Do Technology Standards Induce Innovation in Grid Modernization Technologies?

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Abstract

A next generation of innovation in transformative grid modernization and renewables integration technologies is needed to further accelerate the decarbonization of electricity systems. Few studies have investigated the policy determinants of innovation in this sector to glean insights on how policy may support or hinder the development and deployment technologies. We argue that policies that were successful at supporting the first wave of renewables innovation may not be sufficient to produce similar results in grid modernization technologies. Smart grids technologies are of a different nature. Developing these technologies requires pooling knowledge from various domains, including electrical engineering, information and communications technologies, artificial intelligence, and more. Once developed, they are to be deployed within complex grid networks that are increasingly vulnerable to extreme weather shocks and load balancing challenges. Developing and deploying these technologies will therefore require enhanced coordination, but interoperable technology has the potential to generate the requisite network externalities to confront emerging grid management challenges. In this paper, we look at the effect of interoperability standards and at government R&D incentives in grid-related technologies and renewable energy technologies. We also investigate the role of internal and external knowledge stocks in the different technological domains smart grids innovation draws on. Using firm-level analysis, we find that standards have a negative effect on patenting activity, which suggests that standards may contribute to locking-in technology. We also find evidence of tradeoffs between government R&D incentives in grid technologies and in renewable energy. Finally, our analysis of knowledge stocks suggests that firms that innovate in smart grids do not necessarily have prior experience in IT innovation, but benefit from knowledge spillovers from IT firms.

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Introduction

Technological advances will be paramount for accelerating the energy transition and achieving decarbonization goals. Important technological breakthroughs in the past two decades made solar and wind energy cost competitive with conventional energy technologies (IEC/NEA, 2020). Integrating increasing amounts of renewable energy into electricity systems remains a challenge, due in part to the lack of preparedness of grid infrastructure. In most industrialized economies, grid infrastructure is ageing. Utilities fall short of keeping up with maintenance, let alone, investing in software and hardware to digitalize the grid. Without the adoption of "smart grids" technologies, efforts to further decarbonize energy systems may be jeopardized.

Despite forecasted needs in this area, technology development has been small compared to other areas of green innovation (IEA, 2021). The development of innovation in smart grids is hindered by the types of market failures that generally afflict environmental innovation - environmental externalities and knowledge spillovers (Popp, 2010; 2019). But it faces additional coordination challenges because these technologies must be compatible to function within complex grid networks. In this paper, we hone-in on the role of interoperability standards, as a policy instrument to address these coordination dilemmas. We posit that standards may contribute to reducing the uncertainty faced by inventors if they provide requisite information about the technical specifications and guidelines inventors should follow to enhance the chances that their products will be interoperable with other devices on the market, and ultimately, have commercial value. If this mechanism prevails, we expect that standards will have a positive effect on patenting activity. On the flip side, we consider the possibility that standards may contribute to locking-in technology. If this occurs prematurely, before technology has time to mature, standards may instead suppress patenting activity and act as a disincentive to test potential breakthrough ideas. In this paper, we find preliminary evidence of the latter.

Smart grids are also an area of technology that calls for the pooling of expertise from various technological domains, as it involves developing digital applications to support the distribution and transmission of electricity. Firms that innovate in this space are diverse in terms of age, size and technological backgrounds. Given this, we ask whether firms' prior experience innovating in the smart grid space and in related domains (electricity, ICTs, green technology) determines their success in patenting in smart grids, and whether the effect of standards varies across firms from different backgrounds. Our preliminary results indicate that firms who innovate in smart grids do not necessarily have prior experience in IT innovation, but benefit from knowledge spillovers from IT firms.

In the next section, we start by reviewing the grid management challenges posed by climate change and the integration of renewables, as well as the interoperability challenge. Second, we review two literatures to which this paper contributes: the literature on green energy innovation and the literature on standards and innovation. We then discuss our hypotheses, data and methodology. To translate country-level explanatory policy and control variables to the firm-level, we use information on firms' patents in the pre-sample period to build weights for each firm's main markets. Next, we present results from our firm-level analysis. We conclude with proposed next steps for testing more directly the technology lock-in hypothesis, and for further investigating the heterogeneous effects of standards across different types of firms, such as large electricity incumbents versus IT start-ups that are new to the green innovation and electricity innovation spaces.

Motivation

The challenge of load management in the face of renewables integration and climate change

Energy systems are undergoing profound socio-technological transformations, which are displacing conventional ways of organizing electricity value chains (Stephens et al, 2013; Winfield and Weiler, 2018). Traditionally, the electricity sector was regulated as a natural monopoly, to achieve economies of scale in the face of the high capital investment costs of building power plants and grid infrastructure (Martinot, 2016; Stephens et al, 2013). Until a wave of deregulation in the 1990s, vertically-integrated utilities dominated electricity generation, transmission and retail distribution in most advanced industrialized countries. Technological advances in renewable energy and green energy policies such as net metering, feed-in-tariffs, and renewable portfolio standards, have enabled the increasing penetration of distributed renewable electricity generation. With this trend, there has been a multiplication of electricity generators participating in wholesale and retail markets, connecting to the grid at different locations. This contrasts with the traditional way of organising the production and transportation of electricity - centralized production and top-down distribution - and increasingly poses novel load management challenges for utilities (Stephens et al, 2013; Lin et al, 2013; Winfield and Weiler, 2018, Brown et al, 2018).

Increasingly, grid infrastructure must accommodate the two-way flow of electricity and data within a complex network of electricity generators, consumers and "prosumers"[3]. Utilities need to monitor and balance the load on the grid in real time to keep frequency within a narrow band and avoid brownouts and blackouts. Aging grid infrastructures were not originally built to accommodate such decentralized, two-way communication. In the traditionally vertically-integrated system, information about load only needed to flow from the top down (Lin et al, 2013). With the multiplication of generators and the intermittent nature of renewable electricity generation, utilities are grappling with growing uncertainty about the supply and demand for electricity. Climate change, which is triggering an increase in the frequency of heat waves and cold spells, compounds the load balancing challenge. Extreme weather events result in sudden hikes in electricity demand and may even lead to equipment failure when infrastructure is unfit to withstand extreme temperatures, as shown in Texas in February 2021 (Winfeld and Weiler, 2018; Martinot, 2016; Palensky and Kupzog, 2013; Stephens et al, 2013).

"Smart" electrical equipment that enables the two-way exchange of data in real time, the forecasting of supply and demand for electricity, the monitoring of grid conditions and fault

[3] Actors that both buy and sell electricity on the grid, such as households with rooftop solar facilities participating in net metering programs.

detection, the automation of some load management decisions, the more flexible management of end-user demand, and more, can help meet these growing grid management challenges. These technologies have the potential to transform the grid in a way that will be amenable to and encourage the further integration of intermittent renewables, electric vehicles, and distributed storage units. In other words, the concept of the "smart grid" is more than the application of information and communications technologies to the grid. The aspiration– as it is presented by its champions - is to pave the way to a major socio-technical transition, one that will result in the emergence of a decentralized grid that supports decarbonization goals, all the while ensuring the secure and reliable provision of power in the face of increased pressures from climate change and intermittency in electricity generation.

What makes the grid "smart"?

At this stage however, the "smart grid" remains an aspiration. There is uncertainty surrounding technology development, and how socio-economic structures will adjust to future technological breakthroughs. For this reason, the "smart grid" is a rather elusive and fuzzy concept. It has no clear and widely agreed-upon definition, and has been criticized for being a catch-all term (Muench et al, 2014; Stephens et al, 2013, Martinot, 2016). Many definitions focus on the role of smart grids in leveraging ICTs to achieve desired outcomes, such as more efficient grid management, more reliable power supply, and renewables integration (Martinot, 2016; Palensky and Kupzog, 2013; Lammers and Heldeweg, 2016). In their definition of the smart grid, Stephens and colleagues (2013), highlight the interplay between technology and social structures: "The term 'smart grid' is used to represent a variety of interlinked social and technological changes to electricity systems, particularly modernizing networks that link electricity producers and consumers through advanced information and communication technologies." (Stephen et al, 2013, p. 202). In the context of federal legislation in the United States, the *Energy Independence and Security Act of 2007, Title XIII* defines the smart grid as a set of 10 core characteristics and objectives:

> "(1) Increased use of digital information and controls technology to improve reliability, security, and efficiency of the electric grid. (2) Dynamic optimization of grid operations and resources, with full cyber-security. (3) Deployment and integration of distributed resources and generation, including renewable resources. (4) Development and incorporation of demand response, demand-side resources, and energy-efficiency resources. (5) Deployment of ``smart'' technologies (real-time, automated, interactive technologies that optimize the physical operation of appliances and consumer devices) for metering, communications concerning grid operations and status, and distribution automation. (6) Integration of "smart" appliances and consumer devices. (7) Deployment and integration of advanced electricity storage and peak-shaving technologies, including plug-in electric and hybrid electric vehicles, and thermal-storage air conditioning. (8) Provision to consumers of timely information and control options. (9) Development of standards for communication and interoperability of appliances and equipment connected to the electric grid, including the infrastructure serving the grid. (10) Identification and

> lowering of unreasonable or unnecessary barriers to adoption of smart grid technologies, practices, and services." (EISA, 2007)

In summary, most definitions highlight the networked nature of electricity systems and the process of technological transformation within these complex webs of infrastructures and actors.

<u>The challenge of interoperability for unlocking network externalities</u>

Developing and deploying new technologies – software and hardware - across an increasingly complex and decentralized grid network is an evolved task. This will require investments by various actors located at different points on the grid. These investments could unlock important network externalities: the more users adopt these technologies, the more data and information about grid conditions will be exchanged, enabling more effective load management and reliable provision of power.

Two challenges stand in the way of developing and deploying these technologies at the requisite scale for achieving network externalities. First, as a non-rivalrous but excludable "toll" good, the grid is prone to underinvestment. Under current electricity rate-making regulations, utilities have little incentives to make those investments because they are limited in their ability to recover costs and are facing declining revenues (Lowry et al, 2017, Mandel, 2015, Marques et al, 2013; Schwister and Fiedler, 2015; Brown and Salter, 2010; Brown et al, 2018; De Castro and Dutra, 2013). It is unclear how the cost of these smart grids investments will be shared between utilities and other electricity system actors moving forward. Second, with technology development in the early stages, there is uncertainty about which innovations will emerge as winners. The usefulness of new smart grids technologies – which determines whether they get widely adopted - will be contingent upon ensuring interoperability between devices, developing common data sharing and security protocols, etc. Utilities might be reluctant to become early adopters because of concerns of obsolescence (Stephens et al, 2013; Schwister and Fiedler, 2015). In other words, uncertainty may suppress demand for smart grids technologies, and in turn, investments in research and development. Interoperability is also a concern for inventors: their inventions will be of little commercial value if they are incompatible with other devices on the market. The issue of compatibility therefore poses uncertainty for both utilities and inventors, potentially limiting the development and diffusion of smart grids technologies.

The challenge of interoperability is paramount. Much of the policy discussion and literature on the issue of grid modernization has focussed on this issue (Güngör et al., 2011; Ho & O'Sullivan, 2017; Fang et al., 2012; Li et al, 2017; Iqtiyanillham et al, 2017, Dantas et al, 2018; Tomain, 2012; Lin et al, 2013; Brown et al, 2018). For example, with the EISA Act of 2007, the United States launched a smart grids interoperability standardization process led by the National Institute of Standards and Technology. With Mandates M/441(2009) and M/490(2011), the European Commission has also instructed its standard-setting organizations to develop standards for smart meters and cybersecurity. Similarly, Germany, Canada, Korea and others OECD countries have issued policy roadmaps regarding standardization and interoperability (SCC, 2012; VDE/DKE, 2010; KSGI, 2010).

With limited government intervention in other areas of smart grid policy-making[4], governments have been active in putting the issue of interoperability standards development on the agenda of standard-setting organizations[5]. Standard-setting processes are typically industry-driven and led by technical experts, as they require detailed knowledge of state-of-the-art technology in fast-moving areas of technology (Baron and Spulber, 2018). Participation in these processes is voluntary and the standards issued by standard-setting organizations are non-binding, unless written into regulation (Baron and Schmidt, 2019; Baron and Spulber, 2018). This distinction is important to note: standards developed by SSOs are different from regulatory standards used by in command-and-control policy. Governments sometimes engage in these standard-setting processes and bring attention to certain issues. These processes can therefore be a space for governments to work alongside industry to define some parameters around technology selection. By putting smart grids standardization on the agenda of standard-setting organizations, it may be that governments have prompted coordination efforts and discussions that would not have otherwise happened. For this reason, we conceive of standard-setting in the area of smart grids as a public policy, albeit one whose causal mechanism is radically different from command-and-control regulation. In the next section, we argue that standardization, as a policy intervention, has not received the attention it deserves in the literature on green energy innovation. Given the policy attention the issue of interoperability standards development has received, we argue there is insufficient understanding of the mechanisms through which standards affect inventive activity in smart grids, nor any empirical evidence that they help in stimulating innovation.

