in conventional generation. On the contrary, more past innovation in efficiency-improving conventional generation has a negative but insignificant effect on innovation in storage, both within the firm and externally (spillover effects). The effects of both internal and external generation knowledge stocks on storage are robust to all four definitions of regions for knowledge spillovers (see Appendix C.5), and a variety of other specifications, as presented in the robustness analysis in the appendix.

Finally, an additional storage patent lowers a firm's probability of filing for another storage patent. This result is in line with our theoretical analysis, and it is consistent across a number of different specifications and subsamples (see, for example, Tables 2 and 3, and Appendices C.2 and C.4). However, the results are largely insignificant for the effect of external storage knowledge stocks on innovation in storage.

To summarize, we find the existence of a positive feedback effect between innovation in renewable generation and storage technologies, but our results suggest no such feedback effect between conventional technologies and storage. This implies that more past innovation in renewable technologies stimulates innovation in storage technologies and *vice versa*. Thus, policy efforts directed toward renewable technologies can indirectly promote the advancement of storage technologies, which in turn further promote innovation in renewable technologies.

5.3 How does the fossil-fuel price affect innovation?

Our final objective is to analyze the impact of fossil-fuel prices on innovation in the electricity sector and, particularly, their impact on the direction of innovation (renewable versus conventional). As our baseline specification uses coal prices as a proxy for the fuel price, we focus on the effect of the coal price.[36] Many economists argue in favor of taxing carbon emissions to make fossil fuels more expensive and, thus, to induce a shift from carbon-emitting fossil fuels to cleaner renewable energy sources. This motivates our analysis of how the fuel price affects innovation.

Our results show that a higher coal price reduces innovation in electricity generation and in storage. The negative effects of the coal price on innovation in conventional and storage technologies are in line with our theoretical predictions, given that renewable and conventional electricity production are substitutes (cf. Table 4). The finding that the coal price is a determinant of innovation in conventional electricity generation is also consistent

[36] In section 5.5, we consider the alternative fuel prices natural gas and oil.

with the results of Popp (2002). However, the negative impact of the coal price on innovation in renewable technologies does not fit with our theoretical predictions unless renewable and conventional production are complements.

To understand this result better, consider the following. Whereas our theoretical analysis includes two electricity inputs, intermittent renewable electricity and nonrenewable electricity, the empirical analysis contains a number of different renewable and nonrenewable energy sources. Some of these are better suited to providing base-load power, whereas others are better suited to providing peak-load power. Power plants that provide base-load electricity run 24 hours a day, whereas peak-load plants run only when demand is high. Furthermore, base-load electricity is usually relatively cheap, but these plants are inflexible, as they need a long time to adjust production. In contrast, peak plants are turned on and off frequently, which makes them costly to run, and they require periods of downtime. Among the nonrenewable electricity sources, we have a full suite of both peak-load and base-load options for electricity production. For example, thermal coal-fired power plants might provide base-load power, whereas natural-gas-fired peaker plants provide peak-load power. Intermittent renewable energy sources can also provide both base-load and peak-load power, but to ensure reliability of supply in the absence of efficient electricity storage solutions, these energy sources must be combined with nonrenewable electricity to ensure sufficient base-load and peak-load electricity production.[37]

Our theoretical analysis in section 2.3 shows that the role of the fuel price depends on the substitutability between electricity from intermittent renewable sources and from stable nonrenewable sources. Indeed, the different types of both renewable and conventional production facilities can be substitutes for, or complements to, each other. In general, peak-load plants complement base-load plants. Hence, a natural gas peaker plant complements a coal-fired thermal power plant, but it might also complement intermittent renewable production. Therefore, depending on the efficiency of the electricity storage solution, we might find that for renewable electricity production, conventional electricity is a complement that acts as a buffer, whereas for conventional production as a whole, renewable electricity production is a substitute.

This brings us back to the seemingly odd result that the fossil fuel price has a negative impact on innovation in renewable electricity generation, which implies that renewable and conventional electricity are complements. In light of the above discussion, this might imply

[37]Alternatively, one could supply only renewable electricity, but this would require large investments in renewable electricity generation capacity to ensure sufficient production at all times to balance the grid on and off peak. However, this will change as better solutions for storing electricity become available.

that conventional production is a complement for renewable production, as suggested by the negative impact of the fuel price on renewable innovation, whereas for the complete suite of conventional production alternatives, renewable electricity is a substitute. Thus, until more efficient large-scale storage solutions become available, a higher fuel price hurts innovation in both conventional and renewable generation.

To conclude, we find that a higher fossil fuel price shrinks innovation not only in conventional technologies but also in renewable technologies. Indeed, the results from the richer fixed-effects specification (column (2) of Table 3) suggests that a higher fuel price reduces innovation in renewable technologies more than it reduces innovation in conventional technologies. Given the positive feedback effect between innovation in renewable and storage technologies, less innovation in renewable technologies resulting from a higher fuel price indirectly discourages innovation in storage, which in turn affects renewable innovation. Hence, until more efficient electricity storage solutions exist, taxing fossil fuels is unlikely to boost innovation in renewable and storage technologies, unless one combines such a policy with other instruments that stimulate innovation in these technologies.

5.4 Other determinants

In addition to past innovation and fuel prices, we control for country size (proxied by GDP) and wealth (proxied by GDP per capita). Our results show that the size of a country has a negative impact on the probability of applying for a conventional electricity generation patent, whereas the wealth of a country promotes innovation in renewable technologies. These effects are robust to different model specifications using the full global sample. When we focus on the most innovative countries, the size of a country discourages innovation in conventional electricity generation, whereas wealth does not have a statistically significant effect on innovation (Table 3). We do not find this surprising as the most innovative countries are large and wealthy economies, which exhibit less variation in GDP and GDP per capita than does the full data set.

5.5 Caveats

To complete our empirical analysis, we discuss potential caveats associated with our analysis. Specifically, we investigate the choice of estimator, the need to control for a firm's presample innovation history, our subsample selection of the most innovative countries and firms, and adequate lag structures. We start by considering the choice of estimator.

As only a small number of firms apply for patents every year, we define an unbalanced panel to account for firms entering and exiting the industry over time, as described in section 3. Our baseline estimation with this unbalanced panel uses a generalized Poisson estimator with fixed effects. However, one might argue that our sample portrays the average firm as being more innovative than is the case because we only define firms as active once they apply for a patent. To consider the implications of this, we estimate our baseline specification using a fully balanced panel, which implicitly assumes that all firms are active over the full period (1978–2009). As the data exhibit over-dispersion, with a variance 141 times larger than the mean, we use a negative binomial estimator in this case. Such a model starts from a Poisson regression model and adds multiplicative random effects to represent unobserved heterogeneity (Greene, 1994). Table C.13 shows that our main results are robust to this specification, and therefore, we are confident that our definition of active firms does not significantly affect our results.

In contrast to other studies, we do not control for presample history in our baseline estimation, which is the standard way to capture unobserved heterogeneity across firms at the beginning of the sample period (Blundell et al., 1995). We exclude presample history because, by construction, our unbalanced panel contains only active firms. In addition, the presample period (1963–1978) contains only a few companies, several of which became inactive after a few years. Therefore, unobserved heterogeneity caused by firms' presample history does not represent an issue in our sample. Table C.15 reports the estimation results when we control for each firm's presample innovation history by introducing the average number of registered patents per firm between 1963 and 1978, and an indicator variable taking a value of one if the firm did not register any patent prior to 1978. The results from estimating the baseline model with presample controls and all data on firms in all years confirm that controlling for presample history does not significantly alter our main results.

Another potential issue is the low number of firms and patents for many countries (Figure B.1). To deal with this, we have estimated our model with a complete set of fixed effects for a five-country subsample. We extend the subsample to include the 12 most innovative countries (Table C.14). Our main results are robust to this modification, implying that the implications of our results extend beyond the five most innovative countries. The same is true if we consider the top 10 or 15 countries.[38]

A related issue is the importance of firm size. Our sample totals 13,877 firms, with a

[38]Note that we do not report the results for the top 10 and top 15 subsamples, as they are similar to the other results. However, these results are available from the authors upon request.

large heterogeneity in the number of patents per firm. One might argue that firms with more patents behave differently from other firms, and to address this, we estimate our baseline model for a subsample containing only the top 15% most innovative firms (Table C.4). To be included in the top 15% most innovative firms, firms must have filed more than 15 patent applications. Together, these firms own 78% of all patents in our sample. We consider other cutoff values for what constitutes a large firm, but because our results are robust to different cutoff levels, we present only the results for the top 15%.[39] The results for this subsample are consistent with our main results, suggesting that the largest firms are representative of the full sample.

