Do Technology Standards Induce Innovation in Environmental Technologies When Coordination is Important?

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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 government may support the development and deployment of these 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 the next wave of green innovation since those face higher coordination bottlenecks. We investigate the effects of interoperability standards - an instrument that may facilitate coordination - on patenting using smart grid as an example of a technology that has high interoperability requirements. We find that standards decrease patenting at the extensive and intensive margins, but these results vary across types of firms. We find that this negative effect is driven by large firms, whereas standards increase entry by firms without prior smart grid innovation experience. We interpret this result as an information effect: standards provide useful information to new entrants and may help diversity the range of players innovating in this space.

Acknowledgement

The authors thank Julia Schmidt for sharing her expertise and resources for preparing the standards data, Antoine Dechezleprêtre, Tobias Schmidt, participants at the Spring and Fall 2022 NBER Economics of Innovation in the Energy Sector workshops and participants at the APPAM Fall 2022 research conference for useful comments and suggestions. The authors thank the Searle Centre on Law, Business and Economics for providing access to their database on Technology Standards and Standard-Setting Organizations.

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1.Introduction

Many challenges remain to deploy low-carbon energy at a scale necessary to meet net-zero emission targets by 2050 (Popp et al., 2022). The past two decades have seen a dramatic decline in the cost of solar and wind power generation. In many locations, these technologies are now cost-competitive with fossil fuel generation (IRENA, 2022). Despite these advances, renewable energy technologies have yet to be deployed vastly. Important bottlenecks stand in the way of large-scale adoption because the electrical grid was not designed to accommodate a growing share of intermittent distributed generation. A new wave of green energy innovation that includes complementary technologies to enable the integration of renewables into the grid is needed for continued progress towards decarbonization (Popp et al., 2022).

The International Energy Agency (IEA) estimates that half of the technologies needed to achieve net-zero goals by 2050 in highly polluting sectors such as heavy industry, transportation and electricity generation are still in early stages of development (IEA, 2021). What is needed is not just more innovation, but advances in new sectors of green energy technology (Popp et al., 2022). One of these areas is smart grid technology. These have the potential to radically transform the model of the grid into a network that is decentralized, digitalized, leverages big data analytics and artificial intelligence to automate grid management decision (Colak et al., 2016; Lopes et al., 2020). Such features would be pivotal in enabling a suite of other flexibility tools - such as microgrids, vehicle to grid applications, and demand response – to enhance grid reliability and resilience (Martinot, 2016).

Market failures, such as environmental externalities and knowledge spillovers, affect all types of green innovation (Popp, 2019). Smart grid technology development faces additional bottlenecks in the form of coordination dilemmas. Smart grid devices are networked technologies and must therefore be interoperable (Brown et al., 2018). Policies that have been shown to promote patenting in solar and wind, such as R&D subsidies, consumer subsidies, carbon taxes/energy prices and emissions trading schemes, may not be sufficient to overcome the coordination challenges endemic to the next wave of innovation in enabling technologies.

We study the effects of technology standards - as a possible coordination device for technology selection - on patenting. Technology standards have been under-studied in the literature on green innovation, despite being one of few instruments promoted by governments to specifically support complementary grid technologies. In the aggregate, we find that interoperability standards decrease both the likelihood that a firm develops a smart grid patent in a given year (the extensive margin) and how much it patents in that same year (the intensive margin). This suggests that standards endorse already existing technology and leaves open the question of whether standards affect the quality of innovation through focusing technology selection. In addition, firms that innovate in this space are diverse in terms of age, size and technological backgrounds. We further investigate heterogeneous effects and find that standards facilitate the entry of new inventors. We interpret this result as an information effect: standards provide know-how about accepted practices and technical specifications that would otherwise only be available to industry insiders.

2. Motivation and context

2.1 Transforming electricity systems: building a smarter grid to integrate renewables

Energy systems are undergoing profound socio-technological transformations, which may eventually displace the prevailing top-down model of electricity generation, transmission, and distribution (Stephens et al., 2013). Radical changes have unfolded in electricity systems over the past two decades, calling for more decentralized and digitalized grid networks. Technological advances and green energy policies enabled the deployment of distributed renewable electricity generation. Electricity is now produced in a more decentralized way by facilities of various scales operating in both wholesale and retail markets. This has in turn diminished utilities' control over the supply of electricity because intermittent sources are not as readily dispatchable as conventional electricity (Martinot, 2016). Matching the supply and demand for electricity has become a more involved task, requiring greater flexibility in the management of grid operations (Martinot, 2016; NREL, 2015). During the same period, the consequences of climate change have become increasingly visible. More frequent and acute weather spells further aggravate these grid stability challenges (Martinot, 2016; Palensky and Kupzog, 2013; Stephens et al., 2013). As these challenges become more severe, the need for greater flexibility in the management of grid operations will become more pressing. In fact, the IEA estimates that hour-to-hour grid flexibility needs will quadruple by 2050 (IEA, 2021).

Smart grid technologies will be instrumental in increasing grid resilience and maintaining reliable service in the face of these challenges (Brown et al., 2018). A smart grid would be more effective at coordinating the activities of a multitude of independent actors that operate on the grid, forecasting the supply and demand for electricity, monitoring grid conditions, detecting faults and automating some grid management decisions (Brown et al., 2018; Palensky and Kupzog, 2013). Building a smarter grid implies developing and deploying both hardware and software to collect and utilize highly granular power data in applications that help the grid operate more efficiently (Colak et al., 2016; IEA, 2022; Lopes et al., 2019). Smart grids encompass a range of technologies that include - but are not limited to - smart meters, remote and automated sensing, smart switching, phasor measurement units, hierarchical or distributed control architectures and an array of big data analytics and artificial intelligence applications (Brown et al., 2018; Palenski and Kupzog, 2013;

Lee et al., 2017; Syed et al., 2020). Moving forward, advances in technologies such as the internet of things, cloud computing, 5G networks, artificial intelligence and data analytics are expected to lead to further disruptive innovation in this sector (IEA, 2021). Furthermore, a smart grid is vital to enable a suite of other grid flexibility tools such as grid-integrated smart vehicle charging, responsive load, distributed energy storage, and microgrid islanding (Martinot, 2016).

To achieve the promise of a smarter, more flexible and reliable electrical grid, large scale deployment of smart grid devices will be required. This will necessitate investments by various actors at different locations on the grid, especially as power generation and distribution becomes more decentralized. If smart grids devices are installed across the grid at the requisite scale, it may unlock important networks externalities. As more users adopt these technologies, more data will be exchanged, increasing the usefulness of smart grid devices (Katz and Shapiro, 1985). This may in turn enable the further development of inventions that leverage these data (examples of smart grid technologies at different levels of maturity, including possible future applications, are included in Appendix A1). Achieving this will require coordination to overcome bottlenecks in both technology development and deployment.

2.2. Barriers to smart grid technology development: the challenges of interoperability and of interdisciplinarity

Smart grid devices are networked technologies. They are deployed within a grid system that interconnects devices operated by different actors. As is common with networked technologies, particularly in the information technology sector, these devices must be interoperable (Baron and Spulber, 2018). This raises additional coordination dilemmas for technology development, especially during the early stages. Inventors face uncertainty about which technical specifications or conventions the market will select. In the area of smart grids, such conventions relate to wireless communication protocols, data architecture, and data encryption protocols, for example. For inventors, this uncertainty raises risks that their products may not be compatible with other devices on the market, which could impede their commercial success. For users, this uncertainty may raise the risk of stranded assets, this is, the risk of purchasing smart grid devices that become obsolete as technology evolves (Stephens et al., 2013; Schwister and Fiedler, 2015). This illustrates how uncertainty on the demand side not only affects technology development, but also technology deployment. In addition, power utilities, as potential key users of these smart grid technologies, are notoriously risk-averse (Brown et al., 2018) and under current electricity rate-making regulations, have little incentives to invest in smart grid devices because they are limited in their ability to recover costs while facing declining revenues (Lowry et al., 2017, Mandel, 2015, Marques et al., 2013; Schwister and Fiedler, 2015; Brown et al., 2018; De Castro and Dutra, 2013). All these factors contribute to suppressing demand for smart grid products, which may in turn quell R&D investment levels in this area.

Smart grid technologies are also cross-sectoral and embed specialized knowledge from multiple technological domains. For example, developing technologies for grid network automation requires expertise in both industrial engineering and information engineering (Ghiani et al., 2018). Emerging computer engineering technologies such as the internet of things, cloud computing, 5G networks, artificial intelligence and big data analytics have the potential to be disruptive in the energy sector (IEA, 2021). Smart grid technologies combine knowledge from these frontier areas with expertise in electrical and electronic engineering. Having experience in several complementary technology domains and the ability to broker knowledge across different fields may help inventors be successful at innovating in this space. Because combining knowledge from diverse fields is both important and challenging, in this paper we provide insights about what experience is needed to innovate in smart grids, as well as what kind of external knowledge is helpful to inventors.

2.3 Interoperability standards as a tool for overcoming coordination dilemmas?

The coordination dilemmas discussed previously suggest policy should play an important role for supporting technology development in smart grids. Many of the policy tools that make up the renewable energy policy mix, such as taxes, R&D subsidies, cap-and-trade, and feed-in-tariffs help redress market failures such as environmental externalities and knowledge spillovers (Popp, 2019). However, they do not address the coordination dilemmas described above. The interoperability challenge is ubiquitous in smart grids (Ho & O'Sullivan, 2017; Iqtiyanillham et al., 2017, Lin et al., 2013; Brown et al., 2018). To target those specific challenges, some governments have promoted the development of interoperability standards for the smart grid. For example, with the *Energy Independence and Security Act* of 2007, the United States government mandated the National Institute of Standards and Technology (NIST) to develop such standards. With Mandates M/441(2009) and M/490(2011), the European Commission instructed its standard-setting organizations to develop standards for smart meters and cybersecurity. Similarly, Germany, Canada, Korea and others OECD countries have issued roadmaps in which they signal their commitment to engage in international standardization efforts in this area (SCC, 2012; VDE/DKE, 2010; KSGI, 2010). While standards are omnipresent in modern economies, their effect on patenting has been largely understudied, let alone in the green energy innovation sector. There is a paucity of empirical, large-N, studies that investigate the relationship between standards and innovation. Through investigating the effect of interoperability standards on patenting activity in smart grids, we contribute to two literatures: the literature on green energy innovation and the literature on standards and innovation.

3. Literature review

3.1. Lessons from the literature on green energy innovation

Supporting clean energy innovation at requisite levels to meet net-zero goals will require a mix of policy instruments to address multiple market failures that suppress innovation. The most commonly discussed market failures include environmental externalities and knowledge spillovers (Popp, 2019). The literature provides insights about the effectiveness of policies that target the supply and the demand sides of innovation to address these market failures.

On the demand side, policies may expand market size for green technologies through pricing environmental externalities from fossil fuel generation. Studies find that higher fuel prices, as a proxy for a carbon tax, induce clean energy innovation (Newell et al., 1999; Popp, 2002; Verdolini and Galeotti, 2011; Crabb and Johnson, 2010; Aghion et al., 2016). Other policies that work on the demand side, such as consumer subsidies for the purchase of solar panels, also contribute to raising levels of green energy patenting (Gerarden, 2022). The latter is an example of a technology-specific policy. Technology-neutral policies that expand demand for innovation, such as emissions trading programs, have also been shown to induce innovation (Calel and Dechezleprêtre, 2016). Overall, Johnstone et al. (2010) find that technology-specific policies have a greater impact on emerging technologies, while inventors respond to technology-neutral policies by focussing R&D efforts in technologies that are closer to being cost-competitive with fossil fuel generation.

On the supply side, governments may directly support inventive activity through R&D subsidies. These subsidies compensate inventors for the public good they generate, because knowledge spillovers to other inventors prevent them from fully appropriating the value of their inventions. Costantini et al. (2017) find that technology-push instruments have a smaller effect on innovation than demand-pull instruments. Their results also highlight the importance of balance and comprehensiveness of policy mixes. R&D subsidies are often technology-specific and as such, may also distinctly affect technologies at different levels of maturity. Government R&D support may be particularly beneficial when technology is in the early stages and faces greater uncertainty. Comparing first- and second-generation bio-fuel technology, Costantini et al. (2015) find evidence that technology-push policies were instrumental in encouraging innovation in second generation emerging technology but had no effect on the more mature technology vintage.