Contribution: gaps in the literatures on green innovation and on standards and innovation

<u>Literature on green energy innovation</u>

The dual externalities problem that afflicts green energy innovation is well documented in the literature (Popp, 2010; 2019). Environmental externalities are not accounted for in energy prices, disadvantaging renewable energy in the market since the prices do not capture the value of avoided damages in comparison to fossil fuels. In addition, there tends to be an under-investment in innovation across all sectors, due to knowledge spillovers that prevent inventors from fully capturing the returns on their R&D investments (Popp, 2010; 2019). This dual externality problem justifies government intervention to stimulate inventive activity, through

[4] Other smart grids-related policy interventions include demonstration projects, mandatory smart meter roll-outs or targets, and reforms in utility rate-making to enable performance-based rate-making, time-based pricing and other rate-making scheme that encourage peak-shaving and demand-response. Government investments in research and demonstration projects have been sparse, the most well-known being the pilot project on Jeju Island in Korea, as well as 99 demonstration projects funded through the "Smart Grids Investment Grant (SGIG)" envelope of the American Recovery and Reinvestment Act (ARRA). Studies that have mapped relevant smart grids policies include: Lin et al, 2013; Iqtiyanillham et al, 2017; Dantas et al, 2018; Koenigs et al, 2013; Brown et al, 2018; Martinot, 2016; Winfield and Weiler, 2018; Palensky and Kupzog, 2013; Schiavo et al, 2013.

[5] Here standards refer to voluntary technical specification and guidelines, and not command-and-control policies.

various technology push and demand-pull policy instruments, and get closer to socially-optimal levels of investments.

The most frequently used instruments in a policy-maker's toolbox for supporting renewable energy include feed-in-tariffs, net metering, emissions-trading schemes, renewable portfolio standards, fiscal incentives for R&D and grants for research and demonstration projects. These policies change incentives to correct market failures at different levels and through different channels. For example, feed-in-tariffs subsidize renewable energy and eliminates uncertainty related to price fluctuation by offering renewable energy generators fixed price contracts. Net metering policies enable new actors to participate in electricity markets, by allowing homeowners that produce power from renewable source (such as rooftop solar photovoltaic) to feed their excess production on the grid for later consumption. Renewable portfolio standards act on the quantity side, rather than the price side, by fixing targets for renewable generation.

The literature has extensively investigated the effect of these various environmental policies on innovation. For example, Fabrizi and colleagues (2018) investigate the effectiveness of R&D grants in stimulating green energy innovation. Popp (2002) and Newell and colleagues (1999) show that green innovation is responsive to changes in prices. This highlights the potential for carbon taxes to direct technological change away from fossil fuels. Johnstone and colleagues (2010) investigate the effect of environmental policy on green energy innovations. They find that tradable energy certificates are more effective at steering innovation in technologies that are at an advanced stage of technological development (closer to being competitive with fossil fuels), while feed-in-tariffs can support technological progress at earlier stages of development. Calel and Dechezleprêtre (2016) quantify the effects of the European emissions' trading scheme on innovation.

More recently, studies that use firm-level analysis have enabled a finer understanding of the policy, market conditions and firm-level characteristics that drive firms' decisions to innovate away from fossil fuels. This literature is rooted in the directed technical change and induced innovation literature (Acemoglu et al, 2012; Popp, 2002), with a focus on the role of tax-inclusive energy prices, market size, and knowledge stocks. This approach enables comparisons across different types of firms, and the more precise identification of firms' innovation behaviors, such as switching between green and dirty technologies. Aghion and colleagues (2016) first used this approach to study the global automotive industry. Their firm weights allow to capture firms' unique exposure to changes in policies and market conditions, depending on their respective positioning in various markets and the differential timing of policies across markets. This allows for more precise identification of the effects from variables such as price and policy changes at the firm-level. The authors find that firms innovate more in clean energy when they face higher price-inclusive prices. The firm-level approach also allows to consider the internal and external knowledge stocks firms are exposed to. Aghion et al (2016) find evidence of path dependency from firms' prior innovation experiences. The more experience firms have in clean technology, the more likely they are to continue innovating in this area, and vice-versa. The authors find that path-dependence from exposure to external knowledge stocks also affects the decision to innovate in clean versus dirty energy. Lazkano et al (2017) use a similar approach to study complementarities between innovation in energy storage technologies and innovation in renewable energy versus conventional energy technologies. They find that because storage enhances the elasticity of substitution between the two, firms that have experience with storage innovation also innovate more in both conventional energy and renewables. Finally, Noailly and Smeets (2015) use firm-level analysis to study firm heterogeneity in the electricity sector in a sample of more than 5000 European firms. They compare innovation activity within mixed firms and specialized firms and firms' entry and exit from renewable energy and fossil fuel innovation. They find that most of the increase in European clean innovation is attributable to small, specialized firms. Rather than observing switching between renewables and fossil fuel innovation within firms, the authors find that the increase in the share of renewable innovation is due to the entry of firms specialized in renewables and the exit of firms specialized in fossil fuels. Consistent with this, they also find evidence of path dependency within firms that have large fossil fuel internal knowledge stocks.

From the green innovation literature, in the past two decades we have gained a richer understanding of the effects of policy instruments that seek to redress markets failures and of how policy and market conditions affect firms' innovation decisions. However, there is little literature on the role and effectiveness of policies in redressing coordination challenges of the type encountered in the area of smart grids. Moreover, while there is an abundance of studies that have looked at innovation patterns in renewables, the empirical literature on smart grids innovation is scarce. We know very little about the state of innovation in this area, for example, who are the actors innovating in this area of technology, what are complementarities between the development of smart grid technologies and other critical areas of green innovation such as electric vehicles or electricity storage, and which areas of smart grid technologies are at a more advanced stage of development. Studies that have attempted to map innovation in the smart grids sector are limited to descriptive work (e.g, Marku and Zaitsava 2018), and document the penetration of ICT firms in the electricity innovation market.

Literature on standards and innovation

This paper also contributes to the literature on standards and innovation, in which recent empirical evidence about the effect of standards on inventive activity is limited[6]. A general definition for standards is formulated by the National Institute of Standards and Technology: "A standard is a document that contains technical specifications or other precise criteria to be used consistently as a rule, guideline, or definition of characteristics, to ensure that materials products, processes, personnel or services are competent and/or fit for their intended purposes(s)" (cited in Baron and Spulber, 2018, p.4). Beyond this general definition, standards can be classified along various dimensions. The literature makes the distinction between different types of standards that perform various functions and affect innovation through distinct channels.

[6] Recent empirical studies include Baron and Schmidt (2020) who find evidence that peaks in standardization are followed by the implementation of new inventions, which in turn explain some of the fluctuation in business cycles, and Baron and Pohlmann (2019) who map patents classes to standards classes.

A first distinction is between *de facto* and formal standards. Rules and guidelines may emerge informally to become widely used within an industry. In this case, there is not necessarily a need for a formalized document, if industry actors already have a shared understanding of these guidelines and see the value in abiding by them. Companies may use various strategies such as contracting and advertising to incite others to use its technology as the industry standard (Baron and Spulber, 2018; Katz and Shapiro, 1986; Spulber, 2008). In this case, *de facto* standard may be sufficient for performing coordination functions. Often times however, standards are the product of formal consultative processes piloted by standard-setting organizations (SSOs), within which industry representatives coordinate over technology selection and adoption (Baron and Spulber, 2018; Baron and Schmidt, 2020). These standard-setting processes may be viewed as formal coordination technology selection mechanisms: standardization is a way to reduce uncertainty (Aggarwal et al, 2011), steer expectations about certain technologies (Lerner and Tirole, 2015) and stimulate the coordinated implementation of new technologies across an industry (Baron and Schmidt, 2020; Lerner and Tirole, 2015; Spulber 2018). In fact, there is empirical evidence that standard-setting organizations are effective at cooperatively selecting high value technologies. Rysman and Simcoe (2008) find that patents declared to be essential for the implementation of a standard (standard-essential patents, SEPs) receive more citations than non-SEPs granted within the same industry and year.

Standards developed by SSOs are usually open standards, and differ from proprietary standards (Baron and Spulber, 2018). Proprietary standards are “owned and controlled by a single firm or a group of firms and may be used only with the permission of the standard’s owner or owners” (Baron and Spulber, 2018, p.5). They often perform the function of ensuring product quality, especially across a firm’s networks of suppliers, and the owner of the standard can use intellectual property protection to exclude other firms from producing goods that conform with it. Open standards may also require the use of patented technologies for conformance[7] but they differ in that any firm can use those standards freely. The standards issued by standard-setting organizations typically belong to this category (Baron and Spulber, 2018). Open standards that are designed to facilitate interoperability, in particular, are useful for coordinating the work of independent firms, whose products are used as inputs in the manufacturing of complex technological products or in networked technologies, such as computers and smart phones. The information technology sector is a good example of industries where interoperability is crucial (Baron and Spulber, 2018).

Another distinction is between voluntary standards and regulatory standards. Compliance is voluntary for standards developed by standard-setting organizations (Baron and Spulber, 2018). Governments may write standards into legislation. However, this concerns a minority of standards and no organization has collected information systematically on which standards have been included in legislation. For this reason, the database that we use for this paper does not allow us to identify which standards are mandatory within certain jurisdictions (Baron and Spulber, 2018). We therefore assume that the standards comprised in our sample are voluntary,

[7] In which case, SSOs have rules directing the holders of “standard-essential patents” to grant licenses using fair, reasonable and non-distriminatory terms (Baron and Spulber, 2018).

and that the mechanism at play is information provision rather than coercion. Given that the smart grids sector is in the early stages of technological development and is a fast-moving area of technology, we assume that government officials would exercise caution and refrain from picking and choosing which technical specifications should be mandatory.

Another way of classifying standards is by the functions they perform. Interoperability standards, for example, perform a coordinating function in helping to ensure products and components are compatible. These are the standards we are interested in the context of this study. They help correct coordination failures to achieve network externalities. Quality standards are devised to ensure that products meet certain quality and safety requirements. Information standards provide product descriptions that help inform consumer's choices. The latter two types of standards help correct market failures arising from transactions costs and asymmetries of information. Finally, variety reduction standards may be useful in cases where there is too much trivial differences between products in a market. Those standards help redress inefficiencies through increasing economies of scale (Swann, 2000; Tassey, 1999; DeVries, 1999).

As briefly mentioned previously, concerns about competition and market power often arise in the discussion on the link between standards and patents. Much of the limited theoretical literature on the link between standards and patents has focused on concerns of competition and on ways to keep market power in check when inventions are deemed essential to the implementation of a standard (standard-essential patents) (Lerner and Tirole, 2015). SSO policies that require the licensing on reasonable terms can help mitigate this caveat. However, they often result in costly litigation (Lerner and Tirole, 2015). The literature also raises concerns about the possibility that standards may generate technology lock-in. However, according to Baron and Spulber (2018), this remains much of an open question, with the empirical literature finding mixed or inconclusive evidence of lock-in (they cite the work of: Spulber, 2008; Branove and Gandal, 2003; Angereau et al, 2006; Liebowitz and Margolis, 1990).

To summarize, this paper seeks to contribute to two literatures. First, we contribute to the literature on green energy innovation by calling attention onto the role of standards in policy contexts where coordination failures - in addition to the usual environmental externalities and knowledge spillovers market failures – also threaten to suppress investment in the development and deployment technologies needed to accelerate decarbonization. This paper hones-in on a sector of green energy innovation that has been under-studied, and yet, that will be essential for steering the energy transition forward. This paper also seeks to advance our understanding of the channels through which standards affect innovation. We empirically investigate the effect of interoperability standards to gain insights into which mechanism is at play: information provision and uncertainty reduction, or technology lock-in. Given that this question has found no conclusive answer so far, our empirical findings also contribute to the literature on standards and innovation. In the next section, we formulate research questions and formal hypotheses to be tested.

Research question, theory and hypotheses

The broad research question that motivates this paper is: what are the policy determinants of smart grid innovation? More specifically, we hone-in on a specific mechanism and ask: what effects do interoperability standards have on innovation in smart grids?

We posit that standards may affect innovation in three ways. The direction and magnitude of the effect may differ across the different channels:

- *The information hypothesis*. First, in early stages of technological development, when no technical specifications and protocols have emerged as the norm in the industry, individual inventors face high uncertainty due to a lack of information. For their invention to have commercial value, they need to ensure it will be interoperable with other devices on the market. Standards can provide credible information about which technical specifications and protocols the industry has collaboratively selected and is likely to use in the future. Such information may reduce uncertainty for individual inventors, and some of the risks associated with R&D investments. This might translate into more inventive activity after a standard or set of standards has been released.
- *The technology lock-in hypothesis.* Second, if standards are developed too early in the emergence of new sectors of technology, they may have the opposite effect of stifling innovation. Standards that recommend a certain technology or procedure before actors have had opportunities to test different ideas and concepts may quell experimentation and lock-in sub-par technology.
- *The endorsement hypothesis.* Finally, standards may have a negligible effect on innovation if they merely formalize what the industry had already *de facto* adopted. Alternatively, formal standards may have heterogeneous effects across different types of inventors. *De facto* standards may be sufficient to stimulate R&D investments by electricity sector incumbents who have access to insider information. However, new entrants in this market may need to rely on formal standards to gain insights and information into which protocols and technical specification are broadly accepted before they make R&D investment decisions.

Because these three channels work, at least in part, in opposing directions, the net impact of standards on smart grid innovation is ambiguous. Standards may provide guidance to early innovators, but may also lock-in existing technological norms. Co-ordination of innovation may provide information to potential new entrants in the market, or serve as a barrier to entry by establishing incumbent technology as the standard for a market. Using firm-level patent data allows us to test for heterogeneous impacts across different types of firms.