Our baseline results show that an increase in the coal price reduces innovation in both generation and storage. However, our robustness analysis shows that other fossil-fuel prices, natural gas and oil prices, do not have the same impact on innovation (see Tables C.9 and C.10). This is not surprising as coal is used primarily in base-load production, whereas natural gas is the dominant fuel in peak-load production, and oil often is considered to be a mid-load fuel. We find that the natural gas price does not have a statistically significant impact on innovation in the electricity sector, but the coefficients indicate a positive effect on innovation in efficiency-improving conventional technologies and a negative effect on innovation in renewables and storage technologies. The estimated coefficients for how the oil price affects innovation are generally insignificant, but at the 5% statistical significance level, we find that a higher oil price promotes innovation in renewable technologies (full sample). However, regardless of which fuel we use to proxy the fuel price, our results are consistent in terms of how storage affects innovation in the sector.

A related issue is the potential endogeneity of energy prices in our estimations. Our baseline specification includes electricity input and output prices, both of which might be affected by innovation in the industry. To investigate this potential endogeneity issue further, we exclude the electricity price from our specification and reestimate the model. Table C.11 shows that our baseline specification is robust to this. Another way to deal with the potential endogeneity issue is by lagging potentially endogenous variables, which we turn to next.

Finally, we look into issues related to the lag structure. Our baseline estimates include a two-year lag for the internal and external knowledge stocks, whereas energy prices and macroeconomic indicators are lagged one year. In Appendix C.2, we consider one- and three-year lags for internal and external knowledge stocks. The results show that the coefficient

[39] Whereas the firms with more than 15 patents each account for 15% of firms and 78% of total patents in our sample, firms with more than 20 patents account for 11.7% of firms and 73% of patents.

estimates become slightly more precise as we increase the number of lags, suggesting that it might take a few years after filing a patent for the effect of the new knowledge to materialize in new patents filed (Tables C.2 and C.3). Other than this, the lag structure does not significantly affect our main results.

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

6 Conclusion

There are many calls for more renewable electricity to reduce carbon emissions, but overcoming the intermittency problem is critical for the expansion of renewable electricity. Both policy makers and scientists point to large-scale electricity storage as the remedy for this problem. In this study, we investigate the role of storage in electricity generation. Whereas past economic research on storage focuses on the benefits for renewable technologies, our paper analyzes the role of electricity storage for the entire electricity sector. Building on a directed technological change framework, we model innovation in electricity storage as a process that improves the ease of substitution between renewable and conventional electricity production. This model predicts that better electricity storage solutions promote technological advancements in both renewable and conventional electricity generation when the two are substitutes. Using global firm-level patent data from 1963 to 2011, we present empirical evidence that better storage technologies positively affect innovation in both renewable and efficiency-improving conventional electricity generation.

Our study makes three main contributions to the literature. First, we contribute to the theoretical literature on induced innovation and the environment by proposing a mechanism that endogenizes the elasticity of substitution between clean and dirty inputs in the directed technological change framework. Second, we contribute to the empirical literature on green innovation in the electricity sector, by providing new empirical evidence on the role of electricity storage. Finally, we contribute to the literature on energy prices and innovation by offering new insights about the relationship between fossil fuel prices and innovation in the electricity generation sector.

Our results provide several policy implications. First, our results add nuance to the policy debate on curbing carbon emissions. We find that the development of large-scale storage solutions promote innovation not only in renewable technologies but also in efficiency-improving conventional technologies. In addition, we find evidence for a positive feedback effect between innovation in renewables and in storage, whereas we find no such relationship between innovation in conventional generation and storage. Therefore, whether storage will curb carbon emissions from the electricity sector depends on two main factors: the competitiveness of renewable energy against conventional electricity generation, and the conventional generation mix when storage increases the efficiency of fossil-fuel technologies and reduces the role of ramping costs. This implies that policy makers cannot rely on electricity storage alone to boost the use of renewable energy or to reduce carbon emissions.

Second, our results bring new insights into the debate on carbon pricing in the electricity sector. Contrary to what we initially expected, our empirical results show that a higher input price for fuel (coal) not only discourages innovation in conventional technologies but also reduces innovation in renewable technologies. A plausible explanation for the negative impact on renewables is that without large-scale electricity storage, intermittent renewable electricity relies on conventional electricity as a buffer to ensure grid balance. This suggests that until more efficient storage solutions are available, conventional electricity is a complement for intermittent renewable electricity. In the light of this, the negative impact of the fuel price on innovation in renewables is less surprising. Until better storage solutions are available, policy makers should consider accompanying policy measures when using the fuel price as an instrument to steer innovation toward renewable technologies.

Finally, although our results may be somewhat discouraging in terms of the role of storage in reducing carbon emissions, our empirical results offer more encouraging insights for the efficiency of the electricity sector. We find that better storage solutions can foster efficiency in both conventional and renewable electricity generation. This enables electricity system operators to combine renewable and conventional electricity more efficiently as they face rising pressure to meet an increasing and volatile electricity demand, in addition to stringent environmental regulations. Thus, electricity storage can enhance energy security and reduce blackouts by increasing the flexibility of electricity markets.

To conclude, better storage technologies can solve the main drawback of renewable electricity, the intermittency problem. In addition, our study shows that the development of better electricity storage solutions is beneficial beyond the arena of renewable technologies, as it improves the efficiency of the entire electricity sector. In addition, electricity storage has the potential to reduce emissions from the electricity sector, provided that the necessary policy measures are taken to ensure that renewables remain competitive in a more efficient electricity market.

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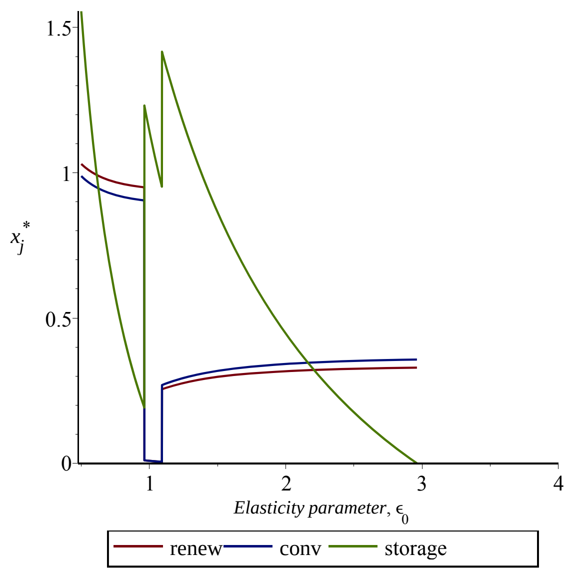
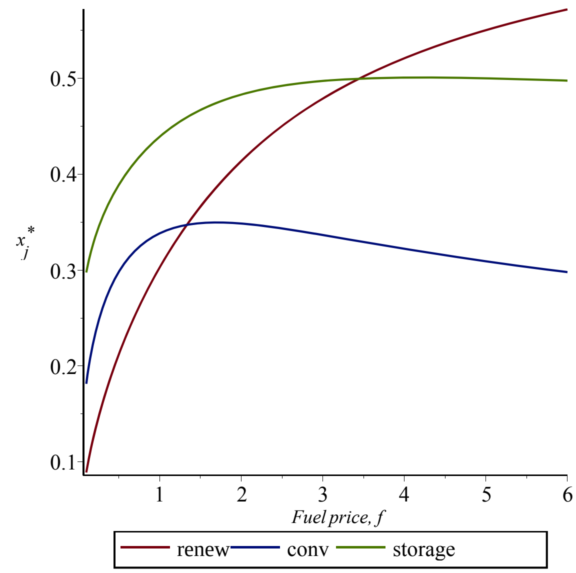
Appendix