Recent studies leverage firm-level analysis to investigate the R&D decisions of firms. Aghion et al. (2016) first used this approach to study the global automotive industry. They find that increases in the price of fossil fuels induce firms to switch from dirty to clean innovation. Firm-level analysis also underscores the importance of knowledge stocks for explaining path-dependency in fossil fuel patenting (Aghion et al., 2016). Using a sample of more than 5000 European firms in the electricity sector, Noailly and Smeets (2015) find that the recent surge in clean energy patenting may be explained by the entry of specialized renewable energy firms and the exit of specialized fossil fuel firms, rather than firms switching from dirty to clean innovation. Using a similar methodology, Lazkano et al. (2017) further find evidence of complementarities between firm's knowledge stocks in energy storage and in renewables. This approach also allows researchers to study credit constraints at the firm-level as an additional market failure that lowers R&D investments in green innovation below socially-optimal levels. For example, Noailly and Smeets (2022) find that firms innovating in renewables are more vulnerable to financial constraints than firms innovating in fossil fuels.

Together these studies highlight the critical role that policy mixes comprising both technology-push and demand-pull instruments play in supporting green energy innovation. But this literature has paid little attention to issues of coordination in technology development and deployment, and to the policy tools that may help address this specific challenge.

3.2. Lessons from the literature on standards and innovation

This paper also contributes to the literature on standards and innovation, in which large-N quantitative empirical evidence about the effect of standards on inventive activity is limited. Standards, like patents, are a vehicle for codifying technical knowledge. Firms use a combination of the two, along with scientific publishing, for disclosing new knowledge (Blind et al., 2022). The National Institute of Standards and Technology defines a standard as: "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). As opposed to regulatory standards, compliance with technology standards is voluntary (Baron and Spulber, 2018). Beyond this overarching definition, standards can be classified along various dimensions: de facto or formal; proprietary or open; quality, information, variety reduction or interoperability standards.

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 no need for a formalized document if industry actors already have a shared understanding of these guidelines and see the value in conforming with those. Companies may use strategies such as contracting and advertising to incite others to use their technology as the industry standard (Baron and Spulber, 2018; Katz and Shapiro, 1985; Spulber, 2008). In this case, *de facto* standard may be sufficient for coordination. Often times, standards are instead the product of formal consultative processes piloted by standard-setting organizations (SSOs) (Baron and Spulber, 2018; Baron and Schmidt, 2019). The standard-setting process may be conceptualized as a process of technology selection that reduces uncertainty (Aggarwal et al., 2011), shapes expectations (Lerner and Tirole, 2015) and informs the coordinated implementation of new technologies across an industry (Baron and Schmidt, 2019; Spulber 2008). Empirical evidence shows that these formal standardization bodies are effective at selecting high value technologies (Rysman and Simcoe, 2008). Smart grids standards included in our sample were developed within such formal standardization bodies. Those are usually open and differ from proprietary standards because they can be accessed by all inventors often at the price of purchasing the standard document (Baron and Spulber, 2018). Given this, they may diffuse information more widely. Another way of classifying standards is by the function they perform in the market. Quality standards are devised to ensure products meet certain quality and safety requirements. Similar to information standards which seek to inform consumer choices, they redress information asymmetries and reduce transactions costs. Variety reduction standards may be useful when differences between products are trivial and prevent economies of scale (Swann, 2000; Tassey, 1999; DeVries, 1999). Finally, interoperability standards – the variety of standards this paper investigates – help coordinate market actors to achieve product or component compatibility, and realize network externalities (Swann, 2000; Tassey, 1999; DeVries, 1999). Those may be particularly helpful to coordinate actors whose products are used as inputs into a same product or network. These are prevalent in the information technologies sector where complex manufactured products and networked technologies are ubiquitous (Baron and Spulber, 2018). Smart grids devices belong to this category of products.

In recent history, it has become more common for standards to be developed through consensus-building processes within formal standard-setting organizations. As a process of technology selection, standards may endorse proprietary technology. This provides economic value to inventors, especially when the technology is deemed essential to the implementation of a standard. Firms therefore have an incentive to engage strategically in these venues (Contreras, 2017; Chiao et al., 2007; Lerner and Tirole, 2015). This has motivated a sway of theoretical and empirical studies that investigate how the institutional rules of SSOs - for example relating to the disclosure of patents, the negotiation of licensing agreements for standard-essential patents, and voting – influence how firms venue-shop between SSOs. These studies are also interested in how different types of firms strategically engage in these venues, and how institutional rules shape the outcome of the standardization process (Lerner and Tirole, 2015; Chiao et al., 2007; Leiponen, 2008; Simcoe, Graham and Feldman, 2009; Simcoe, 2014; Bar and Leiponen, 2014; Kang and Bekker, 2015; Contreras, 2017; Wiegmann et al., 2022). Overall, these concern how the innovation profiles of firms that participate in standard-setting shape standards.

Conversely, few large-N empirical studies investigate how standards shape innovation (Wen et al., 2022). Once a standard embedding specialized technical knowledge is released, the information it contains becomes accessible to a larger group of users. Use of this knowledge is therefore not restricted to firms that participate in the standard development process. How standards affect the inventive activities of firms more broadly is less well understood. For example, standards provide information that reduces technological and legal uncertainty, and is paramount for supporting new inventions in complementary technologies (Wen et al., 2022). Wen and colleagues (2022) find that standards generate high impact innovation by complementor firms in the IT sector – firms not involved in standard development - and that this effect is stronger when standards are developed by vertically-integrated firms that have activities in downstream markets. Standards may not only have an impact on the quantity and quality of innovation, but also the type of innovation that firms conduct. In their study of manufacturing firms in the United Kingdom, Foucard and Li (2021) find that standards favor incremental innovation rather than radical innovation. Through their effect on firm productivity, standards also have macroeconomic effects. Using standards to proxy technology shocks, Baron and Schmidt (2019) find that standards decrease total factor productivity (TFP) in the short run as firms adjust to new technology that is incompatible with incumbent technology, but raises TFP in the long run.

While sparse and covering few sectors of technology, these empirical studies raise several key questions for new research in this area. What is the effect of standards on patenting levels and on the quality of innovation in other sectors of technology? Do standards influence the R&D activities of different types of firms through similar channel(s)? How do they affect the R&D decisions of new industry entrants compared to industry incumbents? Do standards have varying effects on patenting at different stages of technology development? Below we describe our contribution to providing insights to these questions.

4. Theory and hypotheses

In this paper we estimate the effects of interoperability standards on patenting levels in smart grids. The firms that innovate in this space are diverse in terms of age, size and expertise. Given this, we further investigate heterogeneous effects across firms from different backgrounds by considering the role of different knowledge stocks, and by comparing effects between industry incumbents and new entrants. We posit that standards may affect the inventive activities of different types of firms through three channels.

Information mechanism. Standards describe and endorse technical specifications that are useful to the conduct of economic activity (Blind et al., 2022; Tassey, 2000). They embed information that may reduce uncertainty and risks associated with R&D investments (Wen et al., 2022; Blind et al., 2017; Blind et al., 2018, Blind, 2004). When this is the case, standards should encourage inventive activity. This information may be particularly valuable to new industry entrants who do not possess know-how about best practices and industry conventions acquired through experience (Tassey, 2000). Furthermore, this channel may be salient when technology is in the early stages. This is when uncertainty is the highest because different research directions are being explored (Tassey, 2000). Standards provide information about what inventors expect will become the industry norm. Inventors can then take steps to increase the likelihood that their innovations will be compatible with technology being simultaneously developed by other inventors.

H1. Standards increase patenting activity for new industry entrants.

H2. Standards increase patenting activity when technology is in the early stages.

Experimentation stifling mechanism. Experimentation breeds innovation. While standards may provide direction that helps reduce uncertainty, they may also remove incentives to test new ideas if they signal to inventors that the industry has already settled on a convention (Tassey, 2000). This would result in a slow-down in patenting activity, particularly among incumbent firms. Incumbent firms are early experimenters and possess insider industry information before standards make this knowledge explicit and widely available. For this reason, they are likely to have tested many of their most promising ideas prior to the introduction of a standard. For them, the introduction of a standard may signal that the technology they have already developed is satisfactory. It may remove incentives to test further ideas because the expected marginal gain is small. Furthermore, when technology is more mature, standards adoption may be followed by a reduction in patenting activity for this same reason - many promising ideas have already been tested - but also because there is less uncertainty about technology direction in these later stages of technology development. In this case, standards legitimize existing practice (Wiegmann et al., 2022) but provide less useful new information to inventors.

H3. Standards decrease patenting activity for large industry incumbents

H4. Standards decrease patenting activity when technology is mature

Endorsement mechanism. It may also be that standards merely formalize conventions that the industry has already *de facto* widely adopted. In this case, standards may have no effect on the direction of patenting since they endorse what has already become common practice. If standards are introduced at the peak of a patenting boom, they may even be followed by a decline in patenting activity (Wen et al., 2022). This decline might have naturally occurred as technology matured regardless of standardization. In this case, the endorsement mechanism becomes difficult to disentangle from the experimentation stifling mechanism described above, but provides an alternative theoretical explanation for H4.

Because these three channels work, at least in part, in opposing directions, the net impact of standards on smart grid innovation is ambiguous. As such, while we present results for the overall effect of standards on smart grid innovation, we use our firm-level patent data to test for the heterogeneous impacts formulated in H1-H4. These tests allow us to better understand the mechanisms through with technology standards affect innovation.

5. Empirical setting

5.1. Identification of causal effects

We use firm-level patent data to measure smart grid innovation. Our data includes all firms with at least one smart grid patent in the period the years 2000-2016. Appendix B1 presents the patent classes used to identify smart grid innovations. Using methods first described in Noailly and Smeets (2015) and Aghion et al. (2016), we use data on the countries in which firms obtained patents in the pre-sample period to construct weights that capture the importance of each market to a firm. This allows changes in standards, policies, and market conditions in a given country to have varying impacts on different firms, and 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 considers policy and economic conditions in its main markets when making R&D investment decisions. This identification strategy has been increasingly used in recent years to study green innovation (Noailly and Smeets, 2015, 2022; Aghion et al., 2016; Lazkano et al., 2017; Rozendaal and Vollebergh, 2021).

The standards included in our sample originated for the most part in international or regional standard-setting organizations (a list of standards included in our sample is available in Appendix A2). These standards were then released at the country-level by national standardization bodies. For the same standard, country-level adoption sometimes occurs at different times. We use the variation in country-level timing of adoption to estimate the effects of standards on firms' patents.[3] Given this, reverse causality is a negligible threat to the internal validity of our results. In the context we study, firms that have relevant smart grid patents *ex ante* and wish to influence in their favor the drafting of a standard are unlikely to succeed. To position its proprietary technology

[3] In contrast, the initial release of a standard by an international or regional standardization body will be captured by year fixed effects in our model.

in standards developed at international standard-setting organizations such as the International Electrotechnical Commission (IEC), a firm would need to influence sufficient voting country members (Appendix A3 provides further details about the standard-setting process at IEC and why this is unlikely). Even if a firm were to succeed at influencing the outcome of the standard-setting process at the international level, it would need to further influence standard accreditation at the country-level in all its markets for reverse causality to be a concern in our study context. This is unlikely. Concern about firms engaging strategically in the standard setting process is greatest when firms can benefit by having their technologies (and related patents) declared essential to the standard (Lerner and Tirole, 2015). However, we could not find any declarations of standard-essential patents for smart grid standards developed at the IEC. This suggests that firms did not seek to position proprietary technology as essential to the implementation of smart grid patents. Instead, firms are more likely to engage in standard-setting in the smart-grid space because they value the mutual benefits it provides, such as jointly shaping technology development, enabling information-sharing and legitimizing technical solutions. This is consistent with Wiegmann and colleagues' findings about firms' motivations for participating in standardization in the Internet of Things field (Wiegmann et al., 2022).

5.2. Model

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.[4] In our main model, we use Zero-inflated Poisson regression. This

[4] Noailly and Smeets (2015) also use granted patents. Other recent papers, including Aghion et al. (2016), Lazkano et al. 2017), and Rozendaal 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

two-stage estimation strategy first estimates the likelihood that a firm has any smart grid patent with a logit model (e.g., the extensive margin). In the second stage, a Poisson model is used to predict the number of patents per firm in a given year (e.g., the intensive margin). This two-stage estimation strategy is appropriate in our setting because our sample comprises many small firms that seldom patent and it assumes that their excess zeros are generated through a separate process. Furthermore, smart grid innovation is an emerging area of technology. Given this, many new firms appear after the beginning of the sample period, which runs from 2000-2016. To account for this, we use an unbalanced panel that considers the years in which each firm was active.[5]

We write our main model as follows:

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

Here S is a count of standards, RG is government RD&D budgets in grid-related technologies, and RR is government RD&D budgets in renewables. KS represents a firm's internal knowledge stock in smart grids technologies, KG is a firm's internal knowledge stock in green innovation, KE is a firm's internal knowledge stock in electricity, and KI is a firms' internal knowledge stocks in information technologies. Internal knowledge stocks capture the firms' accumulated experience in

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.