Model and variables

We use firm-level patent data to measure smart grid innovation. Our data includes all firms with at least one smart grid patent (defined below) for the years 2000-2016. Using methods first described in Noailly and Smeets (2015) and Aghion et al. (2016), we use pre-sample data on the countries in which firms obtain patents to construct weights for the importance of each market to a firm. This allows changes in standards, policies, and market conditions in a given country to have different impacts on different firms, allowing us to treat lagged values of these variables as plausibly exogenous. No firm is influential enough to affect those variables in all the countries where it operates, yet it is reasonable to expect that a firm would consider the policy conditions - such as the level of standardization and government R&D incentives - in the main markets where it operates when making R&D investment decisions. The use of these models to explore green innovation has grown in recent years, including Noailly and Smeets (2015) on renewable energy, Aghion et al. (2016) on the automotive sector, Lazkano et al. (2017) on energy storage, and Rosendaal and Vollebergh (2021) on emission standards. Using firm-level data also allows us to test for heterogeneous impacts of standards on incumbent firms and new entrants.

Our dependent variable is a count of successful smart grid patent applications filed by firm *i* in year *t*. As patents vary in quality, we only include patent applications subsequently granted by at least one patent office.[8] Because the dependent variable is a count of patents, we begin with a model using pseudo-maximum-likelihood Poisson regression.

$$\begin{aligned} patents_{it} = \exp(&\beta_0 + \beta_1 S_{\,it-2} + \beta_2 log\ RG_{it-2} + \beta_3 log\ RR_{it-2} + \beta_4 \log KS_{it-2} \\ &+ \beta_5 \log\ KG_{it-2} + \beta_6 log\ KE_{it-2} + \beta_7 log\ KI_{it-2} + \beta_8 log\ ES_{it-2} \\ &+ \beta_9 log\ EG_{it-2} + \beta_{10} log\ EE_{it-2} + \beta_{11} log\ EI_{it-2} + \beta_{12} X_{\,it-2} + a_i + y_t + u_{it}) \end{aligned}$$

Where S is a count of standards, RG is government RD&D budgets in grid-related technologies, RR is government RD&D budgets in renewables, KS is a firm's internal knowledge stocks in smart grids technologies, KG is a firm's internal knowledge stocks in green innovation, KE is a firm's internal knowledge stocks in electricity, KI is a firms' internal knowledge stocks in information technologies, ES are external knowledge stocks in smart grids, EG are external knowledge stocks in green innovation, EE are external knowledge stocks in electricity, EI are external knowledge stocks in information technologies, X is a vector of control variables. To represent firm-level fixed effects, a_i, our main specification uses the pre-sample mean of patents. As we explain below, this requires only weak exogeneity of the explanatory variables. Finally, y are year fixed effects. The right-hand side variables are lagged two-years to avoid reverse causality.

Our main policy variables include the certification of standards and government R&D investments to which each firm *i* is exposed. Described in more detail below, these variables are a weighted sum of the policy in each country, c, in time, t, using time-invariant weights based on the market exposure of each firm in the pre-sample period. The internal and external knowledge stocks proxy for both a firm's own R&D experience and potential spillovers from other inventors,

[8] Noailly and Smeets (2015) also use granted patents. Other recent papers, including Aghion et al. (2016), Lazkano et al. 2017), and Rosendaal and Vollebergh (2021) use triadic patents (e.g. patent applications filed at the USPTO, European Patent Office, and Japanese patent office) to eliminate low-quality patents. We do not do that for two reasons. First, because of differences in the electricity grid in North American and Europe, we observed examples where smart grid patents were filed in multiple North American or European countries, but not on the other continent. Second, we are interested in the effect of standards on new entrants. New entrants will include smaller firms that may be less likely to file patent applications abroad.

respectively. Our control variables include other factors that may influence demand for smart-grid technology. These include the percentage of electricity generation from renewable sources and the growth in electricity consumption from the previous year. Both increased renewable penetration and growth in electricity consumption may signal increased pressures on the grid. We include the logged value of household electricity prices as an increase in retail electricity prices may motivate consumers to seek solutions to better manage their electricity consumption, enroll in demand-response programs, etc. To account for changes in overall economic conditions in the markets where firms operate, we also include the logged value of GDP per capita. We include firm and year fixed effects to control for other potential unobservable firm-invariant and time-invariant confounding factors.

Our estimation faces two additional challenges. First, as the knowledge stocks are functions of lagged dependent variables, strict exogeneity does not hold. In such cases, the standard Poisson fixed effects model may produce biased result. As such, our main specification uses the pre-sample mean of patenting activity to proxy for firm fixed effects (e.g., Blundell et al. 1995; Noailly and Smeets, 2015, Rosendaal and Vollebergh 2021). While our dependent variable only includes smart-grids patents, for the pre-sample mean we include a wider range of relevant technologies, including patents pertaining to green innovation, electricity generation, information technology (IT), as well as smart grid patents. Using the pre-sample mean requires assuming that a firm's innovative activity is stationary and follows an AR(1) process. As smart grids are an emerging technology experiencing much patent growth over our sample period, such an assumption would be unrealistic for smart grid patents themselves. Instead, the pre-sample mean can be thought of as the overall propensity to innovate for each firm. Our regressions then ask how standards, R&D spending, and various demand-side factors specifically affect smart-grid patenting conditional on each firm's overall propensity to innovate.

Second, because of the novel nature of smart grid technology, our sample includes many new firms who were not actively patenting in the pre-sample period. To accommodate these firms when using the pre-sample mean, we include a dummy variable for firms with no patents in the pre-sample. Additionally, we explore the potential role of standards on new entrants by estimating two zero-inflated Poisson models. One uses a balanced panel and the other, and unbalanced panel that accounts for the timing of each firm's entry and exit from the market, proxied by their first and last year of patenting activity in relevant technologies (green innovation, electricity generation, information technology, smart grids). The zero-inflated Poisson model first uses a logit model to predict whether a firm has any patents in a given year (e.g., the extensive margin). Then, a Poisson model (using pre-sample means to proxy the firm fixed effect) is used to predict the number of patents per firm in a given year (e.g., the intensive margin).

Data sources

A contribution of this paper is to pool data from two distinct sources, including a novel database on Technology Standards and Standard Setting Organizations (SSOs), to empirically investigate the effect of standardization on inventive activity in the area of grid modernization. Few studies have empirically investigated the link between standards and innovation (Baron and Pohlmann, 2018; Baron and Schmidt, 2019), nor the policy determinants of innovation in smart grids. To address this gap, we use standards data from the Searle Center on Law, Business, and Economics at Northwestern University, in conjunction with patent data from the European Patent Office (EPO).

Overall, our sample includes firms from 19 countries: Austria, Australia, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Italy, Japan, Korea, Netherlands, Norway, Sweden, Turkey and the United States. Some OECD countries were excluded due to incomplete data on standards and household electricity prices. The sample period is 2000-2016. We begin in the late 1990s because there was little invention in the area of smart grids prior to the early 2000s, and we end the sample in 2016 to avoid truncation bias due to the lag between patent application and grant. We exclude patents by applicants that are not firms, such as universities, government agencies and non-governmental organizations, and only keep patents that were granted in at least one of the sample countries. A total of 3,084 firms and 13,844 distinct patent families are included the sample, and we find 1,867 instances of country standards accreditations during the 2000-2016 period.

<u>Standards data</u>

The Searle Center's database provides information on standard documents released by 600 standard-setting organizations around the world (international and domestic SSOs), including standards' release date, version history, international equivalences, amendments, withdrawals and references. To identify which standards are relevant for the smart grid, we use lists available online via the International Electrotechnical Commission (IEC), the European standardization organizations (CEN, CENELEC, ETSI), and the Smart Electric Power Alliance (SEPA). Including lists collated by international, European and North American sources ensures we have adequate geographical coverage of the countries in our sample. The IEC curates a list of international standards that it deems of core or high importance for the smart grid, mapped onto a conceptual schema of the smart grid. As part of European Commission Mandates M/441 and M/490, the CEN, CENELEC and ETSI also curate a list of standards that are relevant to the electrical grid. Finally, in the United States, the Catalogue of Standards developed through a national standard-setting process launched with the Energy Independence and Security Act (EISA) of 2007 is curated by the SEPA. The SEPA and IEC lists are more restrictive, while the "interoperability tool" collated by the European organizations lists standards that are of more general relevance to the electricity sector, and not always specific to smart grid applications. To limit our sample to standards that are of core or high relevance to smart grids technologies, we use the IEC and SEPA lists as our starting point, find their equivalents in the European context, and complete with European standards on advanced metering infrastructure developed in response to Mandate M/411.

We then use an algorithm developed by Schmidt and Steingress (2019) to find all instances of country-level equivalences for these standards in the Searle Centre database. This algorithm fillsin gaps that arise because of different timing of standard accreditations[9]. Schmidt and Steingress' algorithm cross-references information to identify with greater completeness instances of standards harmonizations across countries -- that is, standards released by national and international SSOs that have been declared to be equivalent. This allows to identify the timing of smart grids standards accreditations across our sample countries.

Many standards are composed of multiple parts. We count instances of standards accreditations at the part level. As technology evolves, new parts are sometimes added to existing standards. We conceptualize those as evidence that SSOs and industry are actively coordinating to address emergent technological challenges and opportunities. This warrants counting the release of new parts as stand-alone events. Conversely, not all parts of the standards included in our list are of high relevance to the smart grids. Counting standards at the part level allows us to filter out less relevant parts and reduce the noise in our measure of standards accreditations. In addition, we do not count standards revisions. While revisions might indicate that a standard remains in use and relevant, we make a conceptual distinction between the first time a standard is released – which indicates attention to standardization needs in novel areas - and the release of a new version of an existing standards – which indicates a maintenance level of coordination to ensure the standard remains up-to-date with the latest technological developments.

Having obtained a list of relevant smart-grid standards accredited by each country, we create two alternative measures of standardization for each country. The first is simply a count of standards accredited in country *c* in year *t*. Results using this variable can be interpreted as an event-study approach – how does the accreditation of new standards in a firm's markets affect innovation. The second is a cumulative count of all smart grid standards accredited in country *c* up to and including year *t*. This count can be interpreted as a proxy for the level of standardization in a given market. We use the first measure in our baseline results and the second measure in our robustness checks.

Patent data

To capture innovation, we use patent data from the European Patent Office's PATSTAT database. It is common in the literature to use patent data to proxy for inventive activity. Because patents are filed early in the research and development process, they provide a good indication of when the inventive activity took place. However, because there is a lag between the moment a patent is filed, and the moment it is granted and appears in the database, our sample ends in 2016 to avoid truncation bias.

To identify patents that are relevant for the smart grid, we rely on the Cooperative Patent Classification (CPC), a patent classification system jointly developed by the European Patent Office and the United States Patent and Trademark Office and launched in 2013 to achieve more

[9] For example, SSO B may be declaring its standard to be equivalent to SSOs A and C, but SSO A only declares its standard as being equivalent to country C, because B had not yet accredited the standard when A reported the information (Schmidt and Steingress, 2019).

precise and consistent tagging across country patent offices[10]. The Y class on cross-cutting technologies classifies environmental technologies at a very granular level, including patents relevant for the smart grid. We extract patents that belong to 4 areas of smart grid technology: 1) systems integration and efficiency (CPC classes Y02E 40/70 and Y04S 10), 2) use in buildings (CPC classes Y02B 70/3* and Y02B 90/2*), 3) ICT applications to smart grids (CPC classes Y04S 40* and Y04S 50*), and 4) end-user applications (Y04S 20). Annex 1 presents the full description of these categories. We then identify firms with at least one successful patent application between 2000 and 2016.

We count patents at the level of the patent family: a patent granted in multiple countries counts as one invention. We keep patents that were granted in at least one of our sample countries. Because we assume firms make R&D investment decisions based on the policies and economic conditions of the markets where they do business, we include all companies that have at least one granted smart grid patent in the 19 countries in our sample, regardless of the location of their inventors and applicants. In most cases, inventors and applicants are also located in those countries, and there is strong geographical overlap between a firm's markets – defined as the countries where it has granted patents – and where its R&D and related investment decisions take place.

Internal knowledge stocks

To obtain knowledge stocks for these firms, we collect patents for these firms going back to 1977. As smart grids technology may draw on multiple disciplines, we construct four knowledge stocks[11]: smart grids[12], renewable energy[13], electricity generation[14], or information technology (IT)[15]. We aggregate patent filings from each year into an internal stock of knowledge for each firm. These stocks represent the firm's past patenting history and are the internal knowledge upon which future innovation can build. Defining δ as the depreciation rate of knowledge and P_{ijt} as the successful patent applications in technology *j* filed by firm *i* in year *t*, the internal knowledge stock, K^{INT} is:

$$K_{ijt}^{INT} = (1-\delta)K_{ijt-1}^{INT} + P_{ijt}$$

[10] Older patents were also retroactively classified under the CPC.
[11] Given the interdisciplinary nature of smart grid innovation, there is overlap between these categories. Patents are typically tagged under several different CPC classes, and may appear in more than one of our 4 categories. In these cases, we count the as an invention in each of the categories.
[12] CPC classes: Y02B 70/30, Y02B 70/3225, Y02B 70/34, Y02B 90/20, Y02E 40/70, Y04S 10, Y04S 40, Y04S 50, Y04S 30, Y04S 20.
[13] CPC classes: Y02, Y04
[14] CPC classes: H, F21, F02C, F2B
[15] CPC classes: G06, G01S, G02F, G08B, G08G, G09G, G10L, G11B, G11C, H01P, H01Q, H01P, H01Q, H03B, H03C, H03D, H03F, H03G, H03H, H03J, H03K, H03L, H03M, H04H, H04J, H04K, H04L, H04N, H04Q, H04R, H04S, H04W, G01V3, G01V8, G02B6, G09B5, G09B7, G09B9, H01L2, H01L3, H01L4, H01S5, H04B1, H04B5, H04B7, H04M1, H04M3, B82Y10, G01V15, H01B11, H04M15, H04M17, G07F7/08, G07F7/09, G07F7/10, G07F7/11, G07F7/12, B81B7/02, G07G 1/12, G07G 1/14.