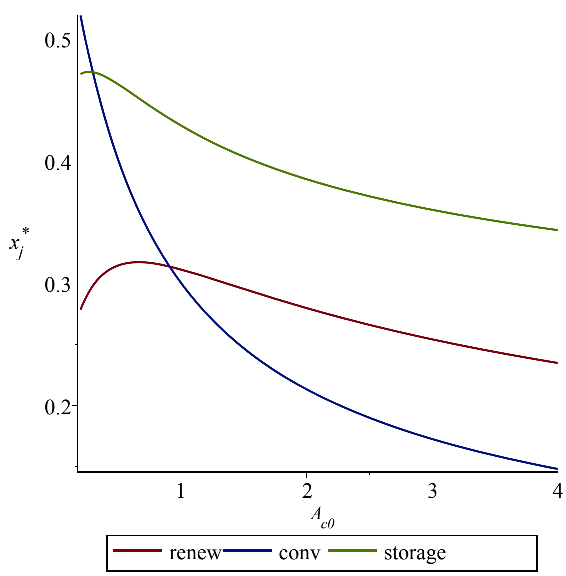
A Comparative statics



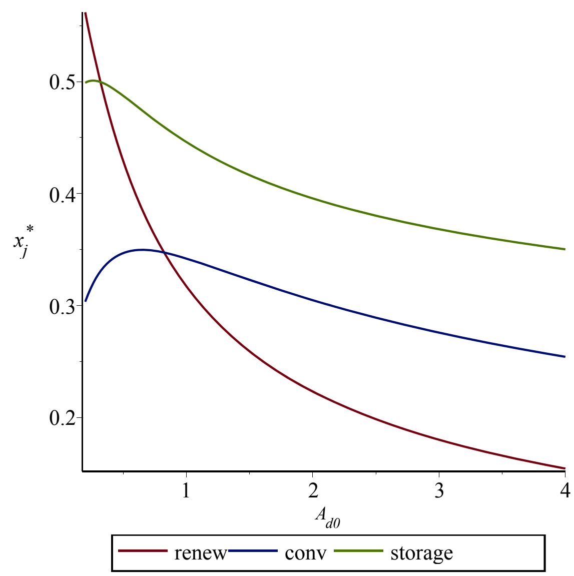
(a) Storage technologies (represented by ϵ_0)



(b) Fuel price (for $\epsilon_0 > 1$)



(c) Renewable technologies (for $\epsilon_0 > 1$)



(d) Conventional technologies (for $\epsilon_0 > 1$)

Figure A.1: Effect of electricity storage, past innovations, and fossil fuel price on the equilibrium level of innovation when renewable and conventional technologies are substitutes (panels b-d). *Note: We use the following parameter values to generate the figure:* $\beta = 0.5,\ \epsilon_0 = 0.8,\ A_{s0} = 0.5,\ A_{c0} = 1,\ A_{r0} = 0.75,\ f = 1.1,\ \phi_c = \phi_r = 1,\ \psi_s = \psi_c = \psi_r = 0.25.$

B Data construction

Table B.1: Variables and sources of data.

Variable	Unit of measure	Source
Patents	Number of patent applications	OECD Triadic Patent Families Database
	Firm characteristics	OECD REGPAT Database
	Firm characteristics	OECD HAN database
Energy prices including taxes	Constant 2005 national prices (in millions of 2005 U.S. $)	IEA Energy Prices & Taxes
Real GDP	Constant 2005 national prices (in millions of 2005 U.S. $)	Penn World Table
Population	Millions of people	Penn World Table

Table B.2: List of countries.

Argentina, Australia, Austria, Bahamas, Barbados, Belgium, Belize, Bermuda, Brazil, Bulgaria, Cameroon, Canada, Cayman Islands, Chile, China, Colombia, Croatia, Cyprus, Czech Republic, Denmark, Dominica, Finland, France, Georgia, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Kenya, Korea, Kuwait, Lithuania, Luxembourg, Malaysia, Mauritius, Mexico, Netherlands, New Zealand, Norway, Panama, Philippines, Poland, Portugal, Romania, Russian Federation, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, Ukraine, United Arab Emirates, Great Britain, United States of America.

B.1 International patent classifications (IPC)

Table B.3: Patent classes for efficiency-improving electricity generation technologies.

IPC code	Description
Coal gasification	
C10J3	Production of combustible gases containing carbon monoxide from solid carbonaceous fuels
Improved burners	[Classes listed below excluding combinations with B60,B68,F24,F27]
F23C1	Combustion apparatus specially adapted for combustion of two or more kinds of fuel simultaneously or alternately,at least one kind of fuel being fluent
F23C5/24	Combustion apparatus characterised by the arrangement or mounting of burners; disposition of burners to obtain a loop flame
F23C6	Combustion apparatus characterised by the combination of two or more combustion chambers
F23B10	Combustion apparatus characterised by the combination of two or more combustion chambers
F23B30	Combustion apparatus with driven means for agitating the burning fuel; combustion apparatus with driven means for advancing the burning fuel through the combustion chamber
F23B70	Combustion apparatus characterised by means for returning solid combustion residues to the combustion chamber
F23B80	Combustion apparatus characterised by means creating a distinct flow path for fluegases or for non-combusted gases given off by the fuel
F23D1	Burners for combustion of pulverulent fuel
F23D7	Burners in which drops of liquid fuel impinge on a surface
F23D17	Burners for combustion simultaneously or alternatively of gaseous or liquid or pulverulent fuel
Fluidised bed combustion	
B01J8/20-22	Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes; with liquid as a fluidising medium
B01J8/24-30	Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes; according to "fluidised-bed" technique
F27B15	Fluidised bed furnaces; Other furnaces using or treating finely divided materials in dispersion
F23C10	Apparatus in which combustion takes place in afluidised bed of fuel or other particles
Improved boilers for steam generation	
F22B31	Modifications of boiler construction, or of tube systems, dependent on installation of combustion apparatus; Arrangements or dispositions of combustion apparatus
F22B33/14-16	Steam generation plants,e.g.comprising steam boilers of different types in mutual association; combinations of low-and high-pressure boilers
Improved steam engines	
F01K3	Plants characterised by the use of steam or heat accumulators, or intermediate steam heaters, therein
F01K5	Plants characterised by use of means for storing steam in an alkali to increases team pressure,e.g. of Honigmann or Koenemann type
F01K23	Plants characterised by more than one engine delivering power external to the plant, the engines being driven by different fluids
Super-heaters	

Table B.3 – continued from previous page

IPC code	Description
F22G	Steam super heating characterised by heating method
Improved gas turbines	
F02C7/08-105	Features, component parts, details or accessories; heating air supply before combustion,e.g. by exhaust gases
F02C7/12-143	Features, component parts, details or accessories; cooling of plants
F02C7/30	Features, component parts, details or accessories; preventing corrosion in gas-swept spaces
Combined cycles	
F01K23/02-10	Plants characterised by more than one engine delivering power external to the plant, the engines being driven by different fluids; the engine cycles being thermally coupled
F02C3/20-36	Gas turbine plants characterised by the use of combustion products as the working fluid; using special fuel, oxidant or dilution fluid to generate the combustion products
F02C6/10-12	Plural gas-turbine plants; combinations of gas-turbine plants with other apparatus; supplying working fluid to a user,e.g. a chemical process, which returns working fluid to a turbine of the plant
Improved compressed-ignitionengines	
[Classes listed below excluding combinations with B60,B68,F24,F27]	
F02B1/12-14	Engines characterised by fuel-air mixture compression; with compression ignition
F02B3/06-10	Engines characterised by fuel-air mixture compression; with compression ignition
F02B7	Engines characterised by the fuel-air charge being ignited by compression ignition of an additional fuel
F02B11	Engines characterised by both fuel-air mixture compression and air compression, or characterised by both positive ignition and compression ignition,e.g.indifferent cylinders
F02B13/02-04	Engines characterised by the introduction of liquid fuel into cylinders by use of auxiliary fluid; compression ignition engines using air or gas for blowing fuel into compressed air in cylinder
F02B49	Methods of operating air- compressing compression-ignition engines involving introduction of small quantities of fuel in the form of a fine mist into the air in the engine's intake
Co-generation	
F01K17/06	Use of steam or condensate extracted or exhausted from steam engine plant; returning energy of steam, in exchanged form,to process,e.g. use of exhaust steam for drying solid fuel of plant
F01K27	Plants for converting heat or fluid energy into mechanical energy
F02C6/18	Plural gas-turbine plants; combinations of gas-turbine plants with other apparatus; using the waste heat of gas-turbine plants outside the plants themselves, e.g. gas-turbine power heat plants
F02G5	Profiting from waste heat of combustion engines
F25B27/02	Machines, plant, or systems, using particular sources of energy; using waste heat, e.g. from internal-combustion engines

Source: Lanzi et al. (2011).

Table B.4: Patent classes for general fossil fuel technologies.

IPC code	**Description**
C10J	Production of fuel gases by carburetting air or other gases without pyrolysis
F01K	Steam engine plants; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles
F02C	Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants
F02G	Hot-gas or combustion-product positive-displacement engine; use of waste heat of combustion engines,not otherwise provided for
F22	Steam generation
F23	Combustion apparatus; combustion processes
F27	Furnaces; kilns; ovens; retorts

Source: Lanzi et al. (2011).

Table B.5: Patent classes for renewable electricity generation technologies.