[5] To proxy for this we use the years in which the firm files for a patent for the first and the last time in relevant patent classes: green innovation, electricity generation, information technology, smart grids. Patent classes used to identify smart grid innovations are described in Table 1 of Appendix B1. Patent classes used to identify green, electricity generation and information technology innovations are described in Table 3 of Appendix B1.

relevant sectors. 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. External knowledge stocks capture the knowledge firms are exposed to based on the location of their inventors.[6] Appendix B2 details how the knowledge stocks variables were constructed. We control for other time-varying factors likely to increase market demand for smart grid devices, and thus potentially increase patenting. These variables are denoted as X. They include income (GDP per capita), household electricity prices, the share of renewables in the electricity mix, and the growth in electricity consumption. The latter two proxy for other energy policies that have supported the deployment of renewables, pulling demand for enabling grid technologies. Moreover, faster growth in electricity consumption may strain existing transmission infrastructure, increasing the value of smart grid technologies to better manage transmission of electricity. When these country-level explanatory variables are weighted and translated to the firm level, they vary over time and across firms. A detailed description of these variables can be found in Appendix B3. All the right-hand side variables are lagged two-years to avoid reverse causality, and our results are robust to using different lags (robustness checks are included in Appendix C2). Finally, we control for unobserved heterogeneity overtime by including year fixed effects, denoted as y. For example, year fixed effects control for general changes in the expected productivity of smart grids innovation over time, allowing our firm-specific standards variable to capture the specific effects resulting from variation in standard adoption in different markets.

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

[6] Appendix B7 details how patent families were assigned an originating country, based on the country of the inventor(s).

standard Poisson fixed effects model may produce biased results (Appendix C3). To control for unobserved confounding firm attributes, we instead include their mean patenting activity in the pre-sample period (e.g., Blundell et al. 1995; Noailly and Smeets, 2015, Rozendaal and Vollebergh 2021).[7] While our dependent variable only includes smart-grids patents, for this pre-sample mean we include a wider range of relevant technologies: green innovation, electricity generation, information technology and smart grids. 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 each firm's overall propensity to innovate. Second, because of the novel nature of smart grid technology, our sample includes many new firms that 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.

5.3. Data

We combine data on standards from a novel database on technology standards with data on patents to investigate the effect of standards on patenting activity in a sample of 2,751 firms.[8] Our sample is comprised of large multinational conglomerates such as Panasonic, Toshiba and General Electric; IT firms such as IBM and Intel; traditional electricity sector players such as Asea Brown Boveri, Infineon and Texas Instruments; clean tech firms that specialize in renewable energy, load management, or other grid services such as Acciona, GridPoint, Voltalis and Solar

[7] To be consistent with the period used when building the policy weights, we go back to 1977 or the first year the firm was active when computing these yearly averages.

[8] We exclude patents by applicants that are not firms, such as universities, government agencies and non-governmental organizations. Appendix B4 details how we cleaned firm names and retrieved their knowledge stocks in areas beyond smart grids.

City.[9] These firms are located in[10] and have at least one granted smart grid patent in 19 sample 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.[11]

5.3.1 Standards data

We find relevant standard document numbers in lists of smart grid standards published by the International Electrotechnical Commission (IEC), the European standardization organizations (CEN, CENELEC, ETSI), and the Smart Electric Power Alliance (SEPA). We keep standards of core and high relevance to the smart grid (the full list of international standards included in our sample is included in Appendix A2). To identify country-level adoptions of smart grid standards we then use the Searle Centre on Law, Business and Economics' database on *Technology Standards and Standard Setting Organizations (SSO*) and Schmidt and Steingress' algorithm (2022) for identifying standards harmonizations.[12] We count standards at the part level: first, to avoid including standard parts that are not directly relevant to the smart grid; second, to acknowledge that standards are updated with new parts as technology evolves. Appendix A5 shows an example of a standard with multiple parts introduced over time and released in different countries at different times. Furthermore, we do not count revisions because those are routinely scheduled to ensure standards stay up-to-date. The concept we intend to measure is the purposive decision to coordinate in the face of emerging technology interoperability challenges. This is best captured by counting only the initial release of a standard part.

[9] Appendix A4 lists the largest smart grid innovators,

[10] Appendix B5 details how home countries were assigned to firms.

[11] Other OECD countries were excluded due to incomplete data on standards and on household electricity prices.

[12] This algorithm fills in gaps in the reporting of equivalences across standards that arise because of different timing of standard releases, to ensure that our data on country-level accreditations of international standards is complete.

5.3.2 Patent data

To capture innovation, we use patent data from the European Patent Office's PATSTAT database. 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 relevant for the smart grid, we rely on the Cooperative Patent Classification (CPC). We extract patents that belong to 4 areas of smart grid technology: 1) systems integration and efficiency, 2) use in buildings, 3) ICT applications to smart grids, and 4) end-user applications (see Appendix B1 for corresponding patent classes).

5.4 Constructing weighted policy variables

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 Rozendaal and Vollebergh 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, Rozendaal and Vollebergh 2021).[13] 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 the share of pre-sample patents in relevant CPC classes filed in our 19 sample countries, since we do not have complete data for our control variables for countries outside of these 19. This weighting scheme assumes that these variables take an average value. By including only firms whose home country is in the 19 countries in our sample, our sample firms have only limited exposure to other markets. Appendix B6 provides further details on country coverage in our sample. Notably, 90% of our sample firms have at least 93% of their granted patents in the 19 countries in our sample. 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 1,755 firms without 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 from the same home country are likely to operate in similar markets – 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. WiTricity corporation is an example of such firms, an American

[13] 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), in Appendix C2.

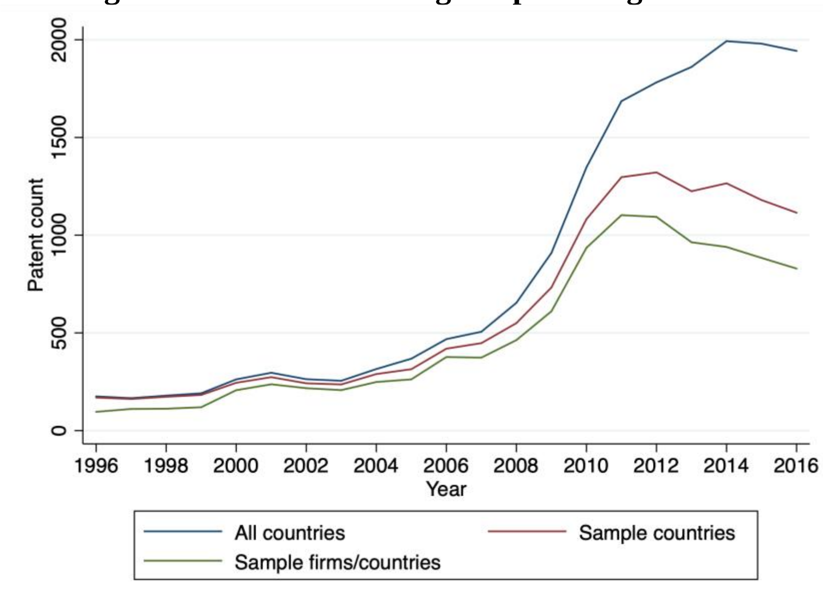
company specializing in wireless electrical vehicle charging founded in 2007. In the period between 2006 and 2016, it produced 41 smart grids patented inventions. Because we have no pre-sample data for WiTricity, we assume that its main markets are the same as other American firms that patent in smart grids, on average. In Appendix C2 we show results for robustness checks that assume that the main market for these new firms is their home country. Such an assumption is more likely to hold for smaller firms with less patenting activity.

6. Descriptive statistics

Smart grid is an emergent area of technology. Figure 1 shows little patenting activity prior to 2000 and that inventive activity has grown significantly since. Patenting in both our sample countries and sample firms peaks in 2011 and declines thereafter, following the trend observed in green energy innovation more generally (Popp, 2020). Patenting in all countries has continued to grow after 2011. This trend is driven by Chinese inventions that were not granted patents outside China.

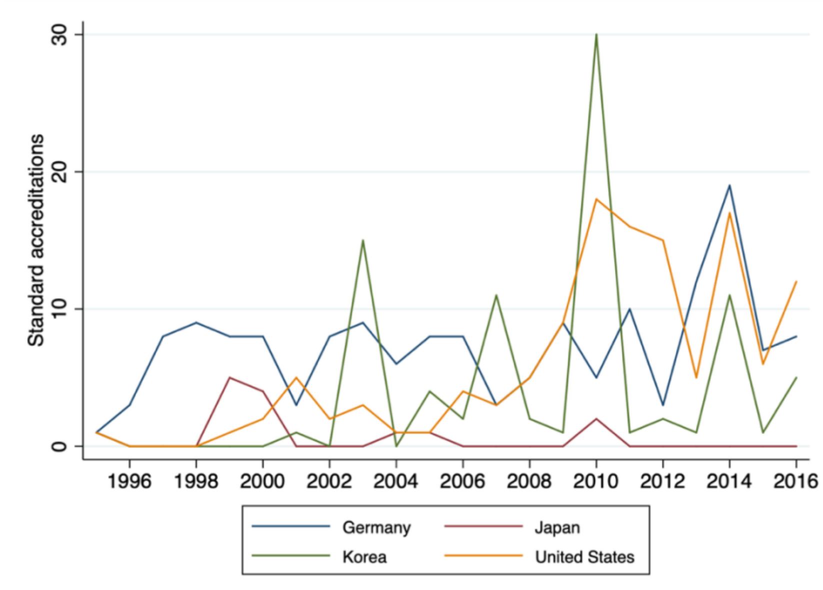
Figure 2 plots, for the same period, the number of standards adopted in a given year in select markets. It shows there was standardization activity during the entire time period under study. It also shows variation in the timing of smart grid standards adoption across these different markets. We use this variation to estimate the effect of standards on patenting levels: each firm has a unique weighted count of standards for each year depending on the combination of markets in which it operates and standardization activity in those markets. Additional summary statistics are included in Appendix B8.

Figure 1. Trends in smart grids patenting



Notes: i) Country-level counts of patents were computed using the country of the inventor and weighted for the number of inventors on a patent. These counts only include granted patents, ii) After excluding patent assignees that are not firms, such as universities, government research laboratories and non-governmental research organizations, patenting in our sample firms and countries still follows the general trend observed in smart grid innovation.

Figure 2. Smart grids standards accreditations in select markets



Notes: Figure 2 shows counts of standards accredited at the country-level in each year. This simple count of patents is the measure we use in our main regression model.

7. Results

7.1 Main model: Zero-Inflated Poisson

Table 1 shows results for our main Zero-Inflated Poisson model using a balanced and an unbalanced panel of firms.[14] With the exception of the coefficients at the extensive margin of patents for the standards and R&D policy variables, results are consistent across the two models. This difference in the first stage of the model is expected. Coefficients in this first stage can be interpreted as firm's entry (extensive margin), and what varies across the two models is the period during which firms are active. Because many new firms enter this market during the sample period, the ZIP model using an unbalanced panel better captures the true effect of these policies on firms' decision to patent at the extensive margin (e.g., whether or not a firm have any patent(s) in a given year). We discuss results pertaining to four areas: (i) the effect of standards, (ii) the effects of other policy variables, (iii) the effects of internal knowledge stocks, (iv) the effects of external knowledge stocks, (v) other demand-pull factors.

Overall, standards reduce the likelihood that firms will patent[15] (e.g., the extensive margin) and the level of patenting (e.g., the intensive margin). Marginal effects for these two stages combined show that an additional standard is associated with an overall reduction in patenting of 7.3%. This is consistent with the experimentation stifling and the endorsement hypotheses. We find no effect from government support to R&D in grid-related technologies, but find that an increase in government support to renewables R&D is associated with a decline in smart grid patenting. This indicates a tradeoff between the two sectors, possibly because firms active in both areas must chose to allocate R&D resources to one or the other. Results for the internal knowledge

[14] In Table 1 we focus on the main results of interest in our study. Appendix C1 shows results for the full model.
[15] The logit model in the first stage predicts the likelihood that a firm has zero patents, so that a positive coefficient signifies decreased likelihood of entry.

stocks variables provide evidence of path-dependency in the R&D activities of firms. Firms with more smart grid experience are more likely to patent in smart grids. Firms that have experience in other areas of green innovation or in electricity also patent more in smart grids. This confirms that knowledge from these sectors is transferable to smart grids. However, while firms with more prior experience in information technologies are no less likely to have a smart grid patents, they produce fewer smart grid patents. Similarly, firms whose inventors are located in countries where more smart grid innovation takes place also are more likely to have smart grid patents, and to have higher patenting levels. This indicates that firms receive knowledge spillovers from other smart grid inventors. External knowledge stocks in other green innovation sectors and in information technologies are associated with fewer patents and entry, respectively. These results suggest specialization within countries. Finally, an increase in the share of renewables in the electricity mix is associated with greater entry. However, when combining the intensive and extensive margin effects, the net marginal effect is negative and insignificant.[16] Given that much of the growth in renewable generation was policy driven during this time period, neither those policy initiatives nor increased grid flexibility challenges stimulated significant growth in smart grid technologies to aid renewables integration

[16] The marginal effect for renewable share is -0.454, with a standard error of 1.051.