We use a 15% depreciation rate as our base case. When taking logs, we add one to all knowledge stocks and include four dummy variables indicating when each knowledge stock equals 0.

External knowledge stocks

External knowledge stocks capture the potential for spillovers from innovations external to the firm. Following Aghion et al. (2016), the external spillovers to which each firm is exposed depends on the countries where its inventors are located. Multinational companies have scientists working in multiple locations in multiple countries. The inventor address on the patent reveals where the inventive activity associated with that particular patent took place. Using all of a firm's patents in our relevant technology categories, we calculate weights for each country using a time-invariant share of the number of inventors on firm *i*'s patents located in country *c*, w_{ic}^{K}. This gives us the stock of external knowledge:

$$K_{ijt}^{EXT} = \sum_{c} w_{ic}^{K} K_{icjt}^{EXT} ,$$

where

$$K_{icjt}^{EXT} = (1-\delta) K_{icjt-1}^{EXT} + P_{cjt} - P_{icjt}$$

represents a stock of knowledge that includes patents granted to other inventors in country *c* at time *t*. Thus, the external knowledge stock assumes that firms are exposed to spillovers in each of the countries where they have inventive activity, and places the greatest weight on spillovers from countries where they do most of their inventive activity.

Note that P_{cjt} includes all patents granted in the relevant patent classes for technology *j* in country *c* at time *t*, not just those assigned to the firms in our sample. This includes patents that may be assigned to public sector organizations such as universities or government laboratories. We include spillovers from multiple technologies since smart grid innovations may arise in multiple sectors. This set-up allows for spillovers from all innovations in relevant fields. For example, spillovers from relevant IT knowledge need not only come from IT firms that actively patent in smart grids. Our external knowledge stock allows for this possibility. [16]

Control variables

The control variables come from two sources, which compile statistics on various aspects of energy systems: the International Energy Agency (IEA) statistics and the British Petroleum Company's Statistical Review of World Energy. Data on government R&D expenditures in relevant energy technologies[17], on domestic net electricity consumption, on household electricity prices

[16] This calculation differs slightly from the spillover pool used in Aghion et al. (2016), which starts with a weighted sum of all other firm's internal knowledge, weighted by the share of patents for each company in country *c*. This limits spillovers to come from other firms in their sample. Aghion et al. (2016)'s paper looks at a single well-defined industry, making such an assumption reasonable in their setting. It is not here.

[17] We include two types of energy R&D. R&D potentially applying to smart grid includes categories 62 (electricity transmission and distribution), 63(energy storage), 69(unallocated other power and storage techs) and 71 (energy

and on gross domestic product are from the IEA. Data on electricity generation from renewable sources is from BP.

Constructing weighted policy variables and controls

Our policy and control variables are collected at the country level. Many of the firms in our sample operate in multiple markets, and will be affected differently by policy changes in each country depending on how important each market is to them. We follow the standard approach in the environmental innovation literature (e.g., Noailly and Smeets 2015, Aghion et al. 2016, Lazkano et al. 2017, and Rosendaal and Volebergh 2021) and construct firm-specific weights based on the countries that they patent in during the pre-sample period (1977-1999). Using the pre-sample period makes the weights weakly exogenous, as they do not change in response to changes in policy in potential markets. These time-invariant weights identify markets to which firms actively participate. To account for market size, we weight each market by $GDP^{0.35}$, using the average GDP for each country in the last five years of the pre-sample (Dechezlepretre et al. 2021, Rosendaal and Volebergh 2021).[18] Defining w_{ci}^{PAT} as the share of firm *i*'s pre-sample patents filed in country *c*, the weight becomes:

$$w_{ci} = \frac{w_{ci}^{PAT} GDP_c^{0.35}}{\sum_{c' \neq c} w_{c'i}^{PAT} GDP_{c'}^{0.35}}$$

We build weights based on all the markets in which a firm has patented in relevant CPC classes, and not only in our 19 sample countries.

Note that this weight differs from the weight used for the external knowledge stock, as the shares are based on where a firm opts to market its goods, rather than where its inventors are located. Coelli et al (2022, cited in Dechezlepretre et al. 2021) show that such weights explain well bilateral trade flows and firm exports. Because smart grids are an emerging technology, most firms have few smart-grid patents during the pre-sample period. Thus, as we did when calculating the pre-sample mean for each company, we use patents in green innovation, electricity generation, or information technology (IT), as well as smart grid patents, when calculating the weights.

Our data include 2,030 firms without any pre-sample patents. For these firms, we use a weighted average (based on total patents in relevant technology areas) of the weights from other firms located in the same country. This assumes that firms in a given country are likely to operate in similar sets of countries – e.g., European firms are likely to patent within Europe and Canadian firms are likely to also patent in the U.S. This assumption is more likely to apply to larger new firms that operate internationally. New firms that are large innovators in the area of smart grids

system analysis). We also include R&D expenditures on renewable energy (Group 3 Renewable Energy Sources), which is both a signal of green intentions and suggests a need for technology to integrate renewables into the grid.

[18] Dechezlepretre et al. (2021) suggest the exponent of 0.35, saying that it fits estimates of the elasticity of exports to GDP of the home country found by Eaton, Kortum, and Kramarz (2011). We include robustness checks using an exponent of 1, as in Aghion et al. (2016).

include Voltalis, a French firm founded in 2006 that sells residential energy management devices and now operates in several European markets. In the period between 2006 and 2016, Voltalis produced 197 patented inventions (counted at the patent family level). Because we have no pre-sample data for Voltalis, we assume that its main markets are the same as other French firms, on average. Similarly, the company Ubitricity, founded in Berlin in 2008 has become one of the larger electric vehicle charging suppliers in Europe. Between 2008 and 2016, is has produced 120 patented inventions[19]. Again, in our main specification, we assume that the relevant markets for Ubitricity are the same as the average German firm. In robustness checks, we assume that the firm only operates in their home country. Such an assumption is more likely to be the case for smaller firms.

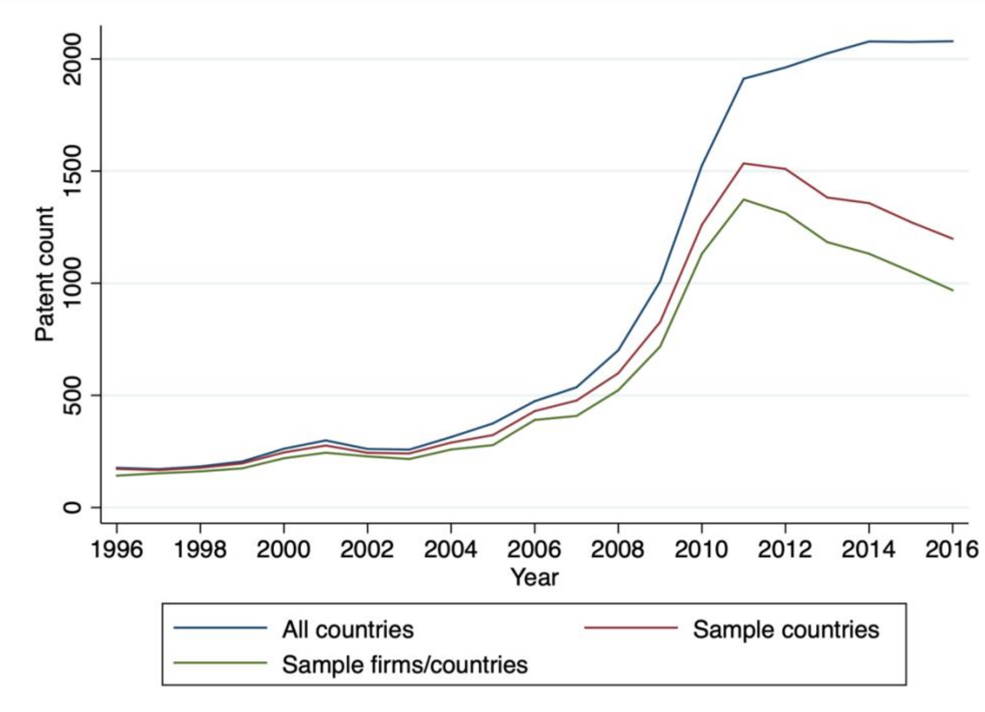
Descriptive statistics

We choose the years 2000-2016 as our sample period. As an emergent area of technology, little patenting activity occurred in smart grids prior to 2000, but it has grown rapidly since. Figure 1. shows patenting activity for the period 1996-2016, comparing trends in global patenting, to patenting in our sample countries by all types of applicants (universities, companies, individuals, etc.), and in our sample countries by our sample firms only.

Globally, smart grids patenting takes off in the early 2000s and peaks in the early 2010s. While global patenting levels off in 2013-2014, patenting activity in our sample countries peaks in 2011 and subsequently declines. Nevertheless, these figures show that the bulk of patenting occurs in our sample countries, giving us satisfying coverage of the universe of smart grids patenting despite our data limitations. Figure 1 also shows that most of the patents granted in these countries were filed by our sample firms. Excluding individual, university, governmental and non-governmental organization applicants does not substantially alter the overall trend.

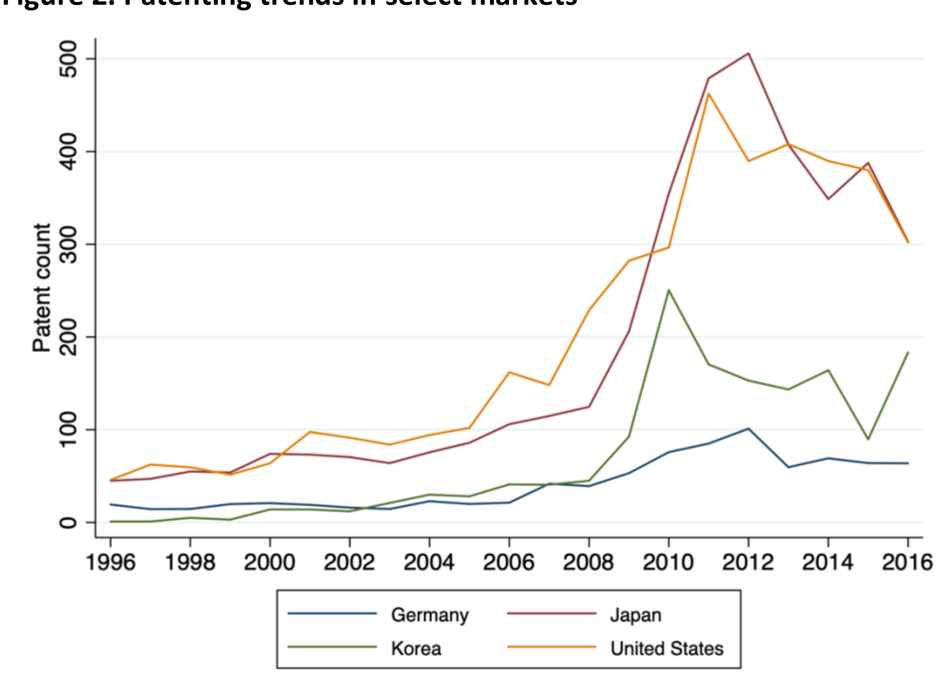
[19] These include inventions that were tagged in at least one of our smart grids CPC classes, as we excluded CPC classes pertaining only to electric vehicles. However, many of these inventions are tagged under several CPC classes, therefore inventions that are relevant to EV and other areas of the smart grids would have been included in our count of relevant patents.

Figure 1. Trends in smart grids patenting



When decomposing patenting in key national markets, we observe a similar trend. Figure 2 shows smart grids patenting in the United States, Germany, Japan and Korea for the years 1996-2016 for our sample firms.

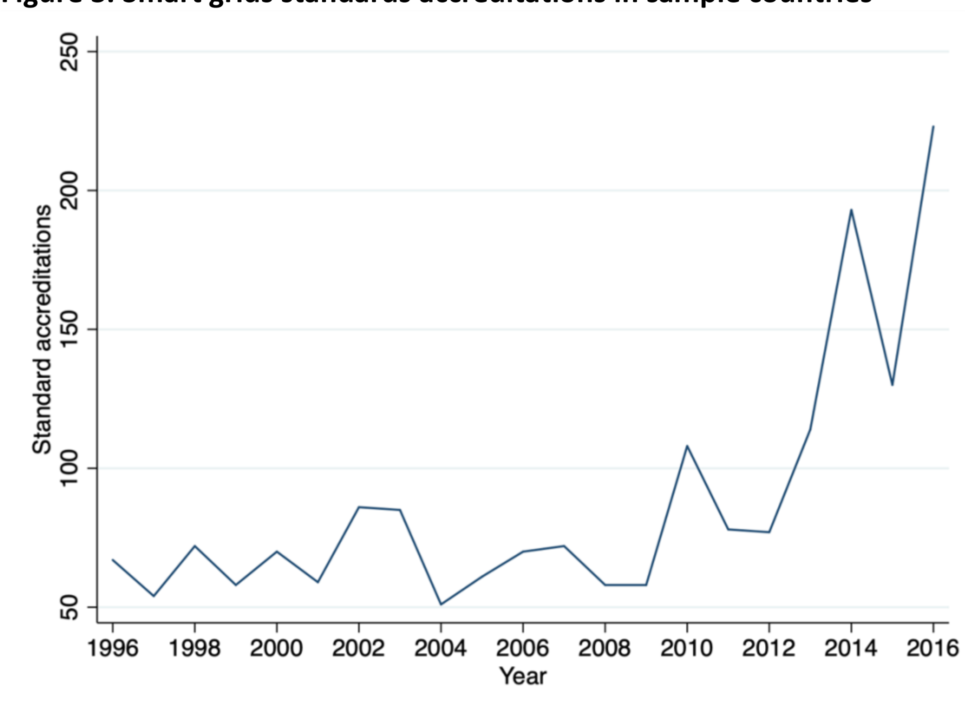
Figure 2. Patenting trends in select markets



In these markets, patenting increases rapidly starting in the mid-2000s and peaks in the years 2010-2011-2012, depending on the country. The subsequent decrease in patenting activity is more pronounced in Japan and Korea[20].