IPC code	Description
H01M 4/86-4/98, 8/00-8/24, 12/00-12/08	**Fuel cells**
H01M 4/86-4/98	Electrodes
H01M 4/86-4/98	Inert electrodes with catalytic activity
H01M 2/00-2/04 , 8/00-8/24	Non-active parts
H01M 12/00-12/08	Within hybrid cells
C10B 53/00, C10J	**Pyrolysis or gasification of biomass**
	Harnessing energy from manmade waste
C10L 5/00	Agricultural waste
C10L 5/42, 5/44	Fuel from animal waste and crop residues
F23G 7/00, 7/10	Incinerators for field, garden or wood waste
C10J 3/02, 3/46, F23B 90/00, F23G 5/027	Gasification
B09B 3/00, F23G 7/00	Chemical waste
C10L 5/48, F23G 5/00, F23G 7/00	Industrial waste
C21B 5/06	Using top gas in blast furnaces to power pigiron production
D21C 11/00	Pulp liquors
A62D 3/02, C02F 11/04, 11/14	Anaerobic digestion of industrial waste
F23G 7/00, 7/10	Industrial wood waste
B09B 3/00, F23G 5/00	Hospital waste
B09B	Landfill gas
B01D 53/02, 53/04, 53/047, 53/14, 53/22, 53/24, C10L 5/46	Separation of components
F23G 5/00	Municipal waste
	Hydro energy
E02B 9/00-9/06	Water-power plants

Table B.5 – continued from previous page

IPC code	Description
E02B 9/08	Tide or wave power plants
F03B, F03C	Machines or engines for liquids
F03B 13/12-13/26	Using wave or tide energy
F03B 15/00-15/22	Regulating, controlling or safety means of machines or engines
B63H 19/02, 19/04	Propulsion of marine vessels using energy derived from water movement
F03G 7/05	**Ocean thermal energy conversion (OTEC)**
F03D	**Wind energy**
H02K 7/18	Structural association of electric generator with mechanical driving motor
B63B 35/00, E04H 12/00, F03D 11/04	Structural aspects of wind turbines
B60K 16/00	Propulsion of vehicles using wind power
B60L 8/00	Electric propulsion of vehicles using wind power
B63H 13/00	Propulsion of marine vessels by wind-powered motors
	Solar energy
H01L 27/142, 31/00 31/078, H01G 9/20, H02N 6	Devices adapted for the conversion of radiation energy into electrical energy
H01L 27/30, 51/42-51/48	Using organic materials as the active part
H01L 25/00, 25/03, 25/16, 25/18, 31/042	Assemblies of a plurality of solar cells
C01B 33/02, C23C 14/14, 16/24, C30B 29/06	Silicon; single-crystal growth
G05F 1/67	Regulating to the maximum power available from solar cells
F21L 4/00, F21S 9/03	Electric lighting devices with, or rechargeable with, solar cells
H02J 7/35	Charging batteries
H01G 9/20, H01M 14/00	Dye-sensitised solar cells (DSSC)
F24J 2/00-2/54	Use of solar heat
F24D 17/00	For domestic hot water systems
F24D 3/00, 5/00, 11/00, 19/00	For space heating
F24J 2/42	For swimming pools
F03D 1/04, 9/00, 11/04, F03G 6/00	Solar updraft towers
C02F 1/14	For treatment of water, waste water or sludge
F02C 1/05	Gas turbine power plants using solar heat source
H01L 31/058	Hybrid solar thermal-PV systems
B60K 16/00	Propulsion of vehicles using solar power
B60L 8/00	Electric propulsion of vehicles using solar power
F03G 6/00-6/06	Producing mechanical power from solar energy
E04D 13/00, 13/18	Roof covering aspects of energy collecting devices
F22B 1/00, F24J 1/00	Steam generation using solar heat
F25B 27/00	Refrigeration or heat pump systems using solar energy
F26B 3/00, 3/28	Use of solar energy for drying materials or objects
F24J 2/06, G02B 7/183	Solar concentrators
F24J 2/04	Solar ponds
	Geothermal energy
F01K, F24F 5/00, F24J 3/08, H02N 10/00, F25B 30/06	Use of geothermal heat

Table B.5 – continued from previous page

IPC code	Description
F03G 4/00-4/06, 7/04	Production of mechanical power from geothermal energy
F24J 1/00, 3/00, 3/06	Other production or use of heat, not derived from combustion, e.g. natural heat
F24D 11/02	Heat pumps in central heating systems using heat accumulated in storage masses
F24D 15/04	Heat pumps in other domestic- or space-heating systems
F24D 17/02	Heat pumps in domestic hot-water supply systems
F24H 4/00	Air or water heaters using heat pumps
F25B 30/00	Heat pumps
	Using waste heat
F01K 27/00	To produce mechanical energy
F01K 23/06-23/10, F01N 5/00, F02G 5/00-5/04, F25B 27/02	Of combustion engines
F01K 17/00;23/04	steam engine plants
F02C 6/18	Of gas-turbine plants
F25B 27/02	As source of energy for refrigeration plants
C02F 1/16	For treatment of water, waste water or sewage
D21F 5/20	Recovery of waste heat in paper production
F22B 1/02	For steam generation by exploitation of the heat content of hot heat carriers
F23G 5/46	Recuperation of heat energy from waste incineration
F24F 12/00	Energy recovery in air conditioning
F27D 17/00	Arrangements for using waste heat from furnaces, kilns, ovens or retorts
F28D 17/00-20/00	Regenerative heat-exchange apparatus
C10J 3/86	Of gasification plants
F03G 5/00-5/08	Devices for producing mechanical power from muscle energy

Source: IPC Green Inventory, World Intellectual Property Organization.

Table B.6: Patent classes for electricity storage.

IPC code	**Description**
B60K 6/28	Characterized by the electric energy storing means, e.g. batteries or capacitors
B60W 10/26	For electrical energy, e.g. batteries or capacitors
H01M 10/44	Methods for charging or discharging
H01M 10/46	Accumulators structurally combined with charging apparatus
H01G 9/155	Hybrid capacitors, i.e. capacitors having different positive and negative electrodes; Electric double-layer [EDL] capacitors; Processes for the manufacture thereof or parts thereof
H02J 3/28	Arrangements for balancing the load in a network by storage of energy
H02J 7/00	Circuit arrangements for charging or depolarizing batteries or for supplying loads from batteries
H02J 15/00	Systems for storing electric energy

Source: IPC Green Inventory, World Intellectual Property Organization.

Table B.7: Total number of patents in renewable technologies following different International Patent Classification (IPC) codes.

Technology	Literature	WIPO - Green Inventory
Renewables	**84,135**	**178,841**
Geothermal	1,156	2,123
Hydro	0	6,337
Natural heat	0	2,351
Solar	21,001	59,905
Thermal	0	43
Waste	0	27,361
Waste heat	0	2,326
Wind	5,778	5,770
Fuel cells	0	71,801
Biomass	0	808
Muscle energy	0	16
Biomass and waste	54,871	0

Note: Literature refers to classification codes provided by Johnstone et al. (2010) while Table B.5 reports WIPO - Green Inventory codes.

Table B.7 reports the total number of patents in renewable technologies following two different classifications: WIPO's IPC Green Inventory and Johnstone et al. (2010) (labelled *Literature*). Our baseline estimates are based on the more extensive WIPO list of codes which totals $178,841$ patents, in contrast to the list often used in the literature that contains $84,135$ patents. The main difference in the patent count comes from fuel cells. Fuel cells provide electrical energy by activating a fuel to convert it into electricity. They generate about 0.6 Volts to 0.9 Volts DC per cell but they do not storage energy like batteries. Thus, they are an important source of renewable electricity generation.

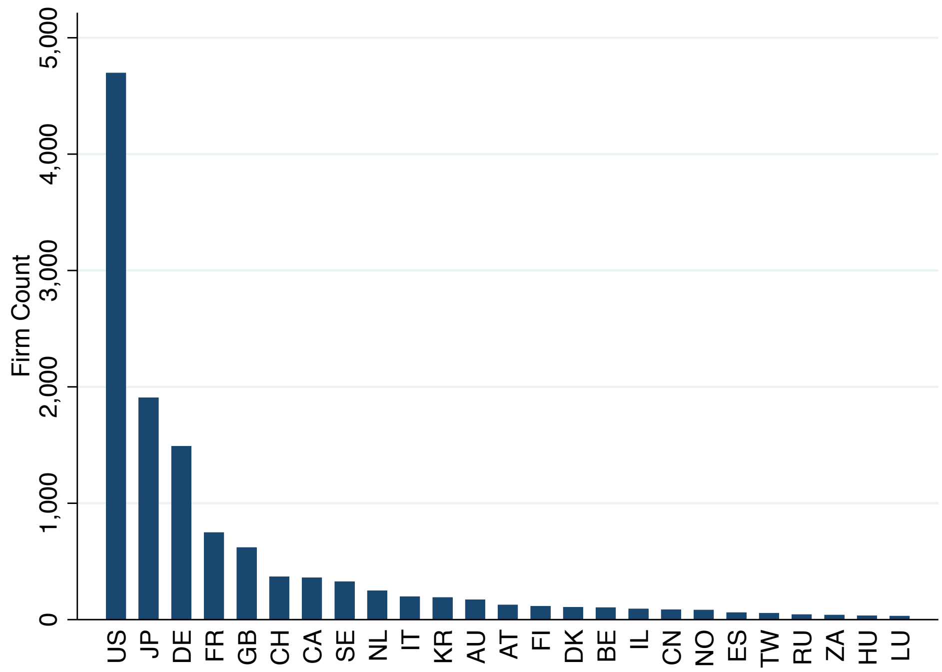


Figure B.1: Firm count by country for top-25 countries.