Table 1. Regression results from Zero-Inflated Poisson regressions

Variables	ZIP, unbalanced Intensive margin	 Extensive margin	ZIP, balanced Intensive margin	 Extensive margin
Standards	-0.038***	0.016*	-0.038***	0.009
	(0.012)	(0.008)	(0.012)	(0.008)
RD&D smart grid	0.116	0.019	0.116	0.071*
	(0.074)	(0.039)	(0.074)	(0.037)
RD&D renewables	-0.197**	-0.033	-0.195**	-0.084*
	(0.091)	(0.050)	(0.091)	(0.047)
Int. knowledge stocks - smart grids	0.598***	-1.436***	0.598***	-1.390***
	(0.032)	(0.050)	(0.032)	(0.051)
Int. knowledge stocks - green tech	0.075**	-0.180***	0.075**	-0.150***
	(0.032)	(0.022)	(0.032)	(0.022)
Int. knowledge stocks - electricity	0.137***	-0.147***	0.137***	-0.122***
	(0.034)	(0.029)	(0.034)	(0.028)
Int. knowledge stocks - ICTs	-0.165***	-0.012	-0.166***	0.020
	(0.029)	(0.025)	(0.029)	(0.024)
Ext. knowledge stocks - smart grids	0.454**	-0.414***	0.463**	-0.239***
	(0.185)	(0.098)	(0.184)	(0.087)
Ext. knowledge stocks - green tech	-0.565***	0.078	-0.563***	-0.069
	(0.151)	(0.096)	(0.151)	(0.092)
Ext. knowledge stocks - electricity	-0.010	0.013	-0.013	-0.075
	(0.177)	(0.094)	(0.177)	(0.088)
Ext. knowledge stocks - ICTs	0.108	0.290***	0.102	0.307***
	(0.151)	(0.101)	(0.150)	(0.096)
Renewables share	-1.077	-1.146**	-1.044	-1.508***
	(0.887)	(0.564)	(0.883)	(0.551)
Marg. effect, standard (combined)	-0.076***		-0.049***	
	(0.021)		(0.014)	
Observations	30,628	30,628	44,370	44,370
Log-likelihood	-47022	-47022	-48675	-48675

Note: The variables RD&D expenditures in grid-related technologies and in renewables technologies were adjusted for PPP and inflation, 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, a dummy for firms with no patents in the pre-sample period, 4 dummies for knowledge stocks that are equal to zero (smart grids, green innovation, electricity and ICT knowledge stocks). Country-level control variables were also weighted and included in all regressions: the share of electricity production from renewables, the growth in electricity consumption, household electricity prices (USD/MWh, real 2015 USD) and GDP per capita (real 2015 USD). All time-varying variables are lagged by 2 time periods. We use the log transformation for all the internal and external knowledge stocks, for GDP per capita and for household electricity prices. Regressions start in 2000 and end in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

7.2. Heterogeneous effects across firms

We hypothesize that standards affect different types of firms through different channels: standards can increase the entry of new innovators in this space through providing information, but can also reduce patenting activity by industry incumbents through removing incentives to test new ideas or endorsing already well-established conventions. To test these hypotheses, we propose two approaches.

First, we estimate an unbalanced Zero-Inflated Poisson model on a sample of large firms and on a sample of small firms separately. This allows coefficients for all variables to vary across the two groups. We use these two groups to proxy for large industry incumbents and new entrants. In most cases, large firms are firms that have been active longer in this space and small firms are new entrants. Large firms are defined as companies that have more than 100 granted patents in the period 1977-2016 in relevant patent classes: green innovation (including smart grids), electricity and information technologies.[17] Small firms are defined as companies that have 100 or fewer granted patents in the same period and patent classes.

Second, we estimate a model in which we interact a dummy variable that identifies firms with no smart grid patents before year t with the standards variable. This allows to test the effect of standards on new entrants more directly. These firms all eventually enter the smart grid space, so this model tests whether they are more likely to enter after standards are introduced.

[17] We use this period and these patent classes to be consistent with the data we used to construct the policy weights.

Table 2. Regression results by firm size

	Large firms		Small firms	
Variables	Intensive margin	Extensive margin	Intensive margin	Extensive margin
Standards	-0.051***	0.043***	-0.001	-0.001
	(0.015)	(0.016)	(0.015)	(0.011)
RD&D smart grid	-0.015	0.085	0.236***	0.062
	(0.117)	(0.067)	(0.081)	(0.050)
RD&D renewables	0.013	0.021	-0.445***	-0.116*
	(0.127)	(0.081)	(0.101)	(0.069)
Int. knowledge stocks - smart grids	0.635***	-1.228***	0.389**	-1.535***
	(0.034)	(0.056)	(0.190)	(0.095)
Int. knowledge stocks - green tech	0.075**	-0.145***	-0.198	-0.068
	(0.037)	(0.025)	(0.154)	(0.062)
Int. knowledge stocks - electricity	0.213***	0.013	-0.017	-0.301***
	(0.046)	(0.036)	(0.064)	(0.052)
Int. knowledge stocks - ICTs	-0.206***	-0.085***	-0.089	-0.005
	(0.036)	(0.032)	(0.072)	(0.049)
Ext. knowledge stocks - smart grids	0.286	-0.358*	0.340	-0.249**
	(0.354)	(0.197)	(0.209)	(0.119)
Ext. knowledge stocks - green tech	-0.624***	0.220	-0.351*	-0.091
	(0.234)	(0.160)	(0.200)	(0.125)
Ext. knowledge stocks - electricity	0.401	-0.193	-0.293*	0.029
	(0.308)	(0.195)	(0.160)	(0.117)
Ext. knowledge stocks - ICTs	0.026	0.241	0.317*	0.296**
	(0.211)	(0.199)	(0.182)	(0.122)
Renewables share	0.424	-1.266	-2.189**	0.287
	(1.098)	(0.815)	(1.052)	(0.902)
Marg. effect, standards (combined)	-0.238***		-0.001	
	(0.062)		(0.011)	
Number of firms	597	597	2,154	2,154
Observations	9,523	9,523	21,105	21,105
Log-likelihood	-23768	-23768	-21228	-21228

Note: These regressions use the same specification and control variables as the main model. Large firms are defined as firms that had more than 100 patents in the ICT, electricity and green innovation patent classes during the period 1977-2016. Small firms are defined as firms that 100 or fewer patents in the same patents class and period. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2 shows that the negative effect of standards is driven by large firms. For these firms, an additional standard decreases patenting by 21.2%. This appears to confirm our hypothesis that standards affect the inventive activity of incumbent firms through the experimentation stifling and/or the endorsement mechanisms. The R&D investment decisions of small firms are more responsive to technology-push policies in the form of government R&D subsidies. This aligns with our expectation that smaller - and presumably more resource-constrained firms – are more influenced by policy. Furthermore, the tradeoff between R&D in smart grids and R&D in renewables is concentrated in these firms. This is not surprising given that smaller and more resource constrained firms do not have the capacity to do R&D in several areas at a time and may need to choose between one or the other. Crowding out might also explain why small firms patent less in smart grids when the share of renewables increases: smaller firms might find entering the renewables market more attractive in markets where policy has supported renewables deployment rather than entering the market for an enabling technology. Combined with the results on government R&D, our results suggest that policies promoting clean energy are insufficient for inducing innovation in complementary energy technologies. Without policies targeting complementary and enabling energy technologies – which are currently missing from the policy mix - markets will not likely deliver sufficient innovation in these areas critical to the energy transition.

Results presented in Table 3 confirm the information hypothesis for new entrants. The coefficient for the interaction term between standards and the zero stocks dummy variable is negative at the extensive margin, indicating that firms with zero patents are less likely to have zero patents when exposed to more standards. The joint significance between the standards coefficient and the interaction term coefficient shows the net effect of standards on these firms. It remains negative and significant at the extensive margin, providing evidence that standards increase entry for new players in this space. While there is a negative effect of standards on the level of smart grid patenting, this occurs for both new entrants and incumbents. That standards increase entry into the smart grid space but not the overall level of patenting activity is suggestive of the role of standards reducing uncertainty. Standards provide clarity on how technology will evolve, allowing innovators to focus their efforts on what they know will be needed rather than trying to anticipate multiple technology scenarios.

7.3 Heterogeneous effects over time

The effect of standards may also vary over time. In the early stages of technology development, when uncertainty about research directions is the highest, information embedded in the standard potentially reduces risks to inventors, thus increasing innovation (H2). Conversely, we also hypothesize that standards reduce patenting in later stages through the experimentation stifling and/or endorsement mechanisms (H4). To test these hypotheses, we allow the effect of standards to change before and after a proposed cutoff year. This cutoff year suggests a moment where technology changes from early-stage to mature. Because the choice of cutoff year is arbitrary, we present results allowing the cutoff to vary between 2008 and 2012. This allows us to ascertain whether our results are not sensitive to the choice of the cutoff year and driven by idiosyncratic events occurring in that year. For example, like other green energy technologies, smart grids experience a peak in patenting around the year 2011 (as shown in Figure 1). While year fixed effects in our model control for such year-specific idiosyncrasies affecting all firms, so that our coefficients are identified based on firms having different exposure to standards in a given year, finding that our results hold for years as early as 2008 provides reassurance about the validity of our results.

Table 3. Effect of standards on new entrants

Variables	Intensive margin	Extensive margin
Standards	-0.033**	0.120***
	(0.015)	(0.013)
Interaction standards and zero stock dummy	-0.014	-0.165***
	(0.015)	(0.011)
RD&D smart grid	0.114	0.004
	(0.073)	(0.039)
RD&D renewables	-0.193**	0.036
	(0.090)	(0.050)
Int. knowledge stocks - smart grids	0.595***	-1.442***
	(0.032)	(0.050)
Int. knowledge stocks - green tech	0.075**	-0.178***
	(0.032)	(0.021)
Int. knowledge stocks - electricity	0.136***	-0.148***
	(0.034)	(0.028)
Int. knowledge stocks - ICTs	-0.165***	-0.003
	(0.029)	(0.024)
Ext. knowledge stocks - smart grids	0.454**	-0.263***
	(0.184)	(0.099)
Ext. knowledge stocks - green tech	-0.563***	0.043
	(0.151)	(0.096)
Ext. knowledge stocks - electricity	-0.017	-0.041
	(0.177)	(0.096)
Ext. knowledge stocks - ICTs	0.113	0.231**
	(0.151)	(0.101)
Renewables share	-1.039	-0.890
	(0.878)	(0.567)
Joint significance	-0.047***	-0.044***
	(0.011)	(0.009)
Observations	30,628	30,628
Log-likelihood	-46872	-46872

Note: This regression uses the same specification and control variables as the main model. This model interacts the standards variables with a dummy variable that indicates whether the firm had any internal knowledge stocks in past periods. As with other variables, we use the second lag. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Regression results for early-stage versus mature technology

	2008		2009		2010		2011		2012	
	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive
Prior to year X	0.038	-0.025	0.088**	-0.045	0.055*	-0.033	-0.012	-0.018	-0.033	0.006
	(0.051)	(0.039)	(0.043)	(0.033)	(0.033)	(0.025)	(0.036)	(0.023)	(0.03)	(0.019)
Marginal effect	0.054		0.124***		0.088**		-0.003		-0.056	
	(0.053)		(0.047)		(0.039)		(0.049)		(0.048)	
Year X and after	-0.040***	0.015*	-0.044***	0.016**	-0.046***	0.018**	-0.040***	0.017**	-0.038***	0.014
	(0.012)	(0.008)	(0.013)	(0.008)	(0.013)	(0.009)	(0.013)	(0.009)	(0.013)	(0.009)
Marginal effect	-0.094***		-0.106***		-0.114***		-0.096***		-0.081***	
	(0.025)		(0.026)		(0.028)		(0.025)		(0.024)	
Observations	30,628	30,628	30,628	30,628	30,628	30,628	30,628	30,628	30,628	30,628
Log-likelihood	-47696	-47696	-47638	-47638	-47631	-47631	-47706	-47706	-47714	-47714

Note: These regressions use the same specification and control variables as the main model, but add an interaction between the count of standards and the cut-off year. The results for *prior to year X* present the joint effect of the main standards coefficient and this interaction. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4 shows regression results for separate regressions using five different cutoff years. Each column represents a regression using a different potential cutoff year. For each regression, we interact the standards variable with a dummy variable indicating years prior to the proposed cutoff for that column.