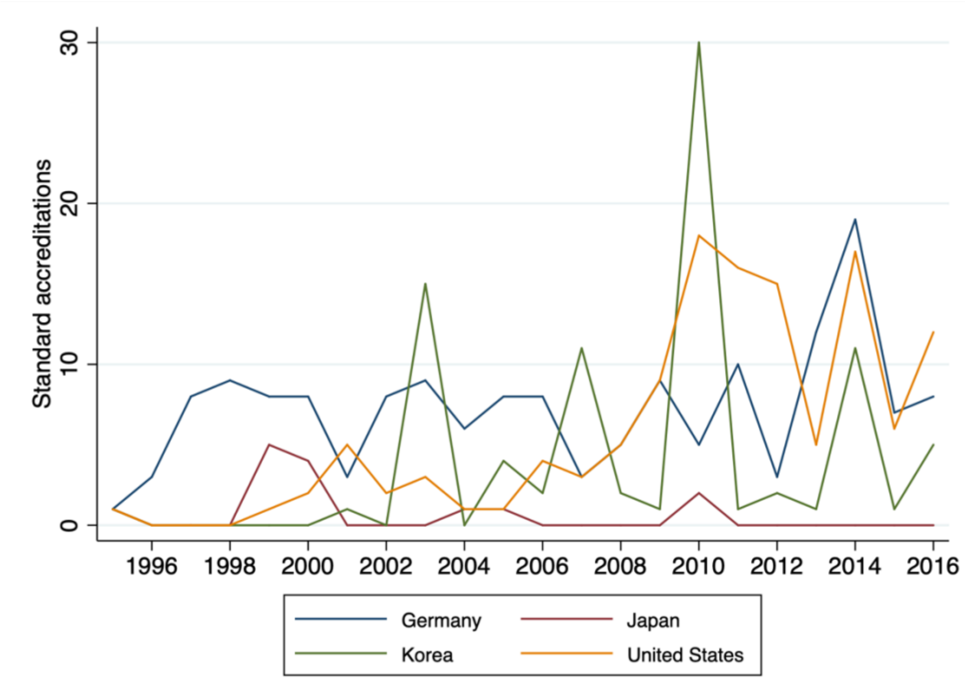
Standards accreditations peak later than smart grids patenting. Figure 3 shows the annual count of standard accreditations in our sample countries. Because we are interested in the timing at which different countries have accredited different standards, in this figure we count standard accreditations at the country level[21]. When decomposing trends in standardization in select key markets, we observe high variation in the timing of accreditation of standards across countries. Figure 4 shows the count of standards accreditation for the years 1996-2016 in the United States, Germany, Japan and Korea.

Figure 3. Smart grids standards accreditations in sample countries



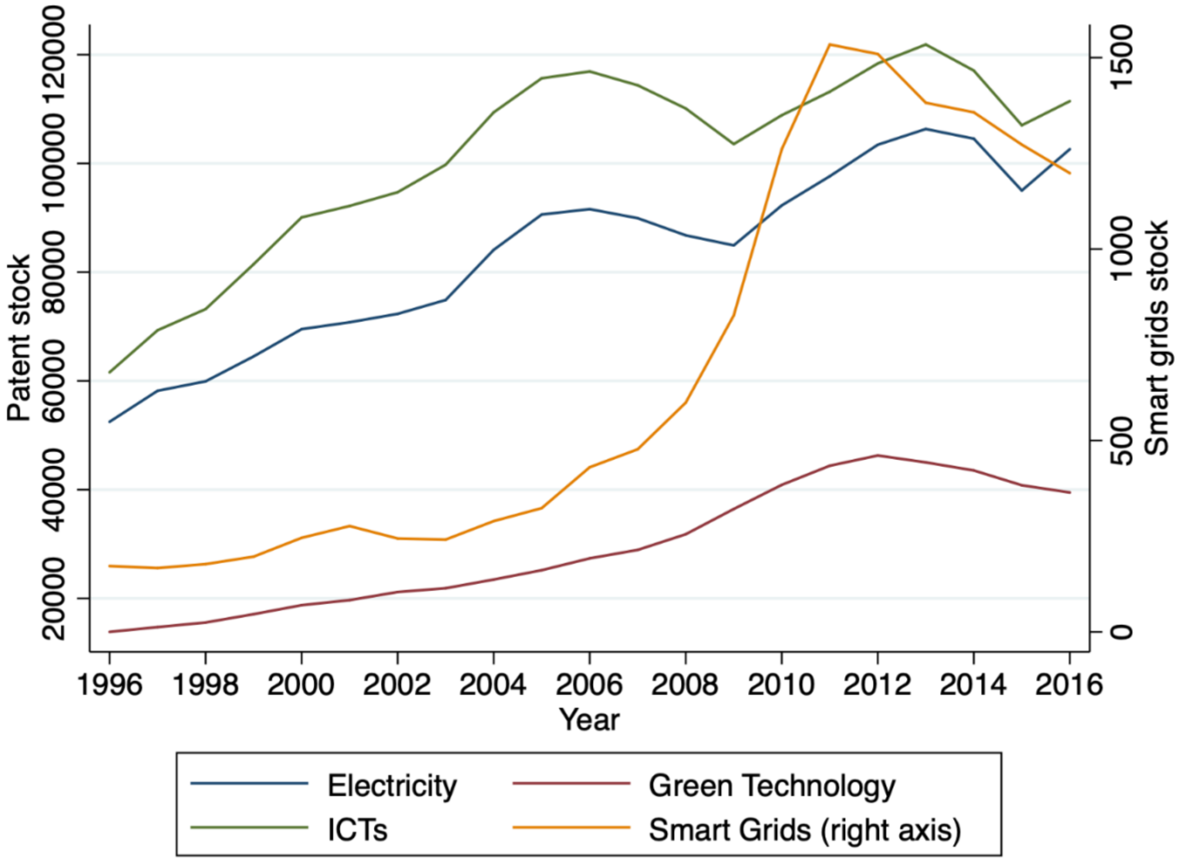
[20] Country-level counts of patents in Figures 1 and 2 were computed using the country of the inventor and weighted for the number of inventors on a patent. These counts only include granted patents.
[21] Each time a country accredits a standard, it gets counts as one. If a same standard was accredited in different countries (in the same or in a different year), it is counted multiple time.

Figure 4. Smart grids standards accreditations in select markets



Our final descriptive statistics show how knowledge stocks in smart grids compare to knowledge stocks in other relevant technological domains. Conceptually, these external stocks capture the pool of knowledge that has accumulated in a given year, and that is available for inventors to built on. Knowledge stocks in smart grids (right axis) are modest relative to larger, more mature industries. However, smart grids is a sector of technology that draws on knowledge from various areas of technology. Figure 5 shows that the pool of relevant knowledge from other sectors upon which smart grids inventors may draw is much larger. It also shows that these knowledge stocks experienced a spurt in the mid-2000s and again in the early 2010s in electricity and information technologies. As expected, knowledge stocks in green innovation have increased steadily between 2000-2016, with a period of more rapid growth around the time of the Great Recession stimulus programs. Consistent with figures 1 and 2, the smart grids knowledge stocks see rapid growth in the past decade.

Figure 5. Country-level knowledge stocks in sample countries[22]



Results and discussion

<u>Zero-inflated model</u>

Our main model uses zero-inflated Poisson regression on an unbalanced panel, to account for firms' different timing of entry and exit from the market. To control for firm-level unobservable heterogeneity, we use firms' average annual count of patents in the pre-sample period to proxy for fixed effects, along with a dummy identifying firms that were inactive in the pre-sample period. The ZIP model first estimates the probability that a firm will patent in a given year (extensive margin), and conditional on whether the firm is likely to patent that year, it estimates the effect of our explanatory variables on the firms' level of patenting (intensive margin). The coefficients from the extensive margin reveal the probability that the firm has zero patents. We use this model as our main specification because of the nature of our data. Our sample contains a majority of small firms that scantly patent, and therefore our data contains a high volume of excess zeros. A zero-inflated Poisson models assumes these excess zeros are generated by a

[22] The patent counts used to construct country knowledge stocks assign patents to countries using information on the location of inventors. Patent counts were also weighted by the number of inventors per patent. Figure 5 shows the sum of country knowledge stocks in our 19 sample countries.

separate process – the decision to patent or not, rather than the decision of how much to patent. In our context, it is more appropriate for explaining the excess zeros for these small infrequent innovators than the alternative fixed effects Poisson and pre-sample means Poisson estimators we present next.

Table 1. Regression results from Zero-inflated Poisson regressions

	Zero-inflated Poisson, unbalanced		**Zero-inflated Poisson, balanced**	
Variables	Intensive margin	Extensive margin	Intensive margin	Extensive margin
Standards	-0.035**	0.015**	-0.035**	0.012
	(0.014)	(0.008)	(0.014)	(0.008)
RD&D smart grid	0.145**	0.019	0.145**	0.056
	(0.063)	(0.036)	(0.063)	(0.036)
RD&D renewables	-0.374***	-0.028	-0.374***	-0.073*
	(0.080)	(0.045)	(0.080)	(0.044)
Int. knowledge stocks – smart grids	0.691***	-1.347***	0.692***	-1.334***
	(0.037)	(0.049)	(0.037)	(0.050)
Int. knowledge stocks – green tech	0.097***	-0.269***	0.097***	-0.228***
	(0.029)	(0.021)	(0.029)	(0.021)
Int. knowledge stocks – electricity	0.023	-0.133***	0.023	-0.105***
	(0.035)	(0.026)	(0.035)	(0.026)
Int. knowledge stocks – ICTs	-0.082***	-0.014	-0.082***	0.010
	(0.031)	(0.022)	(0.031)	(0.022)
Ext. knowledge stocks – smart grids	0.350***	-0.366***	0.350***	-0.248***
	(0.136)	(0.080)	(0.136)	(0.074)
Ext. knowledge stocks – green tech	-0.431***	0.099	-0.431***	0.031
	(0.140)	(0.087)	(0.140)	(0.083)
Ext. knowledge stocks – electricity	-0.343***	0.158**	-0.343***	0.018
	(0.108)	(0.073)	(0.108)	(0.064)
Ext. knowledge stocks – ICTs	0.420***	0.080	0.420***	0.118
	(0.128)	(0.078)	(0.128)	(0.074)
Observations	35,289	35,289	52,428	52,428
Log-likelihood	-58324	-58324	-60254	-60254

Note: The variables RD&D expenditures in grid-related technologies and in renewables technologies are logged and converted into 2015 real USD. All regressions include the firms' average yearly patents in the pre-sample period, a complete set of year dummies and a dummy for firms with no patents in the pre-sample period. The knowledge stocks are logged (after adding 1) and we include dummies for internal knowledge stocks that are equal to zero. Country-level control variables were also weighted and included in all regressions: the share of electricity production from renewables, the growth in electricity consumption, logged household electricity prices (USD/MWh, real 2015 USD) and logged GDP per capita (real 2015 USD). All variables are lagged by 2 time periods. Regressions start in 2000 and end in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

To identify the years in which a firm is active, in the unbalanced panel we use the date of its first and last patent in all relevant technological domains (smart grids, green innovation, electricity, information technologies). We opt for this approach because smart grids are an emergent area of technology and we are interested in capturing effects for firms that are newcomers to this field but have experience innovating in other domains. Table 1 shows regression results for our main model, against results for the same Zero-inflated Poisson model on a balanced panel.

The sign and significance of the coefficient on the standards variables provides some empirical support for our technology lock-in hypothesis. Conditional on patenting, exposure to one additional standard decreases a firm's patenting activity by 3.5 percent. This result is both statistically significant and economically substantial. Our results suggests that more standardization discourage firms from entering the smart grids innovation space (with the caveat that this coefficient is statistically significant only in our unbalanced model). When firms nevertheless enter, standards cause them to reduce their patenting activity. It therefore does not appear that standards provide useful information to industry newcomers that might have helped with overcoming an informational disadvantage from their lack of experience or business relations, nor that standards help reduce uncertainty for inventors already in this space, by giving direction to technology development. It could be that standards merely confirm what has become widely accepted practice by industry actors, and get formalized only after an area of technology has matured. If this were the case, we would see an upward trend in patenting in years prior to standard adoption, with the adoption of standards coinciding with a slowdown in patenting activity. It may also be that standards, if they are overly prescriptive, limit the range of ideas and concepts that inventors set out to test. Firms would not expend resources on R&D for inventions that conflict with prevailing industry standards and stand little chances to be commercialized successfully, unless they think they can dislodge the dominant paradigm. To pinpoint the mechanism that explains our empirical results, in a later part of this section, we present some preliminary analyses of heterogeneous effects for older firms and newer firms. In future iterations of this paper, we intend to conduct further analyses to more directly probe for the mechanisms hypothesized above.