C Robustness analysis

C.1 Conventional electricity generation technologies

Table C.1: Baseline model including all conventional technologies (general and efficiency-improving).

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01108**	.00378	-.00768*	.01094**	.00373	-.00715**
	(.0036)	(.00419)	(.003)	(.00385)	(.00417)	(.00257)
L2.Renewable	-.00195*	-.00161	.002**	-.00179*	-.00132	.00195**
	(.00077)	(.00121)	(.00048)	(.00078)	(.00125)	(.00051)
L2.Conventional	-.0004	.00013	-.0009*	-.00043	.00017	-.00091*
	(.00035)	(.00016)	(.00045)	(.00037)	(.00014)	(.00044)
External knowledge:						
L2.Storage	.00036*	-.00015	-6.9e-05	.00013	-.00038	-.00051†
	(.00017)	(.00018)	(.00025)	(.00021)	(.00029)	(.00029)
L2.Renewable	-9.7e-05**	7.0e-06	1.1e-05	-6.7e-05*	1.8e-05	7.5e-05
	(2.6e-05)	(3.3e-05)	(4.7e-05)	(2.9e-05)	(4.7e-05)	(4.8e-05)
L2.Convetional	8.4e-06	-3.0e-05	-4.6e-05	-1.3e-05	-5.0e-05	-9.1e-05*
	(2.2e-05)	(2.6e-05)	(3.7e-05)	(2.8e-05)	(4.2e-05)	(4.3e-05)
Energy prices (firm level):						
L1.Coal	-.3036*	-.3202†	-.2783	-.4411*	.03585	-.3648
	(.1438)	(.1852)	(.2326)	(.176)	(.2925)	(.3279)
L1.Electricity	.2241	.3267	.1688	.2186	.1089	.1328
	(.1727)	(.2136)	(.2349)	(.2089)	(.2915)	(.3278)
Economic controls (firm level):						
L1.GDP	.01547	.03082	.09653	-.06237	-.1625	.08463
	(.08195)	(.1016)	(.1406)	(.09291)	(.1975)	(.2862)
L1.GDPcap	1.637*	.6414	.08797	.8085	.3257	-1.876*
	(.6425)	(.5549)	(.8495)	(.7236)	(1.09)	(.8001)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51246	34498	12051	40946	27657	10335

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

C.2 Lag structure

Table C.2: Baseline model using one-year lags (L1).

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L1.Storage	.0087**	.00782*	-.00598*	.00839**	.00834*	-.00527*
	(.00305)	(.00357)	(.00241)	(.00314)	(.00381)	(.00225)
L1.Renewable	-.00038	.00031	.00231**	-.00022	.00039	.00212**
	(.00055)	(.00162)	(.00053)	(.00056)	(.00157)	(.00056)
L1.Convetional	-.00254	.00283	-.00095	-.00285	.00376†	-.0003
	(.00242)	(.00205)	(.00597)	(.00255)	(.00223)	(.00611)
External knowledge:						
L1.Storage	.00037**	-.00032	.00022	.00029*	-.00039	1.3e-07
	(.00012)	(.00022)	(.00016)	(.00013)	(.00024)	(.00017)
L1.Renewable	-.0001**	1.9e-05	-6.8e-05†	-9.3e-05**	1.4e-05	-1.8e-05
	(2.3e-05)	(5.2e-05)	(4.0e-05)	(2.8e-05)	(5.4e-05)	(5.1e-05)
L1.Convetional	6.5e-05	-.00021*	-7.9e-05	2.0e-05	-.00019†	-.00018†
	(4.1e-05)	(.0001)	(8.5e-05)	(4.6e-05)	(.00011)	(9.1e-05)
Energy prices (firm level):						
L1.Coal	-.3612*	-.7419**	-.1597	-.479*	-.5801*	-.2705
	(.1542)	(.2091)	(.2301)	(.2067)	(.2691)	(.3201)
L1.Electricity	.05351	.1378	.1872	.1001	.4268	.3435
	(.1913)	(.2743)	(.2464)	(.2291)	(.3228)	(.3422)
Economic controls (firm level):						
L1.GDP	.02071	-.2103**	.3644*	-.04214	-.1897†	.4269
	(.0774)	(.06848)	(.1442)	(.08675)	(.1069)	(.2832)
L1.GDPcap	1.734**	.3901	.2967	1.101	.8421	-1.746
	(.6058)	(.7248)	(.7866)	(.7724)	(1.254)	(1.102)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	43038	11912	10838	34674	9582	9376

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

Table C.3: Baseline model using three-year lags (L3).

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
	(1)	(2)	(3)	(4)	(5)	(6)
Internal knowledge (marginal effects):						
L3.Storage	.0112**	.00672*	-.00954**	.01127**	.00649*	-.00865**
	(.00322)	(.00317)	(.0036)	(.00348)	(.00324)	(.00319)
L3.Renewable	-.00307**	-.00068	.0014*	-.00281**	.00022	.00141*
	(.001)	(.0019)	(.00057)	(.00101)	(.00165)	(.00061)
L3.Convetional	-.00466†	-.00123	-.00264	-.00494†	-.00174	-.0023
	(.00274)	(.00209)	(.00432)	(.00286)	(.00268)	(.00427)
External knowledge:						
L3.Storage	.00034**	-.00043†	.00022	.00022	-.0004	-4.0e-05
	(.00013)	(.00024)	(.00015)	(.00014)	(.00026)	(.00014)
L3.Renewable	-.0001**	5.9e-05	-2.7e-05	-8.4e-05**	6.4e-05	2.3e-05
	(2.4e-05)	(5.3e-05)	(3.1e-05)	(2.8e-05)	(6.0e-05)	(2.7e-05)
L3.Convetional	8.0e-05	-.0002†	-1.4e-05	6.0e-05	-.00017	-9.3e-05
	(5.5e-05)	(.0001)	(8.6e-05)	(6.3e-05)	(.00014)	(9.1e-05)
Energy prices (firm level):						
L1.Coal	-.2683*	-.6973**	-.293	-.4375**	-.7637**	-.5457
	(.1291)	(.2021)	(.2261)	(.1654)	(.2274)	(.3395)
L1.Electricity	.1729	.02914	.2924	.1836	.3914	.3117
	(.1813)	(.2636)	(.2242)	(.2237)	(.2777)	(.3038)
Economic controls (firm level):						
L1.GDP	.0228	-.1794†	.1773	-.1282	-.3249**	.249
	(.09481)	(.103)	(.1141)	(.1036)	(.1103)	(.2024)
L1.GDPcap	1.414*	-.1419	-.01467	.926	.7492	-1.864*
	(.6875)	(.9536)	(.7065)	(.7848)	(.9957)	(.9496)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	59266	14133	13235	47017	11312	11266

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

C.3 Patent selection

Table C.4: Estimates using the list of renewable energy patents compiled by Johnstone et al. (2010).

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.0037	.00508†	-.00499†	.00369	.00534†	-.00416†
	(.00484)	(.00295)	(.00274)	(.00501)	(.00294)	(.00246)
L2.Renewable	-.00021	-.00283**	-.00016	-.00016	-.00323**	9.9e-05
	(.00066)	(.00107)	(.00171)	(.00064)	(.00123)	(.00176)
L2.Convetional	-.00598†	.00048	.00419	-.00651†	.00205	.00447
	(.00363)	(.00224)	(.00658)	(.00375)	(.00262)	(.00642)
External knowledge:						
L2.Storage	-.00011	-8.1e-05	6.6e-05	-.0001	-6.8e-06	2.0e-05
	(.00012)	(.00012)	(1.0e-04)	(.00014)	(.00018)	(.00011)
L2.Renewable	-6.2e-05*	1.2e-06	-3.9e-05	-5.5e-05†	-1.8e-05	-1.1e-05
	(2.7e-05)	(3.3e-05)	(3.1e-05)	(3.0e-05)	(3.7e-05)	(3.2e-05)
L2.Convetional	2.0e-05	-5.2e-05	8.7e-05	-6.7e-06	.00011	3.7e-05
	(6.1e-05)	(.0001)	(9.2e-05)	(6.7e-05)	(.00012)	(.00011)
Energy prices (firm level):						
L1.Coal	-.329	-.5509**	-.1714	-.4832	-.5167*	-.1954
	(.2764)	(.1927)	(.2632)	(.334)	(.215)	(.3753)
L1.Electricity	.1664	.05317	.4788†	.1794	.3612	.5122
	(.2507)	(.2759)	(.2763)	(.3292)	(.2862)	(.3667)
Economic controls (firm level):						
L1.GDP	.04161	-.1193	.4113**	-.08723	-.09084	.09126
	(.1013)	(.1104)	(.134)	(.1861)	(.128)	(.1894)
L1.GDPcap	.7902	.98	.07536	.4518	1.644	-.8824
	(.7377)	(.822)	(.6809)	(1.017)	(1.179)	(.6971)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	28570	12254	10394	22376	9837	8901

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

C.4 Firm size

Table C.5: Baseline model including only the most innovative firms (15% of sample).