Our strongest results are for standards adopted at later stages, which are presented in the bottom half of Table 4. Standards adopted after the cutoff year decrease patenting levels (intensive margin) for any proposed cutoff year, and in all models except a 2012 cutoff year, standards also increase the likelihood of having zero patents (e.g., decreases entry at the extensive margin). In all cases, the marginal effects reveal that late standards decrease patenting by about ten percent. These results support either the experimentation stifling and/or the endorsement hypotheses for later years, but the effect of each of these two mechanisms is difficult to further disentangle. Our results suggest that when technology has matured and many research directions have already been explored, standards lock-in incumbent technology. This removes incentives to test out alternative ideas that go against the established norm, as the resulting devices would be difficult to commercialize.

For standards adopted in the early stages of technological development (top half of Table 4), we see some evidence that standards decrease the likelihood of having zero patents, but the results are sensitive to the cutoff year chosen. Using a cutoff year of 2009 or 2010, standards increase patenting activity at the intensive margin in the early years of the sample. The marginal effects show that early standards increase the level of patenting activity by about ten percent. We find similar results using 2008 as a cutoff, but the coefficients are imprecise. These results provide suggestive evidence supporting the information hypothesis in the early stages: when no clear technology direction has been established, standards may help reduce uncertainty and provide guidance to inventors, which encourages inventive activity. However, these results are not as robust as the results for standards adopted in later stages of technology development.

7.4. Robustness checks

We also verify that our results are not sensitive to the research decisions we made, with respect to the choice of depreciation rate applied to the knowledge stocks, strategy used to build policy weights for new firms with no pre-sample data, GDP-weighting of the policy weights to account for market size, number of lagged periods for the explanatory variables, and the measure used for the standards variable. Appendix C2 shows that our results are robust to using these alternative measurements.

8. Discussion

We find that standards decrease patenting at the extensive and intensive margins in the aggregate. Our analysis also reveals important heterogeneity, which provides more insight for policy than the net effects. These heterogeneous effects show that standards affect the R&D activities of firms through different mechanisms. Different mechanisms mean that the appropriate policy choice varies depending on context and the goals of policy-makers. For example, that standards affect the inventive activities of incumbent firms through an endorsement or experimentation stifling mechanism teaches important lessons for the timing of introduction of standards. If the goal is to encourage incumbent firms to experiment broadly, governments may choose to delay the introduction of standards. If the goal is to encourage entry by new players to increase competition or bring fresh ideas, then it is preferable to introduce standards earlier because they provide useful information to new entrants.

Our inquiry also raises additional unanswered questions about the role of standards in fostering technology development versus diffusion, and tradeoffs between the two. We show that standards reduce patenting, but this result should not be interpreted as evidence that standards are detrimental to innovation. Standards might, in turn, support the diffusion of technologies through lowering uncertainty faced by technology users. In this case, introducing standards when technology is mature may be warranted, if the policy goal is to support technology diffusion rather than development. In many contexts, the level of patenting is a secondary concern to supporting the large-scale deployment of technologies that already exist. This is an important policy tradeoff that calls for further research on the effects of standards on technology diffusion.

Another tradeoff of policy relevance relates to the effect of standards on the quality of innovation as opposed to patent quantity. Even when standards decrease patenting levels, it is possible that they help improve innovation quality through providing information that focusses inventive activity in fewer, more promising research directions. Some findings from the literature clue us in on how standardization contribute to enhancing the quality of innovation, but more work is needed to test this hypothesis. For example, Rysman and Simcoe (2008) find that patents disclosed during the standard setting process are more highly cited and have longer-lasting influence. Their results show that standard-setting organizations are effective at selecting high quality technology. Similarly, Wen et al. (2022) find that in the information technologies sector, standards help complementor firms produce high-impact innovation through lowering technological and legal uncertainty. Investigating the effect of standards on smart grid patent quality is left for future work.

Finally, our results are of more general relevance to many other areas of green energy innovation where coordination is also needed. For example, the effectiveness of green and blue hydrogen as a fuel depends on safe storage and distribution. With adaptations to infrastructure, hydrogen could be blended into natural gas to allow transport using existing natural gas pipelines.

But equipment modification would be necessary for machines to work with higher concentrations of hydrogen. New pipelines and distribution networks could be built, but standards for safely developing this infrastructure need to be agreed upon. Methods to certify the carbon content of hydrogen are also necessary to allow for trade of hydrogen across countries with different climate policies (IEA, 2019). Standards may play an important role in the development of many enabling technologies.

9. Conclusion

In this paper, we argue that complementary technologies will be pivotal in enabling further decarbonization of electricity systems. We posit that the development of the requisite technologies for achieving net-zero goals face important barriers in the form of coordination challenges and interoperability requirements. Using firm-level analysis, we investigate the effects of standards, as a coordination tool, on innovation in smart grids. We contribute to the literature on green energy innovation by casting light on this under-studied sector of innovation, and by considering a policy tool – technology standards – that has received little attention. We advance understanding of the different channels through which standards impact innovation. We find that, while standards lead a decline in the number of patents produced by large firms, they help new players penetrate this sector of innovation. We further find evidence of heterogeneous effects of standards at different stages of technology development. This is of relevance to two literatures. First, the literature on standards and innovation, in which there is a paucity of empirical work. Second, the literature on green energy innovation, which has paid little attention to innovation in enabling and complementary technologies and has not considered technology standards as a possible policy tool for supporting decarbonization efforts. Our findings raise additional questions of policy relevance regarding tradeoffs between technology development and diffusion, and between patent quantity and patent quality that are left to future research.

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APPENDIX A: BACKGROUND ON SMART GRIDS AND STANDARDS

Appendix A1: Examples of smart grid technologies at different stages of maturity

Smart grids encompass a range of technologies that include - but are not limited to - smart meters, remote and automated sensing, smart switching, hierarchical or distributed control architectures and an array of big data analytics and artificial intelligence applications. Below, we provide some examples of smart grid technologies that are at different levels of maturity. As these technologies are deployed, more data will be collected, opening up further possibilities for new inventions that utilize these data. While hardware such as smart meters and synchrophasors are routinely used, the data that is collected by these devices remain under-utilized (Syed et al., 2020). Advances in big data analytics and artificial intelligence are needed to realize the full potential of smart grid technologies.

Advanced metering infrastructure. Resolutely the most salient smart grid technology, smart metering has reached maturity and been deployed at scale in many industrialized economies. Across the United States, utilities had installed 102.9 million smart meters by 2020[18]. These devices have the ability to collect data multiple times per second (Syed et al., 2020), and communicate information to both utilities and their consumers. Because these devices enable remote automated meter readings, they make possible the implementation of time-varying electricity tariffs. Paired with smart appliances, this can enable demand response (NREL, 2015; Palensky and Kupzog, 2013, p.208). The mass deployment of these devices is sometimes equated to the smart grid, but advanced metering infrastructure is just one of many technologies that must be deployed to achieve a smarter and greener grid. Their deployment is a first, but insufficient, step towards the implementation of a smarter electrical grid. (Brown et al., 2018).

[18] https://www.eia.gov/tools/faqs/faq.php?id=108&t=3, consulted on 11 June 2022

Synchrophasors. Another technology that has been widely adopted by utilities is the phasor measurement unit[19]. These devices are capable of monitoring voltage, current and frequency on the grid in real time (Palensky and Kupzog, 2013, p.205; Lee et al., 2017). The data collected by these units is currently used by industry in grid monitoring and post-mortem analysis, but possibilities for using these data to further improve grid management abound (Lee et al., 2017). As more devices are installed at different nodes on the grid, new software applications will become possible due to greater data availability. For example, the data collected by synchrophasors could be used in oscillation monitoring, voltage stability monitoring, angle-frequency monitoring, adaptive protection, model valuation or linear state estimation (Lee et al., 2017)

Smart inverters. Smart inverters are another type of device that is already commercially available. These devices are used to convert DC current from solar photovoltaic installations into AC current that can be fed onto the grid. Their intelligent characteristics also enable them to monitor grid frequency and voltage, and automate decisions that help maintain grid stability (NREL, 2015). For example, these units have the capacity to adjust the output of solar installations in response to grid conditions (Martinot, 2016, p.236; Palensky and Kupzog, 2013, p.207). They may also enable the PV installation to absorb power from the grid if needed to help maintain grid frequency stability, keep installations online during minor disturbances and restart gradually after a power outages to avoid cascading power failures (NREL, 2015).

Blockchain technology. Champions of blockchain technology believe it could revolutionize electricity markets, especially in the area of electricity trading and billing (Fulli et al., 2022; Lopes et al., 2019; Kuzlu et al., 2020). While there is interest on the part of the energy

[19] https://www.energy.gov/articles/how-synchrophasors-are-bringing-grid-21st-century, consulted on 11 June 2022

industry to leverage this technology - apart from a handful of start-up companies that offer services made possible by blockchains (such as WePower, Power Ledger and the Sun Exchange) (Kuzlu et al., 2020) - applications to the electricity sector remain in early stages of development (pilots, use cases) (Fulli et al., 2022; Kuzlu et al., 2020). Blockchain technology is a form of distributed digital ledger that uses computer networks to record and coordinate transactions without the need for centralized oversight. Proponents believe it could enable new community-based/sharing economy business models such as peer-to-peer energy trading (Lopes et al., 2019, p.4-5; Kuzlu et al., 2020). Other possible blockchain applications to the electricity sector encompass microgrids, virtual power plants, renewable energy certificate trading, and electric vehicle charging and payment settlement platforms (Kuzlu et al., 2020). But the availability of comprehensive network of interoperable advanced metering infrastructure will be indispensable to enable blockchain technology in the electricity sector (Fulli et al., 2022).

Big data analytics and artificial intelligence. Other technologies that are likely to flourish as more hardware - such as smart meters, smart sensors, smart inverters – is installed across the grid include big data analytics and artificial intelligence. Without data availability, these technologies' potential remains under-utilized. Challenges extend beyond data acquisition however: several limitations in data storing, processing and security must be overcome to deploy these technologies. (Syed et al., 2020). The digital transformation program implemented by Iberdrola illustrates the potential of big data analytics to the electricity sector. The Spanish utility uses wind generation data in developing curtailment optimization plans and consumer data for designing time-of-use rates (Syed et al., 2020). Beyond a handful of examples however, the commercial deployment of these technologies remains limited (Syed et al., 2020, p.59575; Bose, 2017). Many possible applications that use AI and big data to facilitate grid monitoring and automate power system control decisions can be envisioned. These include, but are not limited to: fault identification and classification, preventative maintenance, transient stability analysis, topology identification, health monitoring of wind generation systems, coordinated electric vehicle charging, hierarchical and distributed control architectures, automated load management, virtual energy storage systems, fault pattern identification, automated design, simulation and controller tuning of wind generation systems and more (Lopes et al., 2019; Palensky and Kupzog, 2013; Syed et al., 2020; Bose, 2017).