Other noteworthy results from Table 1 include the coefficients on our two other policy variables: public R&D expenditures in grid-related areas and public R&D expenditures in renewable energy. As expected, we find that public investment in areas related to the electrical grid, such as electricity transmission and distribution, has a statistically significant positive effect on patenting activity. We also find that when governments provide more R&D incentives to renewables, patenting activity in smart grids decreases. Taken together, these results are interesting because they are indicative of a tradeoff between R&D in smart grids and R&D in renewables. In other words, there may be competition, rather than complementarities, for allocating R&D investments across the two sectors. It may be that firms that invest in R&D in renewables are the same that do R&D in smart grids technologies. When confronted to the decision of which research to conduct they may have to prioritize one at the expense of the other, and chose the areas in which they can take advantage of government incentives. That public R&D only works at the extensive margin is consistent with this explanation – public R&D investments change the mix of innovation in innovative firms, but are not attracting new innovation in a given technological space.This has important policy implications for overall innovation policy for the decarbonization of energy systems. If there is indeed a tradeoff, policy-makers should be mindful to avoid unintended consequences. The bulk of public support has historically gone to R&D in renewables, which has now reached some degree of maturity. To further integrate renewables and decarbonize energy systems, we also need to develop technologies for integrating renewables on the grid. If the bulk of the support goes to renewables, policies may inadvertently slow down the development of these.

A third set of notable results from Table 1 concern knowledge stocks. As expected, having prior experience patenting in the areas of smart grids and green technology has a positive effect on future patenting. Interestingly, internal knowledge stocks in information technologies is associated with a decrease in patenting activity, whereas external stocks in this same category is associated with an increase in patenting. This suggests that large information technology firms are not the ones doing smart grids R&D, but that when smart grids or green tech firms are surrounded by IT companies, they benefit from knowledge spillovers. In other words, being exposed to large stocks of external IT knowledge might be sufficient to meet the IT knowledge needs of smart grid technology development. External knowledge stocks in smart grids are also positively associated with smart grids patenting, indicating that firms do not only benefit from their own experience in smart grids innovation, but also from the experience of other similar firms that operate in the same national markets. However, the negative and statistically significant coefficients on the green technology and electricity knowledge stocks suggest some possible crowding out of smart grids innovation in markets where many firms are active in these areas of technology.

Overall, our results are robust across both specifications, which indicates that using a balanced panel does not bias results substantially: the ZIP model in and of itself works well at dealing with excess zeros even when we do not correct for some firms entering the market after the start of the sample period or exiting before the end of the sample period.

Pre-sample mean estimator and fixed effects Poisson regressions

Table 2 compares the results from our main zero-inflated Poisson specification with alternative specifications: a pre-sample mean Poisson estimator and a fixed effect Poisson estimator. The pre-sample mean estimator uses the mean of firms' patenting activity in the pre-sample period, along with a dummy variable identifying firms that were inactive in the pre-sample period and a full set of year dummy variables. Generally, the results from this model do not meaningfully differ from the results in our ZIP models, in which we also use the pre-sample mean of the dependent variable to proxy for firm fixed effects. This provides reassurance that the pre-sample mean estimation strategy is robust to using different specifications for dealing with excess zeros and the varying timing of firms' entry and exit in the market. One difference is that our main ZIP models provide more precision on the policy variable RD&D budgets in grid-related technologies.

Table 2. Regression results from pre-sample mean estimator and fixed-effects Poisson

Variables	**Pre-sample mean Poisson**	**Fixed Effects Poisson**
Standards	-0.038***	-0.026*
	(0.012)	(0.014)
RD&D smart grid	0.069	0.035
	(0.056)	(0.097)
RD&D renewables	-0.258***	-0.019
	(0.070)	(0.162)
Int. knowledge stocks – smart grids	0.885***	-0.442***
	(0.035)	(0.120)
Int. knowledge stocks – green tech	0.236***	0.102
	(0.027)	(0.152)
Int. knowledge stocks – electricity	0.091***	0.223*
	(0.035)	(0.115)
Int. knowledge stocks – ICTs	-0.053*	0.296**
	(0.032)	(0.121)
Ext. knowledge stocks – smart grids	0.520***	0.423
	(0.128)	(0.289)
Ext. knowledge stocks – green tech	-0.471***	-0.703
	(0.142)	(0.502)
Ext. knowledge stocks – electricity	-0.416***	2.313***
	(0.101)	(0.732)
Ext. knowledge stocks – ICTs	0.466***	0.760
	(0.126)	(0.770)
Observations	52,428	52,428
Log-likelihood		-69537
Pseudo R-squared	0.524	
Number of companies	3,084	3,084

Note: The variables RD&D expenditures in grid-related technologies and in renewables are logged and converted into 2015 real USD. The pre-sample means estimator regression includes firms' average yearly patents in the pre-sample period and a complete set of year dummies. The fixed effect Poisson regression includes firm and year fixed effects. Both models include a dummy for firms with no patents in the pre-sample period. The knowledge stocks are logged (after adding 1) and we include dummies for internal knowledge stocks that are equal to zero. Country-level control variables were also weighted and included in both regressions: the share of electricity production from renewables, the growth in electricity consumption, the logged value of household electricity prices (USD/MWh, real 2015 USD) and the logged value of GDP per capita (real 2015 USD). All variables are lagged by 2 time periods. Regressions start in 2000 and end in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The zero-inflated Poisson model with pre-sample mean and the pre-sample mean Poisson estimator produce consistent results under conditions of weak exogeneity, allowing us to relax the strict exogeneity assumption required by the Poisson fixed effect model. Results from our fixed effects Poisson model confirm our concerns that this model would produce biased results because our knowledge stocks variables violate the strict exogeneity assumption. While the direction and magnitude of our policy variables are not substantially altered, results for our knowledge stocks variables change considerably under the fixed effects model, illustrating the bias that results from requiring strict exogeneity to hold.

Heterogeneous effects

Here we consider the possibility that aggregate estimates conceal differences in the effect of our explanatory variables for different types of firms, which could have important policy implications. For example, it may be that standards help smaller firms or industry newcomers overcome an informational disadvantage and penetrate new technology markets, but that they do not help larger firms or industry incumbents in the same way. Similarly, it may be that government support for R&D is more important in steering the R&D decisions of resource-constrained start-ups and small firms than large firms with substantial R&D budgets. Analyzing heterogeneous effects may also allow us to glean some insights about how knowledge spillovers affect different types of firms: it may be that small firms benefit more from knowledge spillovers in cross-sectional technologies than large firms.

As a preliminary step in our heterogeneity analysis, we compare effects for large firms and small firms. This is a crude categorization of firms, that does not do justice to the multiple dimensions in which firms differ, such as the combination of their size, age, and technological background. For example, it may be particularly interesting to investigate the effects of our policy variables on large electricity incumbents, small IT or green tech start-ups, or on new green tech firms that have grown rapidly. In later iterations of the paper, we will conduct more sophisticated analyses that take these nuances into account.

In the regressions in Table 3, we define large firms as those with more than 100 patents in relevant CPC classes[23] during the period 1977-2016. The distribution of firm size in our sample is highly skewed towards small firms, with the majority (1,908) having fewer than 20 patents in relevant CPC classes. The bulk of patenting activity therefore occurs within large firms. We use our unbalanced zero-inflated Poisson specification on a sample of 687 large firms, and on a sample of 2,387 small firms. We compute results separately, allowing for all the coefficients to vary across the two samples.

This estimation does not allow us to draw conclusions about the effect of standards for small firms, as the estimated coefficients are small and imprecise. It may be that the competing effects of technology lock-in and information cancel each other out for small firms However, our results confirm that standards have a negative effect on the patenting activity of large firms.

[23] We used the same CPC classes as before: smart grids, green energy, electricity, ICTs.

Table 3. Regression results by firm size

	Large firms		Small firms	
Variables	Intensive margin	Extensive margin	Intensive margin	Extensive margin
Standards	-0.054***	0.032**	0.007	0.008
	(0.017)	(0.014)	(0.016)	(0.010)
RD&D smart grid	0.059	0.080	0.231***	0.040
	(0.093)	(0.062)	(0.064)	(0.046)
RD&D renewables	-0.290***	0.012	-0.459***	-0.072
	(0.103)	(0.073)	(0.083)	(0.060)
Int. knowledge stocks – smart grids	0.742***	-1.201***	0.368**	-1.486***
	(0.038)	(0.054)	(0.185)	(0.098)
Int. knowledge stocks – green tech	0.093***	-0.203***	-0.087	-0.163***
	(0.034)	(0.024)	(0.078)	(0.057)
Int. knowledge stocks – electricity	0.070*	0.005	-0.030	-0.280***
	(0.040)	(0.032)	(0.059)	(0.050)
Int. knowledge stocks – ICTs	-0.097**	-0.053*	-0.049	0.013
	(0.038)	(0.028)	(0.058)	(0.047)
Ext. knowledge stocks – smart grids	0.243	-0.165	0.394**	-0.366***
	(0.246)	(0.154)	(0.180)	(0.097)
Ext. knowledge stocks – green tech	-0.368*	0.169	-0.453**	0.036
	(0.211)	(0.148)	(0.211)	(0.110)
Ext. knowledge stocks – electricity	-0.331*	0.216	-0.134	0.206**
	(0.182)	(0.148)	(0.140)	(0.090)
Ext. knowledge stocks – ICTs	0.541***	-0.265*	0.173	0.106
	(0.195)	(0.147)	(0.146)	(0.097)
Number of firms	687	687	2,387	2,387
Observations	11,163	11,163	24,126	24,126
Log-likelihood	-29879	-29879	-26379	-26379

Note: These regressions use the same specification as our main results: zero-inflated Poisson with an unbalanced panel. The variables RD&D expenditures in grid-related technologies and in renewables are logged and converted into 2015 real USD. The regressions include the firms' average yearly patents in the pre-sample period, a complete set of year dummies and a dummy for firms with no patents in the pre-sample period. The knowledge stocks are logged (after adding 1) and we include dummies for internal knowledge stocks that are equal to zero. Country-level control variables were also weighted and included in this regression: the share of electricity production from renewables, the growth in electricity consumption, the log of household electricity prices (USD/MWh, real 2015 USD) and the log of GDP per capita (real 2015 USD). All variables are lagged by 2 time periods. The regression starts in 2000 and ends in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Another intuitive result concerns the effect of government R&D incentives in grid-related technologies. This effect is positive for small firms, which are assumably in greater need of government support. We do not detect an effect for R&D incentives in grid-related technologies in large firms. The effect of public R&D incentives to renewables is negative for both small and large firms. This indicates a possible redirecting of R&D towards renewables at the expense of R&D in smart grids in both small and large firms. We find that this effect is stronger for small firms, which is also tenable and consistent with the previous result: we expect government incentives to have less influence on the R&D investment decisions of large firms.

The heterogeneity analysis also reveals some interesting nuances regarding the effect of knowledge stocks. Internal knowledge stocks in smart grids, green technology and electricity are positive and statistically significant for large firms, whereas electricity internal knowledge stocks were not statistically significant in our aggregate results. This seems to corroborate our expectation that large firms innovating in the smart grids space are electricity sector incumbents. In addition, the negative and statistically significant coefficient on the external knowledge stocks in electricity (only statistically significant for large firms) also suggests these firms may not need knowledge spillovers from other firms, if they already have abundant internal knowledge in this area. Being active in markets where many firms patent in the electricity sector may instead lead to competition and crowding out.

The coefficient on smart grids internal stocks is also of greater magnitude for large firms than in our aggregate results. It is not surprising that large firms have accumulated greater patent stocks upon which they can continue to build. Conversely, the coefficient is of smaller magnitude for small firms. Internal knowledge stocks in smart grids are nevertheless important for small firms. In fact, they are the only internal knowledge stocks that matter at the intensive margin for these firms. However, internal green tech and electricity knowledge does increase entry for small firms. This suggests that small firms are more specialized and less diversified than large firms, and is in accord with our expectations.

Finally, our findings about knowledge stocks in information technologies only hold in the large firm sample: large firms that innovate in the smart grids space are predominantly electricity companies and not IT companies, but they benefit from spillovers from IT companies. It does not appear that small firms benefit from knowledge spillovers from IT companies: it could be that some of these firms are new, highly specialized IT companies that do not need knowledge spillovers in this area. If they are new/small with little accumulated patents, the effect from their internal knowledge stocks in IT technologies may be difficult to detect.

In future iterations of this paper, we intend to probe more directly for the relations hypothesized above. A first step will be to categorize firms in a more sophisticated way. This would enable us to test some of the suppositions made above, for example, about large electricity incumbents, IT start ups or green tech start-ups. To accomplish this, our next steps will involve 1) better identifying the age of the firm and its relevant timing of entry in the smart grids space, and 2) better identifying firms' predominant expertise based on past patenting activity outside of smart grids.

Robustness checks

We verify that our research decisions are not driving the results presented in this paper, especially the assumptions we had to make when building policy weights for firms without pre-sample data, about which depreciation rate is appropriate for the knowledge stocks and which GDP weighting is suitable when accounting for market size in our policy weights. We also test whether our results are robust to using an alternative measure of our standards variable. We find that our results are robust to using different measures for these variables.

The robustness checks presented below use our main specification: an unbalanced zero-inflated Poisson model, with the average pre-sample mean of the dependent variable to proxy for firm fixed effects, a dummy variable that identifies firms with no pre-sample data, and year dummies.