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01078**	.00666*	-.00719**	.01064**	.00671*	-.0063**
	(.00375)	(.0031)	(.00258)	(.00396)	(.00313)	(.00235)
L2.Renewable	-.00144*	1.4e-05	.00212**	-.00137†	.00031	.00194**
	(.0007)	(.00165)	(.00053)	(.00071)	(.00153)	(.00057)
L2.Conventional	-.00365	.00114	-.00079	-.00383	.00126	-.0005
	(.00245)	(.00208)	(.00538)	(.00258)	(.00253)	(.00532)
External knowledge:						
L2.Storage	.0004**	-8.0e-05	.00034*	.00028*	-2.3e-05	.0002
	(.00013)	(.00022)	(.00016)	(.00014)	(.00027)	(.00016)
L2.Renewable	-8.8e-05**	-1.7e-05	-5.2e-05†	-8.5e-05**	-2.2e-05	-4.1e-05
	(2.1e-05)	(4.9e-05)	(3.0e-05)	(2.4e-05)	(6.0e-05)	(3.1e-05)
L2.Convetional	.00011†	-.00014	5.4e-05	5.1e-05	-7.0e-05	-3.1e-05
	(5.9e-05)	(.00014)	(.0001)	(6.8e-05)	(.00018)	(.00011)
Energy prices (firm level):						
L1.Coal	-.3066†	-.5349*	-.2658	-.4706*	-.5884*	-.4258
	(.1636)	(.2635)	(.2474)	(.2034)	(.2553)	(.3563)
L1.Electricity	.1552	-.0036	.09723	.172	.3251	.295
	(.2164)	(.292)	(.2701)	(.2542)	(.3168)	(.3789)
Economic controls (firm level):						
L1.GDP	-.132	-.1521	.03701	-.2779*	-.2459	-.00556
	(.09893)	(.09577)	(.107)	(.113)	(.1788)	(.2222)
L1.GDPcap	1.784**	.5144	.4678	1.223	1.463	-.5979
	(.6517)	(.5709)	(.7666)	(.7553)	(1.351)	(1.146)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	17324	6916	7367	14784	5717	6477

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

C.5 Alternative measures of regional spillovers

Table C.6: Alternative specification of regional spillovers: Countries.

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01158**	.00759*	-.00726*	.01131**	.00785*	-.00654*
	(.00381)	(.00305)	(.00294)	(.00402)	(.00323)	(.00266)
L2.Renewable	-.00183*	-.00041	.00199**	-.00167*	-.00051	.00178**
	(.00078)	(.00167)	(.00053)	(.0008)	(.00168)	(.00056)
L2.Convetional	-.00378	.00087	5.9e-05	-.00398	.0024	.0003
	(.00254)	(.00234)	(.0058)	(.00268)	(.00269)	(.00566)
External knowledge:						
L2.Storage	.00025†	-.0003	.00025	.00014	-.00035	.00015
	(.00015)	(.00024)	(.00021)	(.00015)	(.0003)	(.00021)
L2.Renewable	-4.5e-05*	5.8e-05	-7.5e-05†	-1.4e-05	6.4e-05	-3.9e-05
	(2.3e-05)	(4.8e-05)	(4.3e-05)	(2.1e-05)	(6.7e-05)	(4.4e-05)
L2.Convetional	-2.8e-05	-.00025	.00021	-.00015	-.00028	.00011
	(9.3e-05)	(.00018)	(.00016)	(9.5e-05)	(.00024)	(.00017)
Energy prices (firm level):						
L1.Coal	-.3017†	-.7541**	-.1301	-.5187**	-.6821**	-.3142
	(.1563)	(.2142)	(.2384)	(.1902)	(.2497)	(.3258)
L1.Electricity	.1425	.1295	.02513	.2489	.4588	.3097
	(.1951)	(.2985)	(.2501)	(.2329)	(.3634)	(.3391)
Economic controls (firm level):						
L1.GDP	-.01794	-.2074**	.2434†	-.1946*	-.2144	.3667
	(.08763)	(.07892)	(.1404)	(.09562)	(.1331)	(.331)
L1.GDPcap	1.216†	.5505	-.1616	.5788	.9911	-2.013
	(.6767)	(.8164)	(.8601)	(.7904)	(1.223)	(1.609)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51246	13059	12050	40978	10473	10342

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

Table C.7: Alternative specification of regional spillovers: FIFA regions.

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01116**	.00686*	-.00741*	.01114**	.00736*	-.00669*
	(.00375)	(.00294)	(.00293)	(.00401)	(.00318)	(.00262)
L2.Renewable	-.0019*	-.00039	.00188**	-.00174*	-.00035	.00177**
	(.00077)	(.00175)	(.00053)	(.00078)	(.00176)	(.00057)
L2.Convetional	-.00375	.00087	-.00038	-.00386	.00266	-7.7e-05
	(.00254)	(.00235)	(.00575)	(.00266)	(.00267)	(.00564)
External knowledge:						
L2.Storage	.00036**	-.00011	.0003†	.00022	-.0002	2.8e-05
	(.00013)	(.0002)	(.00016)	(.00014)	(.00024)	(.00016)
L2.Renewable	-9.8e-05**	-1.6e-05	-7.1e-05*	-8.3e-05**	-2.3e-05	-2.9e-05
	(2.4e-05)	(4.2e-05)	(3.5e-05)	(2.5e-05)	(4.6e-05)	(3.9e-05)
L2.Convetional	6.1e-05	-9.6e-05	4.4e-05	-2.7e-06	-8.7e-05	-7.5e-05
	(6.1e-05)	(.00013)	(9.1e-05)	(6.8e-05)	(.00015)	(.0001)
Energy prices (firm level):						
L1.Coal	-.2735†	-.7506**	-.1867	-.4392*	-.68**	-.3068
	(.1414)	(.208)	(.2274)	(.1849)	(.2304)	(.3231)
L1.Electricity	.1039	.1104	.1457	.08632	.4006	.2157
	(.1871)	(.2913)	(.2381)	(.229)	(.3564)	(.3414)
Economic controls (firm level):						
L1.GDP	-.055	-.2108**	.2005	-.2452*	-.2148†	.4266
	(.08738)	(.07962)	(.1403)	(.0976)	(.1306)	(.3796)
L1.GDPcap	1.566*	.6528	.3344	.8978	1.111	-2.487
	(.6779)	(.8132)	(.9642)	(.7553)	(1.272)	(1.714)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51246	13059	12050	40978	10473	10342

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

Table C.8: Alternative specification of regional spillovers: Global.

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
	(1)	(2)	(3)	(4)	(5)	(6)
Internal knowledge (marginal effects):						
L2.Storage	.01195**	.00676*	-.01041**	.01226**	.00715†	-.01026**
	(.0037)	(.00327)	(.00276)	(.00395)	(.00365)	(.00264)
L2.Renewable	-.00188*	-.00153	.0045*	-.00171*	-.00032	.00377†
	(.00083)	(.00258)	(.00176)	(.00084)	(.00254)	(.00208)
L2.Convetional	-.00304	.01483	-.03032	-.00306	-.0025	-.0207
	(.0026)	(.03307)	(.02294)	(.00274)	(.03796)	(.0277)
External knowledge:						
L2.Storage	.00038	-.00022	-.00299**	.00042	-.00014	-.0036**
	(.00032)	(.00164)	(.00095)	(.00036)	(.00204)	(.00106)
L2.Renewable	-7.3e-05*	-.00095	.00249	-8.0e-05*	.0003	.00195
	(2.8e-05)	(.00239)	(.00161)	(3.1e-05)	(.00284)	(.00191)
L2.Conventional	.00033**	.01399	-.03036	.00035**	-.00478	-.02099
	(5.2e-05)	(.03262)	(.02262)	(6.3e-05)	(.03764)	(.0272)
Energy prices (firm level):						
L1.Coal	-.00024	-.7595**	-.1975	-.00056	-.7645**	-.3041
	(.1539)	(.2046)	(.246)	(.203)	(.252)	(.3403)
L1.Electricity	1.8e-05	.163	.1004	2.3e-05	.5376	.3132
	(.1831)	(.3031)	(.2367)	(.2245)	(.4023)	(.3219)
Economic controls (firm level):						
L1.GDP	2.5e-05	-.2181**	.1826	-.00017	-.2371†	.4384
	(.08918)	(.08083)	(.1498)	(.1441)	(.1332)	(.387)
L1.GDPcap	3.2e-05	.7685	-.00104	3.5e-07	1.392	-2.67
	(.7208)	(.8106)	(.9677)	(.9395)	(1.252)	(1.747)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51246	13059	12050	40978	10473	10342

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

C.6 Alternative specification of energy prices

Table C.9: Alternative specification of fossil fuel price: Natural gas price.