Appendix A2: List of sampled standards

STANDARD NUMBER	STANDARD NAME
ANSI C 12.1	Electric Meters - Code for Electricity Metering
ANSI C 12.18	Protocol Specification for Ansi Type 2 Optical port (communication between a C12.18 decide and a C12.18 client via an optical port)
ANSI C 12.19	American national Standard for Utility Industry End Device Data Tables
ANSI C 12.20	Electricity Meters - 0.2 and 0.5 Accuracy Classes
ANSI C 12.21	Protocol Specification for Telephone Modem Communication
ANSI C 12.22	Protocol Specification for Interfacing To Data Communication Networks
ANSI/ASHRAE 135	A Data Communication Protocol for Building Automation and Control Networks
ANSI/CEA 709.1	Control Network Protocol Specification
ANSI/CEA 709.2	Control Network Power Line (PL) Channel Specification
ANSI/CEA 709.3	Free-Topology Twisted-Pair Channel Specification
ANSI/CEA 709.4	Fiber-Optic Channel Specification
ANSI/CEA 852-B	Tunneling Device Area Network Protocols Over Internet Protocol Channels
ANSI/CEA 852.1	Enhanced Protocol for Tunneling Component Network Protocols Over Internet Protocol Channels
ANSI/NEMA SG-IPRM 1	Smart Grid Interoperability Process Reference Manual
CEA/CEDIA-CEB 29	Recommended Practice for the Installation of Smart Grid Devices
CEN/CLC/ETSI/TR 50572	Functional reference architecture for communications in smart metering systems
CLC/TS 50568-4	prTS 50568-4: Electricity metering data exchange – The Smart Metering Information Tables and Protocols (SMITP) suite – Part 4: Physical layer based on B-PSK modulation +Data Link Layer
CLC/TS 50568-8	prTS 50568-8: Electricity metering data exchange – The Smart Metering Information Tables and Protocols (SMITP) suite – Part 8: PLC profile based on B-PSK modulation
CLC/TS 52056-8-4	prTS 52056-8-4: Electricity metering data exchange – The DLMS/COSEM suite – Part 8-4: Communication profile for power line carrier neighborhood networks using OFDM modulation Type 1
CLC/TS 52056-8-5	prTS 52056-8-5: Electricity metering data exchange – The DLMS/COSEM suite – Part 8-5: Communication profile for power line carrier neighborhood networks using OFDM modulation Type 2

EN 13757-1	Communication systems for meters - Part 1: Data exchange
EN 13757-3	Communication systems for meters - Part 3: Application protocols
EN 13757-4	Communication systems for meters - Part 4: Wireless MBus communication
EN 13757-5	Communication systems for meters - Part 5: Wireless M-Bus relaying
EN 50491-11	General requirements for Home and Building Electronic Systems (HBES) and Building Automation and Control Systems (BACS) - Part 11: Smart metering - Application specification - Home display
EN 50491-12	General requirements for Home and Building Electronic Systems (HBES) and Building Automation and Control Systems (BACS) - Part 12: Smart grid - Application specification - Interface and framework for customer
EN 61508	EN 61508 - Communication networks and systems in substations - Part 3: General requirements
EN 62056-1-0	EN 62056-1-0: Electricity metering data exchange – The DLMS/COSEM suite – Part 1-0: Framework
EN 62056-3-1	EN 62056-3-1: Electricity metering data exchange – The DLMS/COSEM suite –Part 3-1: Use of local area networks on twisted pair with carrier signalling
EN 62056-4-7	EN 62056-4-7: Electricity metering data exchange – The DLMS/COSEM suite – Part 4-7: COSEM transport layers for IPv4 and IPv6 networks
EN 62056-5-3	EN 62056-5-3: Electricity metering – Data exchange for meter reading, tariff and load control – Part 5-3: COSEM Application layer
EN 62056-6-1	EN 62056-6-1: Electricity metering data exchange – The DLMS/COSEM suite – Part 6-1: Object identification system (OBIS)
EN 62056-6-2	EN 62056-6-2: Electricity metering data exchange – The DLMS/COSEM suite – Part 6-2: COSEM interface classes
EN 62056-7-6	EN 62056-7-6: Electricity metering data exchange – The DLMS/COSEM suite – Part 7-6: The 3-layer, connection oriented, HDLC based communication profile
EN 62056-8-3	EN 62056-8-3: Electricity metering data exchange – The DLMS/COSEM suite – Part 8-3: Communication profile for power line carrier neighborhood networks using S–FSK modulation
EN 62056-9-7	EN 62056-9-7: Electricity metering data exchange – The DLMS/COSEM suite – Part 9-7: Communication profile for TCP-UDP/IP networks

EN 62056-9-8	Electricity metering data exchange – The DLMS/COSEM suite Part 9-8: Communication profile using SML services
EN 62325-301	Framework for energy market communications - Part 301: Common Information Model (CIM) extensions for markets
EN 62325-351	Framework for energy market communications - Part 351: CIM European market model exchange profile
EN 62325-450	Framework for energy market communications - Part 450 : profile and context modelling rules
EN 62325-451-1	Framework for energy market communications - Part 451-1: Acknowledgement business process and contextual model for CIM European market
EN 62325-451-2	Framework for energy market communications - Part 451-2: Scheduling business process and contextual model for CIM European market
EN 62325-451-3	Framework for energy market communications - Part 451-3: Transmission capacity allocation business process (explicit or implicit auction) and contextual models for European market
EN 62325-451-4	Framework for energy market communications - Part 451-4: Settlement and reconciliation business process, contextual and assembly models for European market
EN 62325-451-5	Framework for energy market communications - Part 451-5: Problem statement and status request business processes, contextual and assembly models for European market
EN 62325-503	Framework for energy market communications - Part 503: Market data exchanges guidelines for the IEC 62325-351 profile
ETSI TR 102691	Machine-to-Machine communications (M2M); Smart Metering Use Cases
ETSI TR 102886	Electromagnetic compatibility and Radio spectrum Matters (ERM); System Reference document (SRdoc): Spectrum Requirements for Short Range Device, Metropolitan Mesh Machine Networks (M3N) and Smart Metering (SM) applications
ETSI TR 102935	Machine-to-Machine communications (M2M); Applicability of M2M architecture to Smart Grid Networks; Impact of Smart Grids on M2M platform

ETSI TR 103055	Electromagnetic compatibility and Radio spectrum Matters (ERM); System Reference document (SRdoc): Spectrum Requirements for Short Range Device, Metropolitan Mesh Machine Networks (M3N) and Smart Metering (SM) applications
ETSI TR 103240	Powerline communication recommendations for smart metering and home automation
ETSI TS 102887	Electromagnetic compatibility and Radio spectrum Matters (ERM); Short Range Devices; Smart Metering Wireless Access Protocol
ETSI TS 102887-1	TS102887-1 Smart Metering wireless access protocol: part 1: Physical layer
ETSI TS 102887-2	TS102887-2 Smart Metering wireless access protocol: part 2: Data Link Layer (MAC)
ETSI TS 103 908	PowerLine Telecommunications (PLT) - BPSK Narrow Band Power Line Channel for Smart Metering Applications
IEC 60870-6-2	Telecontrol equipment and systems - Part 6: Telecontrol protocols compatible with ISO standards and ITU-T recommendations - Section 2: Use of basic standards (OSI layers 1-4)
IEC 60870-6-501	Telecontrol equipment and systems - Part 6: Telecontrol protocols compatible with ISO standards and ITU-T recommendations - Section 501: TASE.1 Service definitions
IEC 60870-6-502	Telecontrol equipment and systems - Part 6: Telecontrol protocols compatible with ISO standards and ITU-T recommendations - Section 502: TASE.1 Protocol definitions
IEC 60870-6-503	Telecontrol Equipment and Systems - Part 6-503: Telecontrol Protocols Compatible with ISO Standards and ITU-T Recommendations - TASE.2 Services and Protocol.
IEC 60870-6-601	Telecontrol equipment and systems - Part 6: Telecontrol protocol s compatible with ISO standards and ITU-T recommendations - Section 601: Functional profile for providing the connection-oriente d transport service in an end system connected via permanent acc ess to a packet switched data network
IEC 60870-6-602	Telecontrol equipment and systems - Part 6-602: Telecontrol protocols compatible with ISO standards and ITU-T recommendations - TASE transport profiles
IEC 60870-6-701	Telecontrol equipment and systems - Part 6-701: Telecontrol protocols compatible with ISO standards and ITU-T recommendations - Functional profile for providing the TASE.1 application service in end systems
IEC 60870-6-702	Telecontrol Equipment and Systems: part 6-702: Telecontrol Protocols Compatible with ISO standards and ITU-T Recommendations - Functional Profile for Providing the TASE.2 Application Service in End Systems.

IEC 60870-6-802	Telecontrol Equipment and Systems - Part 6-802: Telecontrol Protocol Compatible With ISO Standards and ITU-T Recommendations - TASE.2 Object Models
IEC 61334-3-1	Distribution automation using distribution line carrier systems - Part 3-1: Mains signalling requirements - Frequency bands and output levels
IEC 61334-3-21	Distribution automation using distribution line carrier systems - Part 3: Mains signalling requirements - Section 21: MV phase-to-phase isolated capacitive coupling device
IEC 61334-4-1	Distribution automation using distribution line carrier systems - Part 4: Data communication protocols - Section 1: Reference model of the communication system
IEC 61334-4-33	Distribution automation using distribution line carrier systems - Part 4-33: Data communication protocols - Data link layer - Connection oriented protocol
IEC 61334-4-41	Distribution automation using distribution line carrier systems - Part 4: Data communication protocols - Section 41: Application protocol - Distribution line message specification
IEC 61334-4-42	Distribution automation using distribution line carrier systems -Part 4: Data communication protocols - Section 42: Application protocols - Application layer
IEC 61334-4-511	Distribution automation using distribution line carrier systems - Part 4-511: Data communication protocols - Systems management - CIASE protocol
IEC 61334-4-512	Distribution automation using distribution line carrier systems - Part 4-512: Data communication protocols - System management using profile 61334-5-1 - Management Information Base (MIB)
IEC 61334-4-61	Distribution automation using distribution line carrier systems - Part 4-61: Data communication protocols - Network layer - Connectionless protocol
IEC 61334-6	Distribution automation using distribution line carrier systems - Part 6: A-XDR encoding rule
IEC 61400-25-1	Wind energy generation systems - Part 25-1: Communications for monitoring and control of wind power plants - Overall description of principles and models
IEC 61400-25-3	Wind turbines - Part 25-3: Communications for monitoring and control of wind power plants - Information exchange models
IEC 61400-25-4	Wind energy generation systems - Part 25-4: Communications for monitoring and control of wind power plants - Mapping to communication profile

IEC 61400-25-5	Wind turbines - Part 25-5: Communications for monitoring and control of wind power plants - Conformance testing
IEC 61400-25-6	Wind turbines - Part 25-6: Communications for monitoring and control of wind power plants - Logical node classes and data classes for condition monitoring
IEC 61850-1	Communication Networks and Systems for Power Utility Automation - Part 1: Introduction and overview
IEC 61850-10	Communication networks and systems for power utility automation - Part 10: Conformance testing
IEC 61850-3	Communication Networks and Systems for Power Utility Automation - Part 3: General Requirements
IEC 61850-4	Communication Networks and Systems for Power Utility Automation - Part 4: System and Project Management
IEC 61850-5	Communication Networks and Systems for Power Utility Automation - Part 5: Communication Requirements For Functions and Device Models
IEC 61850-6	Communication Networks and Systems for Power Utility Automation - Part 6: Configuration Description Language for Communication In Electrical Substations Related to IEDs
IEC 61850-7-1	Communication Networks and Systems for Power Utility Automation - Part 7-1 Basic Communication Structure - Principles and Models
IEC 61850-7-2	Communication Networks and Systems for Power Utility Automation - Part 7-2 Basic Information and Communication Structure - Abstract Communication Service Interface (ACSI)
IEC 61850-7-3	Communication Networks and Systems for Power Utility Automation - Part 7-3 Basic Communication Structure - Common Data Classes
IEC 61850-7-4	Communication Networks and Systems for Power Utility Automation - Part 7-4 Basic Communication Structure - Compatible Logical Node Classes and Data Object Classes
IEC 61850-7-410	Communication Networks and Systems for Power Utility Automation - Part 7-410: Basic Communication Strucutre - Hydroelectric Power Plants - Communiction for Monitoring and Control
IEC 61850-7-420	Communication Networks and Systems for Power Utility Automation - Part 7-420: Basic Communication Structure - Distributed Energy Resources and Distribution Automation Logical Nodes
IEC 61850-8-1	Communication networks and systems for power utility automation - Part 8-1: Specific communication service mapping (SCSM) - Mappings to MMS (ISO 9506-1 and ISO 9506-2) and to ISO/IEC 8802-3

IEC 61850-9-2	Communication networks and systems for power utility automation - Part 9-2: Specific communication service mapping (SCSM) - Sampled values over ISO/IEC 8802-3
IEC 61968-1	Application integration at electric utilities - System interfaces for distribution management - Part 1: Interface architecture and general requirements
IEC 61968-11	Application integration at electric utilities - System interfaces for distribution management - Part 11: Common information model (CIM) extensions for distribution
IEC 61968-13	Application integration at electric utilities - System interfaces for distribution management - Part 13: CIM RDF Model exchange format for distribution
IEC 61968-2	Application integration at electric utilities - System interfaces for distribution management - Part 2: Glossary
IEC 61968-3	Application integration at electric utilities - System interfaces for distribution management - Part 3: Interface for network operations
IEC 61968-4	Application integration at electric utilities - System interfaces for distribution management - Part 4: Interfaces for records and asset management
IEC 61968-8	Application integration at electric utilities - System interfaces for distribution management - Part 8: Interfaces for customer operations
IEC 61968-9	Application integration at electric utilities - System interfaces for distribution management - Part 9: Interfaces for meter reading and control
IEC 61970-1	Energy management system application program interface (EMS-API) - Part 1: Guidelines and general requirements
IEC 61970-2	Energy management system application program interface (EMS-API) - Part 2: Glossary
IEC 61970-301	Energy management system application program interface (EMS-API) - Part 301: Common Information Model (CIM) base
IEC 61970-401	Energy management system application program interface (EMS-API) - Part 401: Component interface specification (CIS) framework
IEC 61970-453	Energy management system application program interface (EMS-API) - Part 453: CIM based graphics exchange