Policy weights

We constructed policy weights based on the ratio of patents a firm has in the markets it patented in during the pre-sample period, in broader relevant categories[24]. It is a feature of the sector we are studying that several firms are too new to have patents prior to 2000. For these firms, we had to make assumptions. In our main specification, we assume that the main markets for these firms are the average markets of all other companies from the same home country for which we have pre-sample data. In this robustness check, we instead assume that those firms conduct all their business in their home country and therefore that only the policies and economic conditions in their home country is relevant. In other words, we assign a weight of one to these companies' home country. Note that some firms drop when conducting this robustness check. Thus, in Table 4 we first verify (columns 3 and 4) that our results hold for our main specification when using this

[24] We use broader categories – smart grids, green innovation, electricity, information technology – because smart grids is a new sector of technology with little patenting activity pre-2000. Using only smart grids patents would not allow us to build the weights.

Table 4. Robustness check: alternative weighting of the policy variables

	Main specification		Main weights on restricted sample		Alternative weights	
Variables	Intensive margin	Extensive margin	Intensive margin	Extensive margin	Intensive margin	Extensive margin
Standards	-0.035**	0.015**	-0.043***	0.018**	-0.021**	0.005
	(0.014)	(0.008)	(0.014)	(0.008)	(0.009)	(0.004)
RD&D smart grid	0.145**	0.019	0.142**	0.016	0.060	-0.001
	(0.063)	(0.036)	(0.067)	(0.037)	(0.042)	(0.018)
RD&D renewables	-0.374***	-0.028	-0.412***	-0.016	-0.237***	0.037
	(0.080)	(0.045)	(0.081)	(0.046)	(0.050)	(0.024)
Int. knowledge stocks – smart grids	0.691***	-1.347***	0.693***	-1.328***	0.713***	-1.354***
	(0.037)	(0.049)	(0.034)	(0.050)	(0.039)	(0.050)
Int. knowledge stocks – green tech	0.097***	-0.269***	0.105***	-0.256***	0.081***	-0.260***
	(0.029)	(0.021)	(0.029)	(0.021)	(0.030)	(0.021)
Int. knowledge stocks – electricity	0.023	-0.133***	0.006	-0.147***	0.040	-0.147***
	(0.035)	(0.026)	(0.038)	(0.027)	(0.036)	(0.027)
Int. knowledge stocks – ICTs	-0.082***	-0.014	-0.074**	-0.006	-0.089**	0.005
	(0.031)	(0.022)	(0.034)	(0.023)	(0.035)	(0.023)
Ext. knowledge stocks – smart grids	0.350***	-0.366***	0.394***	-0.368***	0.205	-0.267***
	(0.136)	(0.080)	(0.148)	(0.090)	(0.174)	(0.091)
Ext. knowledge stocks – green tech	-0.431***	0.099	-0.374***	0.037	-0.212	-0.096
	(0.140)	(0.087)	(0.143)	(0.094)	(0.159)	(0.097)
Ext. knowledge stocks – electricity	-0.343***	0.158**	-0.547***	0.228**	-0.235	0.123
	(0.108)	(0.073)	(0.144)	(0.094)	(0.172)	(0.091)
Ext. knowledge stocks – ICTs	0.420***	0.080	0.557***	0.057	0.341**	0.159*
	(0.128)	(0.078)	(0.156)	(0.096)	(0.149)	(0.096)
Observations	35,289	35,289	33,292	33,292	33,073	33,073
Number of firms	3,084	3,084	2,849	2,849	2,849	2,849
Log-likelihood	-58324	-58324	-53392	-53392	-53493	-53493

Note: All three models use zero-inflated Poisson with an unbalanced panel that accounts for firms' entry and exit years. The variables RD&D expenditures in grid-related technologies and in renewables are logged and converted into 2015 real USD. All regressions include the firms' average yearly patents in the pre-sample period, a complete set of year dummies and a dummy for firms with no patents in the pre-sample period. The knowledge stocks are logged (after adding 1) and we include dummies for internal knowledge stocks that are equal to zero. Country-level control variables were also weighted and included in all regressions: the share of electricity production from renewables, the growth in electricity consumption, the log of household electricity prices (USD/MWh, real 2015 USD) and the log of GDP per capita (real 2015 USD). All variables are lagged by 2 time periods. Regressions start in 2000 and end in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Robustness check: alternative depreciation rate for knowledge stocks

Unbalanced ZIP, 20% depreciation		
Variables	Intensive margin	Extensive margin
Standards	-0.035**	0.016**
	(0.014)	(0.008)
RD&D smart grid	0.144**	0.022
	(0.063)	(0.036)
RD&D renewables	-0.368***	-0.033
	(0.078)	(0.045)
Int. knowledge stocks – smart grids	0.696***	-1.370***
	(0.037)	(0.050)
Int. knowledge stocks – green tech	0.097***	-0.279***
	(0.029)	(0.021)
Int. knowledge stocks – electricity	0.033	-0.137***
	(0.034)	(0.027)
Int. knowledge stocks – ICTs	-0.087***	-0.014
	(0.031)	(0.023)
Ext. knowledge stocks – smart grids	0.330**	-0.363***
	(0.132)	(0.078)
Ext. knowledge stocks – green tech	-0.440***	0.099
	(0.135)	(0.085)
Ext. knowledge stocks – electricity	-0.333***	0.152**
	(0.109)	(0.073)
Ext. knowledge stocks – ICTs	0.438***	0.083
	(0.126)	(0.078)
Observations	35,289	35,289
Log-likelihood	-58075	-58075

Note: This model uses the same specification as our main specification: zero-inflated Poisson with an unbalanced panel that accounts for firms' entry and exit years. The variables RD&D expenditures in grid-related technologies and in renewables technologies are logged and converted into 2015 real USD. The regression includes the firms' average yearly patents in the pre-sample period, a complete set of year dummies and a dummy for firms with no patents in the pre-sample period. The knowledge stocks are logged (after adding 1) and we include dummies for internal knowledge stocks that are equal to zero. Country-level control variables were also weighted and included in this regression: the share of electricity production from renewables, the growth in electricity consumption, the log of household electricity prices (USD/MWh, real 2015 USD) and the log of GDP per capita (real 2015 USD). All variables are lagged by 2 time periods. The regression starts in 2000 and ends in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

smaller sample.[25] Columns 5 and 6 show the effect of alternative weights. The effect of standards is somewhat smaller, with standards decreasing patenting by about 2 percent. The effect at the intensive margin becomes insignificant. The effect of other variables remains similar across specifications.

Depreciation rate

Another research decision we made pertains to the choice of the depreciation rate we apply to our external and internal knowledge stocks variables. In our main specification, we use a 15% depreciation rate, which implies that older patents stay longer in the stocks. In Table 5, we allow knowledge stocks to depreciate faster, at a rate of 20%. Both rates are commonly used in the literature, and using one or the other does not substantively alter our results.

GDP weighting

In our main specification we weight our policy weights by GDP to the power of 0.35, based on Dechezlepretre et al.'s (2021) suggestion that this value fits estimates of the elasticity of exports to GDP of the home country found by Eaton, Kortum, and Kramarz (2011). In Table 6 we weight by simple GDP (e.g. using an exponent of 1), as in Aghion et al. (2016). This alternative GDP weight places more importance on the size of each market. This changes the magnitude of our coefficients but does not alter our results meaningfully, as the signs and significance levels of our variables remain unchanged. The one exception is the effect of standards at the extensive margin, which is estimated less precisely and becomes insignificant.

Cumulative stocks

Finally, in Table 7 we conduct a robustness check using an alternative measure of our standards explanatory variables: a cumulative count of standards. Instead of capturing response to the addition of one standard, the model below captures patenting response to the entire stock of standards – or overall level of standardization – in a country in a given year. Again, except for the extensive effect of standards, using this measure does not alter our results in a meaningful way.

[25] When assuming firms with no pre-sample data only operate in their home country, some firms drop from the data set for two reasons. First, we have a minority of firms for which the home country is outside of our sample countries. Those firms were included in our sample in our main specification because they had granted patents in some of our sample countries and we assigned them the average weights from firms from the same home country for which we had pre-sample data. Therefore, in our main specification, some of the weights we have for these firms are in our sample countries. However, these firms drop when we assign their home country to be their only market. The second reason why some firms drop out of the sample in this robustness check is due to missing values in our electricity price variable. We are missing values for Sweden for the years 1998-2006 and for Australia for the year 2005-2011. In the main specification, our weighting ignores the missing values when computing the weighted average price for a firms' markets. We are therefore nevertheless able to construct a value for electricity price for these firms. In our robustness check, we have missing values for companies from Australia and Sweden for these years. We therefore drop these firms altogether from the robustness check.

Table 6. Robustness check: alternative GDP weighting for policy weights

	Unbalanced ZIP, alternative GDP weight	
Variables	Intensive margin	Extensive margin
Standards	-0.052***	0.013
	(0.019)	(0.010)
RD&D smart grid	0.263***	0.015
	(0.080)	(0.046)
RD&D renewables	-0.565***	-0.049
	(0.099)	(0.057)
Int. knowledge stocks – smart grids	0.669***	-1.359***
	-0.031	(0.049)
Int. knowledge stocks – green tech	0.098***	-0.264***
	(0.028)	(0.021)
Int. knowledge stocks – electricity	0.039	-0.143***
	(0.033)	(0.026)
Int. knowledge stocks – ICTs	-0.090***	-0.008
	(0.030)	(0.022)
Ext. knowledge stocks – smart grids	0.427***	-0.429***
	(0.129)	(0.069)
Ext. knowledge stocks – green tech	-0.558***	0.172**
	(0.140)	(0.084)
Ext. knowledge stocks – electricity	-0.325***	0.152**
	(0.106)	(0.067)
Ext. knowledge stocks – ICTs	0.445***	0.094
	(0.120)	(0.078)
Observations	35,289	35,289
Log-likelihood	-57925	-57925

Note: This model uses the same specification as our main specification: zero-inflated Poisson with an unbalanced panel that accounts for firms' entry and exit years. The variables RD&D expenditures in grid-related technologies and in renewables are logged and converted into 2015 real USD. The regression includes the firms' average yearly patents in the pre-sample period, a complete set of year dummies and a dummy for firms with no patents in the pre-sample period. The knowledge stocks are logged (after adding 1) and we include dummies for internal knowledge stocks that are equal to zero. Country-level control variables were also weighted and included in this regression: the share of electricity production from renewables, the growth in electricity consumption, the log of household electricity prices (USD/MWh, real 2015 USD) and the log of GDP per capita (real 2015 USD). All variables are lagged by 2 time periods. The regression starts in 2000 and ends in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Robustness check: alternative measure of the standards variable

Unbalanced ZIP, cumulative count of standards		
	Intensive margin	Extensive margin
Standards (cumulative)	-0.012***	0.000
	(0.003)	(0.002)
RD&D smart grid	0.146**	0.008
	(0.061)	(0.036)
RD&D renewables	-0.453***	-0.026
	(0.080)	(0.047)
Int. knowledge stocks – smart grids	0.687***	-1.345***
	(0.037)	(0.049)
Int. knowledge stocks – green tech	0.100***	-0.268***
	(0.029)	(0.021)
Int. knowledge stocks – electricity	0.027	-0.132***
	(0.036)	(0.026)
Int. knowledge stocks – ICTs	-0.086***	-0.016
	(0.031)	(0.022)
Ext. knowledge stocks – smart grids	0.267**	-0.369***
	(0.132)	(0.081)
Ext. knowledge stocks – green tech	-0.342**	0.091
	(0.142)	(0.089)
Ext. knowledge stocks – electricity	-0.283**	0.167**
	(0.110)	(0.074)
Ext. knowledge stocks – ICTs	0.361***	0.081
	(0.136)	(0.080)
Observations	35,289	35,289
Log-likelihood	-58236	-58236

Note: This model uses the same specification as our main specification: zero-inflated Poisson with an unbalanced panel that accounts for firms' entry and exit years. The variables RD&D expenditures in grid-related technologies and in renewables technologies are logged and converted into 2015 real USD. All regressions include the firms' average yearly patents in the pre-sample period, a complete set of year dummies and a dummy for firms with no patents in the pre-sample period. The knowledge stocks are logged (after adding 1) and we include dummies for internal knowledge stocks that are equal to zero. Country-level control variables were also weighted and included in all regressions: the share of electricity production from renewables, the growth in electricity consumption, the log of household electricity prices (USD/MWh, real 2015 USD) and the log of GDP per capita (real 2015 USD). All variables are lagged by 2 time periods. Regressions start in 2000 and end in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Conclusion

The primary goal of this paper is to quantify the effect of interoperability standards on patenting activity. Our focus on standards is motivated by the unique challenges faced by the next generation of technologies for decarbonizing electricity systems. Smart grid technologies can help grid operators grapple with growing load management challenges from climate change and intermittent renewable sources. To unlock potential network externalities, these technologies will need to be compatible. Standards are one tool policymakers can use to give direction to technology development to facilitate interoperability. In this paper we find that, on the contrary, standards decrease patenting activity in smart grids. We hypothesize that this occurs through a technology lock-in mechanism. However, this does not necessarily imply that standards are detrimental to innovation in general. It may be that standards have different effects at different stages of the innovation process. For example, while standards slow down patenting activity, on the flip side, it could be that they accelerate the deployment of technologies. Considerations of the tradeoffs between technology development and diffusion, and of the optimal timing for introducing standards during the innovation process, is paramount for policy and left for future research.