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01106**	.00759*	-.00767**	.01123**	.00788*	-.00699**
	(.00374)	(.003)	(.00294)	(.00401)	(.00326)	(.00253)
L2.Renewable	-.00184*	-.00048	.00192**	-.00172*	-.00043	.0018**
	(.00078)	(.00168)	(.00053)	(.00079)	(.00176)	(.00056)
L2.Convetional	-.00378	.00114	-.00035	-.0039	.00268	-.00011
	(.00256)	(.00226)	(.00569)	(.00268)	(.00274)	(.00552)
External knowledge:						
L2.Storage	.00023†	-6.8e-05	1.0e-05	.00019	-.00014	-.00023
	(.00012)	(.00018)	(.00019)	(.00014)	(.00019)	(.00022)
L2.Renewable	-7.7e-05**	-2.8e-05	-1.3e-05	-8.4e-05**	-3.7e-05	7.9e-06
	(2.0e-05)	(3.7e-05)	(3.5e-05)	(2.3e-05)	(3.7e-05)	(4.2e-05)
L2.Convetional	5.3e-05	-.00012	1.7e-06	-4.5e-06	-.0001	-9.8e-05
	(5.8e-05)	(.00012)	(9.2e-05)	(6.8e-05)	(.00016)	(.0001)
Energy prices (firm level):						
L1.Natural gas	-.1685	.189	-.4785†	.0281	.235	-.5259
	(.123)	(.1764)	(.2719)	(.1448)	(.3327)	(.3263)
L1.Electricity	.1757	-.09767	.4425	-.05359	-.05087	.5905
	(.2216)	(.2729)	(.2694)	(.2815)	(.3661)	(.4413)
Economic controls (firm level):						
L1.GDP	-.0246	-.08822	.2078	-.144	-.1602	.3921
	(.0829)	(.1054)	(.1357)	(.09399)	(.1282)	(.3241)
L1.GDPcap	1.501*	.9339	-.06481	.8537	1.24	-2.289
	(.6602)	(.7158)	(.8608)	(.764)	(1.194)	(1.562)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51246	13059	12050	40978	10473	10342

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

Table C.10: Alternative specification of fossil fuel price: Oil price.

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01144**	.00767*	-.00755*	.01138**	.00727*	-.00666*
	(.00374)	(.00308)	(.00307)	(.00398)	(.00306)	(.00276)
L2.Renewable	-.00188*	-.00052	.00194**	-.00173*	-8.7e-05	.00181**
	(.00077)	(.00167)	(.00053)	(.00079)	(.00166)	(.00057)
L2.Conventional	-.00374	.0011	-.00031	-.00394	.00118	7.5e-05
	(.00255)	(.00221)	(.00573)	(.00267)	(.00271)	(.00566)
External knowledge:						
L2.Storage	.00036**	-9.0e-05	.0002	.00025†	-.0001	-3.5e-06
	(.00012)	(.0002)	(.00014)	(.00013)	(.00025)	(.00015)
L2.Renewable	-9.3e-05**	-1.8e-05	-4.1e-05	-8.9e-05**	-2.3e-05	-1.7e-05
	(2.1e-05)	(4.3e-05)	(2.6e-05)	(2.5e-05)	(5.8e-05)	(2.7e-05)
L2.Conventional	9.6e-05†	-.00011	4.5e-05	4.6e-05	-3.3e-05	-3.6e-05
	(5.3e-05)	(.00012)	(8.6e-05)	(6.2e-05)	(.00016)	(9.3e-05)
Energy prices (firm level):						
L1.Oil	.2929*	.2878	-.07955	.3106	-.1732	-.5122
	(.1489)	(.2514)	(.2683)	(.2079)	(.3798)	(.3641)
L1.Electricity	-.03835	-.1894	.09068	-.09617	.1307	.4501
	(.2273)	(.2515)	(.2474)	(.2865)	(.371)	(.3619)
Economic controls (firm level):						
L1.GDP	-.00234	-.01692	.06382	-.09664	-.2544	.03722
	(.07749)	(.1055)	(.07215)	(.09102)	(.1619)	(.1439)
L1.GDPcap	1.611**	.7713	.3937	.9579	1.936†	-.6743
	(.5578)	(.5507)	(.627)	(.699)	(1.116)	(.7391)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51244	13051	12058	40942	10488	10324

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

Table C.11: Baseline model excluding the electricity price.

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01125**	.00676*	-.00741*	.01117**	.00728*	-.00674*
	(.00377)	(.00299)	(.00297)	(.00403)	(.00322)	(.00262)
L2.Renewable	-.00189*	-.00034	.00188**	-.00174*	-.00026	.00178**
	(.00077)	(.00177)	(.00053)	(.00078)	(.00178)	(.00057)
L2.Convetional	-.00378	.00087	-.00035	-.0039	.00249	-.0002
	(.00253)	(.00234)	(.00571)	(.00266)	(.00268)	(.00556)
External knowledge:						
L2.Storage	.00031*	-.00014	.00021	.00018	-.00023	-2.9e-05
	(.00012)	(.0002)	(.00015)	(.00013)	(.00024)	(.00015)
L2.Renewable	-8.8e-05**	-1.8e-05	-4.8e-05	-7.6e-05**	-2.2e-05	-2.2e-05
	(2.1e-05)	(4.1e-05)	(3.4e-05)	(2.3e-05)	(4.5e-05)	(3.5e-05)
L2.Convetional	5.2e-05	-.00013	2.3e-05	-1.6e-05	-.00012	-.00011
	(6.0e-05)	(.00013)	(9.3e-05)	(6.8e-05)	(.00017)	(.0001)
Energy prices (firm level):						
L1.Coal	-.2468	-.724**	-.1872	-.4072†	-.5515*	-.2896
	(.1613)	(.2118)	(.2301)	(.2094)	(.2323)	(.3368)
Economic controls (firm level):						
L1.GDP	-.05717	-.2247**	.1757	-.2421**	-.2794*	.385
	(.08122)	(.07986)	(.1374)	(.0918)	(.1243)	(.3807)
L1.GDPcap	1.586*	.6899	.3905	.9228	1.279	-2.405
	(.6938)	(.8689)	(.9158)	(.8161)	(1.278)	(1.719)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51246	13059	12050	40978	10473	10342

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

C.7 Caveats

Table C.12: Fully balanced panel data set and negative binomial regression model.

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.00555**	.00225	.00372*	.00331**	.00223	.00323*
	(.00107)	(.00173)	(.00147)	(.0011)	(.00172)	(.00154)
L2.Renewable	.00687**	.00648**	.00402**	.00654**	.00593**	.00359**
	(.0002)	(.00044)	(.00034)	(.0002)	(.00045)	(.00035)
L2.Conventional	.00247**	.00485**	-.00355*	.00062	.00619**	-.00315*
	(.00064)	(.00067)	(.00139)	(.00065)	(.00084)	(.00142)
External knowledge:						
L2.Storage	.00037**	7.6e-05	.0005**	-1.4e-05	-.00031**	-1.6e-05
	(2.4e-05)	(6.9e-05)	(6.0e-05)	(3.2e-05)	(8.9e-05)	(8.2e-05)
L2.Renewable	-4.9e-05**	1.2e-06	-7.1e-05**	3.6e-05**	7.3e-05**	1.9e-05
	(4.5e-06)	(1.2e-05)	(1.2e-05)	(6.7e-06)	(1.7e-05)	(2.0e-05)
L.Convetional	1.0e-06	-.00011**	3.0e-06	-.00011**	-.00023**	-.00023**
	(1.3e-05)	(3.5e-05)	(3.6e-05)	(2.2e-05)	(5.7e-05)	(5.9e-05)
Energy prices (firm level):						
L1.Coal	-.3471**	-.4294**	-.5504**	-.5886**	-.5601**	-.5843**
	(.02761)	(.06589)	(.07786)	(.05209)	(.1317)	(.1384)
L1.Electricity	.101**	-.01547	.3786**	.1366*	.2305	.2211
	(.02872)	(.06809)	(.07401)	(.06004)	(.1414)	(.1538)
Economic controls (firm level):						
L1.GDP	-.041**	-.184**	-.1506**	-.7243**	-.7274**	-.6438**
	(.01299)	(.0279)	(.03729)	(.03345)	(.07048)	(.1045)
L1.GDPcap	.55**	.1689	.9747**	1.229**	.8156	-.7104
	(.06415)	(.1386)	(.1938)	(.2467)	(.6347)	(.5758)
Constant	-8.663**	-2.815†	-11.88**	-5.629*	-2.764	14.69*
	(.6797)	(1.499)	(1.988)	(2.583)	(6.372)	(6.162)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	271596	42396	41396	207589	33230	33503

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

Table C.13: Fully balanced panel data set and negative binomial regression model including all conventional patents (general and efficiency-improving).