IEC 61970-501	Energy management system application program interface (EMS-API) - Part 501: Common Information Model Resource Description Framework (CIM RDF) schema
IEC 62051-1	Electricity metering - Data exchange for meter reading, tariff and load control - Glossary of terms - Part 1: Terms related to data exchange with metering equipment using DLMS/COSEM
IEC 62052-11	Electricity metering equipment (AC) - General requirements, tests and test conditions - Part 11: Metering equipment
IEC 62052-21	Electricity metering equipment (a.c.) - General requirements, tests and test conditions - Part 21: Tariff and load control equipment
IEC 62052-31	Electricity metering equipment (AC) - General requirements, tests and test conditions - Part 31: Product safety requirements and tests
IEC 62053-11	Electricity metering equipment (a.c.) - Particular requirements - Part 11: Electromechanical meters for active energy (classes 0,5, 1 and 2)
IEC 62053-11	Electricity metering equipment (a.c.) - Particular requirements - Part 11: Electromechanical meters for active energy (classes 0,5, 1 and 2)
IEC 62053-21	Electricity metering equipment (a.c.) - Particular requirements - Part 21: Static meters for active energy (classes 1 and 2)
IEC 62053-23	Electricity metering equipment (a.c.) - Particular requirements - Part 23: Static meters for reactive energy (classes 2 and 3)
IEC 62053-31	Electricity metering equipment (a.c.) - Particular requirements - Part 31: Pulse output devices for electromechanical and electronic meters (two wires only)
IEC 62053-52	Electricity metering equipment (AC) - Particular requirements - Part 52: Symbols
IEC 62053-61	Electricity metering equipment (a.c.) - Particular requirements - Part 61: Power consumption and voltage requirements
IEC 62054-11	Electricity metering (a.c.) - Tariff and load control - Part 11: Particular requirements for electronic ripple control receivers
IEC 62054-21	Electricity metering (a.c.) - Tariff and load control - Part 21: Particular requirements for time switches

IEC 62056-21	Electricity metering - Data exchange for meter reading, tariff and load control - Part 21: Direct local data exchange
IEC 62056-31	Electricity metering - Data exchange for meter reading, tariff and load control - Part 31: Use of local area networks on twisted pair with carrier signalling
IEC 62056-4-7	Electricity metering data exchange - The DLMS/COSEM suite - Part 4-7: DLMS/COSEM transport layer for IP networks
IEC 62056-42	Electricity metering - Data exchange for meter reading, tariff and load control - Part 42: Physical layer services and procedures for connection-oriented asynchronous data exchange
IEC 62056-46	Electricity metering - Data exchange for meter reading, tariff and load control - Part 46: Data link layer using HDLC protocol
IEC 62056-53	Electricity metering - Data exchange for meter reading, tariff and load control - Part 53: COSEM application layer
IEC 62056-61	Electricity metering - Data exchange for meter reading, tariff and load control - Part 61: Object identification system (OBIS)
IEC 62056-62	Electricity metering - Data exchange for meter reading, tariff and load control - Part 62: Interface classes
IEC 62058-11	Electricity metering equipment (AC) - Acceptance inspection - Part 11: General acceptance inspection methods
IEC 62058-21	Electricity metering equipment (AC) - Acceptance inspection - Part 21: Particular requirements for electromechanical meters for active energy (classes 0,5, 1 and 2)
IEC 62059-31-1	Electricity metering equipment - Dependability - Part 31-1: Accelerated reliability testing - Elevated temperature and humidity
IEC 62351-1	Power systems management and associated information exchange - Data and communications security - Part 1: Communication network and system security - Introduction to security issues
IEC 62351-3	Power systems management and associated information exchange - Data and communications security - Part 3: Communication network and system security - Profiles including TCP/IP
IEC 62351-4	Power systems management and associated information exchange - Data and communications security - Part 4: Profiles including MMS and derivatives

IEC 62351-5	Power systems management and associated information exchange - Data and communications security - Part 5: Security for IEC 60870-5 and derivatives
IEC 62351-6	Power systems management and associated information exchange - Data and communications security - Part 6: Security for IEC 61850
IEC 62351-7	Power systems management and associated information exchange - Data and communications security - Part 7: Network and System Management (NSM) data object models
IEC 62541-1	OPC unified architecture - Part 1: Overview and concepts
IEC 62541-2	OPC Unified Architecture - Part 2: Security Model
IEC 62541-3	OPC Unified Architecture - OPC Unified Architecture - Part 3: Address Space Model
IEC 62541-4	OPC Unified Architecture - OPC Unified Architecture - Part 4: Services
IEC 62541-5	OPC Unified Architecture - OPC Unified Architecture - Part 5: Information Model
IEC 62541-6	OPC Unified Architecture - OPC Unified Architecture - Part 6: Mappings
IEC 62541-7	OPC Unified Architecture - OPC Unified Architecture - Part 7: Profiles
IEC/TR 61334-1-1	Distribution automation using distribution line carrier systems - Part 1: General considerations - Section 1: Distribution automation system architecture
IEC/TR 61334-1-2	Distribution automation using distribution line carrier systems - Part 1-2: General considerations - Guide for specification
IEC/TR 61334-1-4	Distribution automation using distribution line carrier systems - Part 1: General considerations - Section 4: Identification of data transmission parameters concerning medium and low-voltage distribution mains
IEC/TR 62357-1	Power systems management and associated information exchange - Part 1: Reference architecture
IEC/TS 61334-5-2	Distribution automation using distribution line carrier systems - Part 5-2: Lower layer profiles - Frequency shift keying (FSK) profile
IEC/TS 61334-5-3	Distribution automation using distribution line carrier systems - Part 5-3: Lower-layer profiles - Spread spectrum adaptive wideband (SS-AW) profile
IEC/TS 61334-5-4	Distribution automation using distribution line carrier systems - Part 5-4: Lower layer profiles - Multi-carrier modulation (MCM) profile

IEC/TS 61334-5-5	Distribution automation using distribution line carrier systems - Part 5-5: Lower layer profiles - Spread spectrum - fast frequency hopping (SS-FFH) profile
IEC/TS 62351-2	Power systems management and associated information exchange - Data and communications security - Part 2: Glossary of terms
IEEE 1377	IEEE Standard for Utility Industry Metering Communication Protocol Application Layer (End Device Data Tables)
IEEE 1547	Standard for Interconnecting Distributed Resources with Electric Power Systems
IEEE 1701	IEEE Standard for Optical Port Communication Protocol to Complement the Utility Industry End Device Data Tables
IEEE 1815.1	IEEE Standard for Exchanging Information Between Networks Implementing IEC 61850 and IEEE Std 1815(TM) [Distributed Network Protocol (DNP3)]
IEEE 1901	IEEE Standard for Broadband over Power Line Networks: Medium Access Control and Physical Layer Specifications
IEEE 1901.2	IEEE Standard for Low-Frequency (less than 500 kHz) Narrowband Power Line Communications for Smart Grid Applications
IEEE 2030	IEEE 2030-2011 IEEE Guide for Smart Grid Interoperability of Energy Technology and Information Technology Operation with the Electric Power System (EPS), End-Use Applications, and Loads
IEEE 2030.5	IEEE Adoption of Smart Energy Profile 2.0 Application Protocol Standard
IEEE C37.239	IEEE Standard Common Format for Event Data Exchange (COMFEDE) for Power Systems
IEEE Std 1815	IEEE Standard for Electric Power Systems Communications -- Distributed Network Protocol (DNP3)
IETF RFC 6272	Internet Protocols for the Smart Grid
ISO/IEC 15067-3	Information technology - Home Electronic Systems (HEC) application model - Part 3: Model of a demand-response energy management system for HES
ITU-T G.9902	G.9902 (10/12) Narrowband orthogonal frequency division multiplexing power line communication transceivers for ITU-T G.hnem networks
ITU-T G.9903	Narrowband orthogonal frequency division multiplexing power line communication transceivers for G3-PLC networks

ITU-T G.9904	G.9904 (10/12) Narrowband orthogonal frequency division multiplexing power line communication transceivers for PRIME networks
ITU-T G.9960	Unified high-speed wire-line based home networking transceivers - Foundation
ITU-T G.9972	G.9972 : Coexistence mechanism for wireline home networking transceivers
NEMA SG-AMI 1	Requirements for Smart Meter Upgradeability

Appendix A3: Primer on the standard-setting process

The rules and procedures specific to the organizations that develop standards have a bearing on whether standards are at risk of being endogenously determined. Technology endorsement by a standard has economic value and firms with a large smart grid patent portfolio may seek to influence the standard-setting process to strategically position their inventions. This may in turn affect their level of inventive activity after standards are introduced. Below, we argue that the likelihood that standards and patents are co-determined in the context of our study is low because the institutional rules and procedures for developing and adopting standards at the International Electrotechnical Commission (IEC) do not allow direct participation by firms. For firms to influence technology selection during the drafting, comment-and-response and voting process at the IEC - where most of standards in our sample originated - firms would need to successfully influence the majority of IEC member country organizations. Furthermore, our identification of the causal effect of standards on patenting uses variation in country-level accreditations. For standards to be endogenously determined, firms would need to successfully control the outcome of similar drafting, comment-and-response and voting processes at the country-level in all the national markets where they operate. We believe this is highly unlikely. Below we describe the standard-setting process at the IEC as an example. The process in European standard-setting organizations – ETSI/CEN/CENELEC – that also developed some smart grid standards is similar.

Standard-setting at the IEC

The International Electrotechnical Commission is a non-governmental organization composed of 62 full members and 26 associate members[20]. Individuals and firms can only

[20] https://www.iec.ch/national-committees, consulted September 9th 2022

influence the standard-setting process through national committees or liaison organizations. National committees coordinate the technical inputs of stakeholders at the national-level and represent the interests of their country at the IEC. Typically, they are housed in national standards bodies that are part of national governmental structures or are mandated by government. For example, the United States National Committee[21] of the IEC is part of the American National Standards Institute (ANSI) and is composed of more than 4,000 members, many from industry. Technical experts from industry, government, academia, and consumer or labor groups may also participate in the work of technical committees as liaison organizations. To be eligible, liaison organizations must have a sufficient degree of representativity, such as industry consortia, professional associations or scientific societies[22]. Examples of organizations that have a memorandum of understanding with the IEC to participate as liaisons include the European Network of Transmission System Operations, the International Conference on Electricity Distribution and the IEEE Power & Energy Society. This implies that individual firms cannot independently participate, and instead must work through a liaison organization to provide technical inputs to working groups that draft standards.

Overall, the standard development process follows these stages: the proposal stage, the preparatory stage, the committee stage, the enquiry stage, the approval stage, and the publication stage[23]. These stages aim at building consensus. Below we provide a short account of this process, with a view to clarifying how firms may provide input, as this is the main concern for identification in our study (e.g., this account is not intended to be exhaustive).

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[21] https://www.ansi.org/usnc-iec/usnc-overview, consulted September 9th 2022
[22] https://www.iec.ch/global-partnerships, consulted September 9th 2022
[23] https://www.iso.org/stages-and-resources-for-standards-development.html, consulted on 9 September 2022

Various actors can propose a new standard project: a national committee, the secretariat of a technical committee or subcommittee, or a category A liaison. However, only participating members – this is, the national committees of full member countries – can vote to approve a new work item, and ultimately decide which standards are developed. To move forward, a work item must receive the approval of two-thirds of the country members participating in the relevant technical committee. Therefore, industry consortia and other stakeholders that participate as liaisons are limited to proposing new work items and contributing technical inputs during the drafting of standards. Category A liaisons, which have the highest level of participation, must be approved by two-thirds of IEC members to engage in the activities of a technical committee and are appointed for a period of two years. To be eligible, they must be not-for-profit legal entities with a broad regional or international membership base. In addition, they must demonstrate that they have relevant technical expertise, sufficient representativity in their area, and show commitment to consensus decision-making in their internal rules and processes.