A second notable finding from this paper concerns the tradeoff between public R&D incentives in grid-related technologies and in renewables. This finding has important policy implications. As renewable energy technologies mature –after receiving substantial support in their infancy stage and beyond -policy makers may want to make decisions about which nascent technologies they should support next to meet the future needs of the energy transition. If there are tradeoffs between R&D incentives to smart grids and renewables to the extent that public investment in one might undermine innovation in the other, policy-makers should proceed with caution when deciding how to allocate public R&D resources and choosing when the time is ripe to transition resources from one area to the other.

Finally, the literature on smart grids innovation is scarce, and little is known about the inventors active in this space. We find that there is a heterogeneous mix of small and large firms, new and established firms, and firms from varied technological backgrounds. We glean further insights from analyzing the effect of internal and external stocks on the patenting activities of these firms. Because smart grids innovation - as a cross-sectoral area of technology - requires drawing on knowledge from diverse fields, we look beyond knowledge stocks in smart grids and include knowledge stocks in an array of broader technological domains. We find that firms who innovate in this space do not necessarily have prior experience in information technologies, as long as they can benefit from knowledge spillovers from IT firms. Our results also suggest that there is crowding out of smart grids innovation in markets where many firms innovate in green tech. Moving forward, we will conduct heterogeneity analyses to gain further insights into which knowledge stocks matter for different types of firms, and to better understand the effect of our policy variables on different firm profiles. This may provide insights that are relevant for policy. Policy-makers may be interested in learning which firms benefit most from certain policy interventions and how to tailor policy to different types of firms to achieve desired innovation outcomes. For example, governments may be concerned with attracting and supporting new entrants in this space. They may be concerned with effectively targeting which start-up companies have the potential to become trailblazers in this space, or how they might incentivize large electricity incumbent firms to do more R&D in this area. The analyzes we intend to conduct moving forward may provide some insights relevant to these questions.

Bibliography

Acemoglu, Daron, Philippe Aghion, Leonardo Burszty and David Hemous. (2012). "The Environment and Directed Technical Change". *American Economic Review*, 102(1): 131-166.

Aggarwal, N. Q. Dai and E. Walden. (2011). "The more the merrier? How the number of partners in a standard-setting initiative affects shareholders' risk and return." *MIS Quarterly*, 35(2): 445-462.

Aghion, Philippe, Antoine Dechezleprêtre, David Hémous, Ralf Martin and John Van Reenen. (2016). "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry". *Journal of Political Economy,* 124(1).

Baicker, Katherine, and H. Levy. (2013) "Coordination versus competition in health care reform" *The New England journal of medicine,* 369(9): 789-791.

Baron, Justus and Daniel F. Spulber. (2018). "Technology Standards and Standard Setting Organizations: Introduction to the Searle Center Database". *Journal of Economics and Management Strategy*, 27(3): 462-503.

Baron, Justus and Julia Schmidt. (2019). "Technological Standardization, Endogenous Productivity and Transitory Dynamics". Banque de France Working Paper no.503.

Baron, Justus and Tim Pohlmann. (2018). "Mapping standards to patents using declarations of standard-essential patents". *Journal of Economics and Management Strategy*, 27(3): 504-534.

Brown, A, and R Salter. (2010) "Smart Grid Issues in State Law and Regulation." *Galvin Electricity Initiative*, 17.

Brown, Marilyn A., Shan Zhou and Majid Ahmadi. (2018). Smart grid governance: An international review of evolving policy issues and innovations. *WIREs Interdisciplinary Reviews: Energy Environment,* 7(5):e290

Calel, Raphael and Antoine Dechezleprêtre. (2016). "Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market". *The Review of Economics and Statistics, 91(1):* 173-191.

Coelli, F., Moxnes, A., and Ulltveit-Moe, K. (2022). Better, faster, stronger: Global innovation and trade liberalization. Forthcoming in *The Review of Economics and Statistics*.

Dantas, Guilherme de A. , Nivalde J. de Castro, Luis Dias, Carlos Henggeler Antunes, Pedro Vardiero, Roberto Brandao, Rubens Rosental, Lucca Zamboni. (2018) "Public policies for smart grids in Brazil". *Renewable and Sustainable Energy Reviews,* 92: 501-512.

De Castro, Luciano and Joisa Dutra. (2013). "Paying for the smart grid". *Energy Economics* 40: S74-S84.

Dechezleprêtre, Antoine, David Hémous, Morten Olsen and Carlo Zanella. (2021). "Induced Automation: Evidence from Firm-Level Patent Data". *University of Zurich, Department of Economics, Working Paper No.384.*

DeVries, H.J. (1999). *Standardization – A business Approach to the Role of National Standardization Organizations Kluwer Academic Publishers*, Boston, Dordrecht, London.

Eaton, J., Kortum, S., and Kramarz, F. (2011). An anatomy of international trade: evidence from French firms. *Econometrica*, 79(5):1453-1498.

Energy Independence and Security Act (EISA), H.R. 6, 110th Cong. (2007). https://www.congress.gov/bill/110th-congress/house-bill/6/text

Fabrizi, A., G. Guarini, and V. Meliciani. 2018. “Green Patents, Regulatory Policies and Research Network Policies.” *Research Policy*. 47: 1018-1031.
Ho, Jae-Yin and Eoin O’Sullivan. (2017). “Strategic standardisation of smart systems: A roadmapping process in support of innovation.” *Technological Forecasting and Social Change*, 115: 301-312.
IEA 2021. “Patents and the energy transition.” Paris, International Energy Agency.
IEA/NEA. 2020. “Projected costs of generating electricity, 2020 Edition”. Paris: International Energy Agency and Nuclear Energy Agency.
Iqtiyanillham, Nur, M. Hasanuzzaman and Hosenuzaman, M. (2017). “European smart grid prospects, policies and challenges”. *Renewable and Sustainable Energy Reviews,* 67: 776-790.
Johnstone, Nick, Ivan Haščič and David Popp (2010). “Renewable Energy policies and Technological Innovation: Evidence Base on Patent Counts”. *Environmental and Resource Economics* 45(1): 133-155.
Katz, M.L. and C. Shapiro.(1985). “Network externalities, competition, and compatibility.” *American Economic Review*, 75(3): 424-440.
KSGI. (2010). "Korea's Smart Grid Roadmap 2030: Laying the Foundation for Low Carbon, Green Growth by 2030". *Ministry of Knowledge Economy and Korea Smart Grid Institute.*
Lammers, Imke and Michiel A. Heldeweg. (2016). “Smart design rules for smart grids: analysing local smart grid development through an empirico-legal institutional lens” *Energy, Sustainability and Society*, 6:36
Lazkano, Itziar, Linda Nøstbakken and Martino Pelli (2017). “From Fossil Fuels to Renewables: The Role of Electricity Storage”. *European Economic review 99:* 113-129.
Lerner, J. and J. Tirole. (2015). “Standard-essential patents”. *Journal of Political Economy*, 123(3): 547-586.
Lin, Chen-Chun, Chian-Han Yang and Joseph Z. Shyua. (2013).” A comparison of innovative policy in the smart grid industry across the pacific: China and the USA”. *Energy Policy* 57:119-132.
Lowry, M., M. Makos and J. Deason. (2017). “State Performance-Based regulation Using Multiyear Rate Plans for U.S. Electric Utilities”. Lawrence Berkeley National Laboratory, Report Prepared for the U.S. Department of Energy.
Mandel, Benjamin H. (2015). “The Merits of an ‘Integrated’ Approach to Performance-Based Regulation”. *The Electricity Journal, 28(4): 8-17.*
Marku, Elona and Maryia Zaitsava. (2018). “Smart Grid Domain: technology structure and innovation trends”. *International Journal of Economics, Business and Management Research* 2(4): 390-403.
Marques, Vítor, Nuno Bento and Paulo Moisés Costa. (2014). “The ‘Smart Paradox’: Stimulate the deployment of smart grids with effective regulatory instruments”. *Energy*, 69: 96-103.
Martinot, Eric. (2016). “Grid Integration of Renewable Energy: Flexibility, Innovation, and Experience”. *Annual Review of Environmental Resources* 41:223-51.
Muench, Stefan, Sebastian Thuss and Edeltraud Guenther (2014). “What hampers energy system transformations? The case of smart grids”. *Energy Policy,* 73: 80-92.
Newell, Richard and Adam Jaffe. (1999). “The Induced Innovation Hypothesis and Energy-Saving Technological Change”. *The Quarterly Journal of Economics,* 114(3): 941-975.

Noally, Joëlle and Roger Smeets. (2015). “Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level patent data”. *Journal of Environmental Economics and Management, 72(C): 15-37.*

Palensky, Peter and Friederich Kupzog. (2013). “Smart Grids”. *Annual Review of Environment and Resources* 38:201-226.

Popp, David. (2002) “Induced Innovation and Energy Prices”. *American Economic Review*, 92(1): 160-180.

Popp, David. (2010). “Innovation and Climate Policy”. *Annual Review of Resource Economics,* 2: 275-298.

Popp, David. (2016). Economic analysis of scientific publications and implications for energy research and development”. *Nature Energy*, 1(4): 1-8.

Popp, David (2019). “Environmental Policy and Innovation: A Decade of Research”. NBER Working Paper 25631.

Popp, David, Jacquelyn Pless, Ivan Hascic and Nick Johnstone (2020) “Innovation and Entrepreneurship in the Energy Sector”, in Aaron Chatterji et al. *The Role of Innovation and Entrepreneurship in Economic Growth*. University of Chicago Press.

Rozendaal, Rik L. and Herman Vollebergh. (2021). “Policy-induced Innovation in Clean Technologies: Evidence from the Car Market”. CESifo Working Paper 9422-2021.

Rysman, M. and T. Simcoe. (2008). “Patents and the performance of voluntary standard-setting organizations”. *Management Science,* 54(11): 1920-1934.

SCC. (2012). “The Canadian Smart Grid Standards Roadmap: A strategic planning document”. *CNC/IEC Task Force on Smart Grid Technology and Standards*.

Schmidt, Julia and Walter Steingress. (2019). “No Double Standards: Quantifying the Impact of Standard Harmonization on Trade”. Banque de France Working Paper No. 729.

Schwister, Fabian and Marina Fieder. (2015). “What are the main barriers to smart energy information systems diffusion?” *Electron. Markets* 25: 31-45.

Spulber D. (2008). “Consumer coordination in the small and in the large: implications for antitrust in markets with network effects.” *Journal of Competition Law and Economics,* 4(2): 207-262.

Stephens, Jennie C. , Elizabeth J. Wilson, Tarla R. Peterson and James Meadowcroft. (2013). “Getting Smart? Climate Change and the Electric Grid”. *Challenges, 4:* 201-216.

Swann, Peter G. M. (2000). “The Economics of Standardization”, *Manchester Business School, Final Report for Standards and Technical Regulations Directorate Department of Trade and Industry*, 57p.

Tassey, Gregory. (2000). “Standardization in Technology-Based Markets” *Research Policy,* 29(4): 587-602.

Tomain, Joseph P. (2012). “Smart Grid, Clean Energy and US Policy”. *Competition and Regulation in Network Industries,* 13(2): 187-211.

VDE/DKE. (2010). “The German Standardization Roadmap E-Energy/Smart Grid”. German Commission for Electrical, Electronic and Information Technologies of DIN and VDE.

Winfield, Mark and Scott Weiler. (2018). “Institutional diversity, policy niches, and smart grids: A review of the evolution of Smart Grid policy and practice in Ontario, Canada”. *Renewable and Sustainable Energy Reviews,* 82: 1931-1938.

Annex 1. Sectors of smart grids technologies

Technology	Corresponding patent class (Cooperative Patent Classification)
Systems integration and efficiency	Y02E 40/70: Smart grids as climate change mitigation technology in the energy generation sector. Y04S 10/00: Systems supporting electrical power generation, transmission or distribution (and all its subclasses: 10/12, 10/123, 10/126, 10/14, 10/16, 10/18, 10/20, 10/22, 10/30, 10/40, 10/50, 10/52)
Smart grids in buildings	Y02B 70/30: Systems integrating technologies related to power network operation and communication or information technologies for improving the carbon footprint of the management of residential or tertiary loads, i.e. smart grids as climate change mitigation technology in the buildings sector(…) (and all of its subclasses: 70/3225, 70/34) Y02B 90/20: Smart grids as enabling technology in the buildings sector.(This category overlaps with Y04 S 20*)
ICTs applications to smart grids	Y04S 40/00: Systems for electrical power generation, transmission, distribution or end-user application management characterised by the use of communication or information technologies, or communication or information technology specific aspects supporting them (and all of its subclasses: 40/12, 40/121, 40/124, 40/126, 40/128, 20/18, 40/20). Y04S 50/00: Market activities related to the operation of systems integrating technologies related to power network operation and communication or information technologies (and all of its subclasses: 50/10, 50/12, 50/14, 60/16).
End-user applications	Y02S 20/00: Systems supporting the management or operation of end-user stationary applications, including also the last stages of power distribution and the control, monitoring or operation of management systems at the local level (and all of its subclasses: 20/12, 20/14, 20/20, 20/221, 20/222, 20/242, 20/244, 20/246, 20/248, 20/30).

*Note: these definitions are from the European Patent Office's Cooperative Patent Classification. A patent can be tagged under multiple categories. In most cases, the broad sectors of technology are enough to capture all the sub-classes under which a patent is tagged. When it is not the case, and a patent is tagged under 2 distinct sectors of technology, the patent will count as 1 in each category (i.e. it will be counted twice, for example, as an innovation in buildings and an innovation in ICTs, and included in the patent count of each of the two regressions). The full definitions of the CPC scheme may be found here: https://www.cooperativepatentclassification.org/cpcSchemeAndDefinitions/table