	Dependent variable: firm-level patents					
	All countries			Top five countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.00575**	.00982	.00403**	.00302**	.00227	.00308*
	(.00106)	(.00637)	(.00145)	(.0011)	(.00142)	(.00153)
L2.Renewable	.00681**	.0009	.00378**	.00647**	.00596**	.00352**
	(.0002)	(.00169)	(.00034)	(.0002)	(.00029)	(.00035)
L2.Conventional	.0004**	.00423**	-.00018	.00013	.0013**	-.00029
	(8.2e-05)	(.00122)	(.00018)	(8.9e-05)	(9.3e-05)	(.00019)
External knowledge:						
L2.Storage	.00037**	.00013	.00055**	-5.4e-05	-.00011	-.00035*
	(3.7e-05)	(.00032)	(9.6e-05)	(5.9e-05)	(7.5e-05)	(.00017)
L2.Convetional	-5.0e-05**	-8.0e-05	-8.0e-05**	4.8e-05**	6.2e-05**	8.4e-05*
	(7.1e-06)	(5.1e-05)	(1.9e-05)	(1.1e-05)	(1.4e-05)	(3.4e-05)
L2.Regionspillover_d	8.8e-07	-9.9e-05**	6.5e-06	-1.8e-05**	-3.2e-05**	-7.4e-05**
	(3.5e-06)	(2.1e-05)	(9.8e-06)	(6.9e-06)	(8.6e-06)	(2.0e-05)
Energy prices (firm level):						
L1.Coal	-.3559**	-1.096	-.5748**	-.5549**	-.4278**	-.5386**
	(.02822)	(.)	(.07944)	(.0528)	(.06986)	(.1427)
L1.Electricity	.116**	-1.511	.4168**	.1631**	.1078	.2509
	(.02879)	(.)	(.07443)	(.06008)	(.077)	(.1539)
Economic controls (firm level):						
L1.GDP	-.04745**	1.088**	-.1587**	-.7809**	-.8244**	-.6693**
	(.0132)	(.04617)	(.03785)	(.0355)	(.04229)	(.09929)
L1.GDPcap	.5548**	-6.723**	1.003**	1.349**	2.541**	-.5933
	(.06391)	(.07846)	(.1941)	(.2412)	(.357)	(.5783)
Constant	-8.673**	71.53	-12.23**	-6.553*	-19.77**	13.78*
	(.6757)	(.)	(1.981)	(2.586)	(3.655)	(6.343)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	271594	160629	41423	207544	123313	33465

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

Table C.14: Sub-sample of the twelve most innovative countries.

	Dependent variable: firm-level patents					
	All countries			Top twelve countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01123**	.00682*	-.00754*	.01116**	.00708*	-.00725*
	(.00376)	(.00306)	(.00302)	(.00378)	(.00295)	(.00296)
L2.Renewable	-.00188*	-.00042	.00191**	-.00182*	-.00027	.00187**
	(.00078)	(.00175)	(.00053)	(.00077)	(.0016)	(.00053)
L2.Conventional	-.00378	.00082	-.00034	-.00383	.00106	-.00042
	(.00254)	(.00223)	(.00575)	(.00258)	(.00207)	(.00568)
External knowledge:						
L2.Storage	.00034**	-9.5e-05	.00023	.00033**	-4.2e-05	.0003*
	(.00012)	(.00021)	(.00014)	(.00012)	(.00022)	(.00015)
L2.Convetional	-8.7e-05**	-1.9e-05	-4.3e-05†	-8.6e-05**	-4.2e-06	-5.6e-05*
	(2.0e-05)	(4.7e-05)	(2.6e-05)	(2.3e-05)	(4.6e-05)	(2.8e-05)
L2.Regionspillover_d	1.0e-04†	-.0001	4.4e-05	9.0e-05	-2.7e-05	6.6e-05
	(5.4e-05)	(.00012)	(8.6e-05)	(6.1e-05)	(.00013)	(8.9e-05)
Energy prices (firm level):						
L1.Coal	-.3012*	-.5945*	-.2324	-.298*	-.8182**	-.1834
	(.1422)	(.2467)	(.2289)	(.1437)	(.219)	(.2399)
L1.Electricity	.1638	.00831	.09989	.117	.3491	.1532
	(.1974)	(.2714)	(.2405)	(.2141)	(.2413)	(.2647)
Economic controls (firm level):						
L1.GDP	-.107	-.1618†	.01759	-.1805†	-.156†	.1096
	(.08953)	(.08629)	(.09268)	(.09912)	(.08395)	(.1594)
L1.GDPcap	1.665**	.496	.4916	1.696*	.8272†	1.068
	(.6027)	(.4841)	(.6449)	(.7317)	(.4787)	(.9429)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51244	13051	12058	47474	12114	11548

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

Table C.15: Baseline model with presample history.

	Dependent variable: firm-level patents					
	All countries			Top twelve countries		
	Renewable	Conventional	Storage	Renewable	Conventional	Storage
Internal knowledge (marginal effects):						
L2.Storage	.01123**	.00682*	-.00754*	.01118**	.00703*	-.00646*
	(.00376)	(.00306)	(.00302)	(.00401)	(.00308)	(.00269)
L2.Renewable	-.00188*	-.00042	.00191**	-.00172*	-3.3e-05	.00176**
	(.00078)	(.00175)	(.00053)	(.00079)	(.00162)	(.00057)
L2.Conventional	-.00378	.00082	-.00034	-.00392	.00108	1.0e-05
	(.00254)	(.00223)	(.00575)	(.00265)	(.00266)	(.00565)
External knowledge:						
L2.Storage	.00034**	-9.5e-05	.00023	.00023†	-4.5e-05	.00012
	(.00012)	(.00021)	(.00014)	(.00013)	(.00025)	(.00015)
L2.Convetional	-8.7e-05**	-1.9e-05	-4.3e-05†	-7.9e-05**	-2.2e-05	-3.0e-05
	(2.0e-05)	(4.7e-05)	(2.6e-05)	(2.3e-05)	(5.6e-05)	(2.6e-05)
L2.Regionspillover_d	1.0e-04†	-.0001	4.4e-05	5.2e-05	-9.4e-06	-1.9e-05
	(5.4e-05)	(.00012)	(8.6e-05)	(6.2e-05)	(.00016)	(9.3e-05)
Energy prices (firm level):						
L1.Coal	-.3012*	-.5945*	-.2324	-.4605**	-.6607**	-.3823
	(.1422)	(.2467)	(.2289)	(.1765)	(.241)	(.3242)
L1.Electricity	.1638	.00831	.09989	.1872	.3222	.3113
	(.1974)	(.2714)	(.2405)	(.2379)	(.2987)	(.3406)
Economic controls (firm level):						
L1.GDP	-.107	-.1618†	.01759	-.2573*	-.2863†	.02906
	(.08953)	(.08629)	(.09268)	(.1001)	(.1565)	(.205)
L1.GDPcap	1.665**	.496	.4916	1.133	1.646	-.4367
	(.6027)	(.4841)	(.6449)	(.7172)	(1.18)	(1.04)
Presample history:						
Renewable	-32.91**	8	8.073	-21.85**	4.775	16.36
	(10.39)	(10.33)	(.)	(6.128)	(27.75)	(47.1)
Conventional	3248**	7.707	9977	6921**	-1.401	-115.1
	(20.3)	(27.34)	(.)	(33.63)	(991.9)	(182.5)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
Year x Country FE	No	No	No	No	No	No
Number of observations	51244	13051	12058	40942	10488	10324

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

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