Once a work item is proposed, the project for a new standard moves to the preparatory stage. Licensing, patenting and conformance assessment issues are discussed at this stage. Participating national committees nominate technical expects to contribute to the working group that will draft the standard. Once a draft standard is ready, it is circulated for comment and subject to voting by national committees that are members of the parent technical committee. This stage is optional as the draft standard can also move directly to the enquiry stage. This opens up the draft standard to commenting by member countries and stakeholders for a 12-week period and concludes with a vote by all IEC country members. For a draft standard to be released, it must receive the approval of two thirds of the members of its parent technical committee and no more than one fourth of negative votes by all members. If technical changes are requested, the technical committee revises the text of the standard and the final draft international standard is subject to another vote before being published. Finally, after the end of the voting period, the technical committee must prepare a report in which it responds to all comments received. Throughout this process, representatives from the private sector can therefore be appointed as technical experts either by national committees or liaisons to contribute inputs and participate in the work of a working group, committee or sub-committee, or as observers who may comment on the draft standard. Voting, however, remains the prerogative of national committees[24].

Standard-setting in national-level standardization organizations

Standards can originate in international standard setting organization (SSOs), regional SSOs, national-level SSOs and smaller/less formal SSOs. It is often the case that standards developed by a national-level standardization body are later adopted by an international SSO and vice-versa (Baron and Spulber, 2018, p.489). To identify smart grid standards, we use lists that include, for the most part, international standards and find all associated country-level accreditations. When national-level standardization bodies adopt an international standard, they must indicate the level of correspondence. They may endorse the standard or reprint it with or without identical translation, in which case the country-level standard is considered identical to the original international standard. Country standardization bodies may also republish the standard with technical deviations. When those technical deviations are clearly identified and explained, the national standard is considered a modified version of the international standard. When those technical deviations are not clearly identified, it is labeled as not equivalent. National standardization bodies must identify the degree of correspondence with the international standard

[24] https://storage-iecwebsite-prd-iec-ch.s3.eu-west-1.amazonaws.com/2021-07/isoiecdir1%7Bed17.0%7Den.pdf, consulted on 9 September 2022

when they release a standard document. In our sample, the vast majority of country-level accreditations are declared identical.

National standardization bodies have consensus-building processes that mirror those of international standard-setting organizations (SSOs). For example, the Standards Council of Canada (SCC) has a parallel process in which it releases a notice of intent when an international SSO makes a decision to develop a new standard. During the drafting process, the SCC provides inputs to international standard development[25]. Once the draft international standard is circulated, the SCC launches a two-month public review, providing an opportunity to feedback comments from Canadian stakeholders to the international standard-setting process. Once the final draft international standard is circulated, the SCC might develop Canadian technical deviations, where applicable, before releasing the standard domestically. Adoption of an international standard at the national level therefore accomplishes various functions. Through this multi-layered process of consensus-building, the standard diffuses geographically (Baron and Spulber, 2018, p.492). This may contribute to giving it standing and showing widespread acceptability of the endorsed technology. Furthermore, local adoption enhances accessibility through the publication of the standard document in the reference library of the domestic SSO, often translated into local language, and sometimes through a commitment by the domestic SSO to oversee conformance testing.

[25] https://www.scc.ca/sites/default/files/publications/SIRB_RG_Adoptions_v0.1_2017-04-24.pdf, consulted on 9 September 2022

Table A4. Geographical diffusion of sample standards

Number of country accreditations	**Frequency**	**Number of country accreditations**	**Frequency**
1	24	**8**	5
2	11	**9**	3
3	16	**10**	16
4	17	**11**	53
5	13	**12**	18
6	8	**13**	1
7	5	**14**	6

Country-level variation in standard counts in our sample come from two sources. First, there is differential timing of adoption of the same standard across countries. This is coherent with the overall trend that Baron and Spulber observe Searle Center's data on technology standards (2018). They observe that while it is typical for national-level SSOs to adopt a standard within 18 months of the release of an international standard, it may take up to 10 years for some countries to adopt (Baron and Spulber, 2018, p.490). Cross-country variation in standard counts in our sample also come from countries adopting different combinations of standards. There is sizeable variation in the amplitude of geographical diffusion across our sample of standards, with 24 standards being harmonized only in one of our sample countries, and 6 standards being harmonized in 14 of our 19 sample countries. There is a group of 11 mostly European countries that tend to adopt standards as a block. Table A3 shows descriptive statistics on geographical diffusion. The column number of country accreditations shows the number of countries that have adopted a given standard, and the column frequency indicates the number of standards with a given level of geographic diffusion.

Appendix A4. List of largest smart grid innovators

Firms that innovate in the smart grid space are diverse in terms of age, size and background. The group of biggest smart grid innovators is comprised of large diversified conglomerates, auto makers, electronics companies and large electricity sector players.

Panasonic	409	International Business Machines	175
Mitsubishi	404	Toyota	158
General Electric	393	Kyocera Corporation	155
Toshiba	372	Schneider Electric	151
Siemens	354	Samsung	145
Hitachi	313	Sony	129
Asea Brown Boveri	283	Itron	117
Chugoku Electric Power	197	Korea Electric Power Corporation	113
LG	181	LS Electric (LSIS)	104
Nippon Electric Corporation	179	Fujitsu	102

Appendix A5: Counting standard parts

Standard documents are composed of multiple parts, which are added overtime as new technological challenges surface. Because of this, in many instances not all parts of a standard are directly relevant to smart grids. Also, the year of the initial release of a standard may not accurately represent when specific attempts at coordinating over smart grid interoperability occurred since many of the parts that concern smart grids were added subsequently. Since we are interested in only including parts that are relevant to the smart grid, we count standards at the part level. This also allows us to capture the years in which standard parts concerning smart grids were adopted to more accurately measure when coordination efforts in this specific area occurred.

To illustrate this, standard *IEC 61400: Wind energy generation systems* is described below. The table below shows examples of different components that are part of this standard, with the years these new parts were first released by the international standard-setting body. In this example, we kept in our sample of standards only the parts 25-1 to 25-6 which are directly relevant to smart grids. The variation we leverage in our regression analysis comes from differential timing of adoption of standard parts at the country-level. For various reasons, countries choose to adopt international standards at different times, with delays between the international release and country adoption that range from zero to 10 years across various technologies (Baron and Spulber, 2018, p.490). We observe similar variation in our sample of smart grid standards. For example, Germany accredited standard part IEC 61400-25-2 in 2006 whereas Switzerland accredited it in 2007.

Standard part	**First release**
Part 1: Design Requirements	1994
Part 2: Small wind turbines	1996
Part 3-1: Design requirements for fixed offshore wind turbines	2019
…	
Part 25-1 Communications for monitoring and control of wind power plants – Overall description of principles and models	2006
Part 25-2 Communications for monitoring and control of wind power plants - Information models	2006
Part 25-3 Communications for monitoring and control of wind power plants - Information exchange models	2006
Part 25-4 Communications for monitoring and control of wind power plants – Mapping to communication profile	2008
Part 25-5 Communications for monitoring and control of wind power plants - Compliance testing	2006
Part 25-6 Communications for monitoring and control of wind power plants – Logical node classes and data classes for condition monitoring	2010

APPENDIX B: DATA CONSTRUCTION

Appendix B1: Definition of smart grids technologies included in sample, policy weights and knowledge stocks

1. Patent classes included in smart grid sample

Technology	Patent class from the 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	Y04S 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. The full definitions of the CPC scheme may be found here: https://www.cooperativepatentclassification.org/cpcSchemeAndDefinitions/table

2. Patent classes used when building policy weights

To identify each firm's relevant markets, we consider its granted patents in a broader set of relevant patent classes. Smart grids is a new sector of technology with little patenting activity in the pre-sample period. Considering only smart grid inventions would not allow us to build policy weights from pre-sample data. For this reason, we consider related technologies because they are likely to be marketed the same markets as firms' smart grid inventions.

Technology field	Corresponding patent classes
Electricity	Cooperative patent classification (CPC): H (and all subclasses)
Green innovation	Cooperative patent classification (CPC): Y (and all its subclasses with the exception of Y10)
Information and communication technologies	J-tag, taxonomy of ICT technologies based on the International Patent Classification (IPC). Select patent classes[26]: 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.
Other[27]	B60: Vehicles in general (and all its subclasses) F02C: Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants (and all its subclasses) F02B: Internal-combustion piston engines; combustion engines in general (and all its subclasses) F16D: Couplings for transmitting rotation; clutches; brakes (and all its subclasses) F25B: Refrigeration machines, plants or systems; combined heating and refrigeration systems; heat pump systems (and all its subclasses) F25D: Refrigerators; cold rooms; ice-boxes; cooling or freezing apparatus not otherwise provided for (and all its subclasses) G05: Controlling; regulating (and all its subclasses) F21: Lighting (and all its subclasses) B62D: Motor vehicles; Trailers (and all its subclasses)

[26] The full taxonomy is available in Inaba, Takashi and Mariagrazia Squicciarini (2017). From the J-tax taxonomy, we selected technology areas that have applications in the electricity sector.

[27] These were added to account for additional patent classes in which the largest smart grid innovators have experience. We used data on all the patents held by the 30 largest smart grid innovators and collated the most frequent patent classes that were not already covered by the three previous categories (electricity, green innovation and ICTs).

3. Patent classes used to build internal and external knowledge stocks

Knowledge stocks	Corresponding patent classes
Smart grids	Cooperative patent classification (CPC): Y02B 70/30, Y02B 90/20, Y02E 40/70, Y04S 10, Y04S 20, Y04S 40, Y04S 50 (and all their subclasses).
Green technology	Cooperative patent classification (CPC): Y02, Y04 (and all their subclasses, excluding smart grid classes above)
Electricity	Cooperative patent classification (CPC): H, F21, F02C, F2B
Information and communication technologies	International Patent Classification (IPC): 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

Appendix B2: Building knowledge stocks

Internal knowledge stocks

To obtain internal knowledge stocks for the sample 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: smart grids, renewable energy, electricity generation, and information technology (IT).[28] For each of these areas of technology, 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 *d* 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:

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

We use a 15% depreciation rate (δ) 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 zero.

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 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

[28] 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 patent as an invention in each of the categories.

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. To build these stocks, we considered all the countries in which our sample firms have inventive activities and not just our 19 sample countries.

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.

Appendix B3: Control variables

Share of electricity generation from renewable sources. Greater renewables integration may further exacerbate grid pressures and generate demand for smart grid technologies, thereby inducing innovation. This variable also proxies for policies that encourage renewables adoption. The deployment of renewable energy technologies across the markets we study would not have happened without policy. OECD data on the stringency of green energy policies such as feed-in-tariffs, emissions taxes and emissions trading schemes are unavailable for the years 2013-2016. We therefore cannot include those variables in our main model. Given this, we use data from the International Energy Agency's World Energy Balances Highlights on electricity generation from renewable sources as a share of total electricity generation. This includes energy generated from hydro, geothermal, solar, wind, tide/wave/ocean, biofuels and renewable waste.

Growth in electricity consumption. We include this variable to also control for grid pressures that are potentially exacerbated by growth in the demand for electricity. We use net electricity consumption in billion kilowatt-hours from the Energy Information Administration's World Statistics and compute the yearly percent change in consumption.

Household electricity prices. Changes in electricity prices may induce innovation through their effect on the demand for end-user smart grid technologies. These technologies can help utility consumers manage their electricity consumption. Demand for these products may grow with electricity prices. We use household electricity price data from the International Energy Agency, that we deflated and adjusted for purchasing power parity. Prices are in 2015 US dollars.

GDP per capita. We also control for GDP per capita because the income where a firm operates also affects demand for its products and its level of investment in research and development activities. Gross domestic product and population data used to compute GDP per capita are from the Organisation for Economic Co-operation and Development. We deflated and adjusted for purchasing power parity. Prices are in 2015 US dollars.

Government incentives to R&D in grid-related technologies. We control for other public policies that target innovation in grid technologies. We use data on Energy Technology RD&D Budgets from the International Energy Agency, which tracks government spending by energy technologies at the country-level. We select technologies at the two-digit level because more granular categories have many missing values. We select the following categories as being relevant to grid modernization technologies: 62 Electricity transmission and distribution, 63 Energy storage, 69 Unallocated other power and storage techs, and 71 Energy system analysis. We interpolate missing values. We adjust for power purchasing parity and inflation. Values are expressed in 2015 US dollars.

Government incentives to R&D in renewable energy technologies. We control for other public policies that target innovation in renewable energy technologies as those may affect innovation in smart grids due to spillovers or tradeoffs. We use data on Energy Technology RD&D Budgets from the International Energy Agency. For this variable we use spending in technology Group 3: Renewable energy sources. We interpolate missing values and adjust for power purchasing parity and inflation. Values are expressed in 2015 US dollars.

Appendix B4: Cleaning firm names and retrieving firms' knowledge stocks

We assume that internal knowledge can be accessed by all inventors within the same firm, including within multinational corporations whose inventors are located in different countries. A firm's internal knowledge stocks reflect its accumulated experience innovating in relevant areas, upon which all its inventors can further build when conducting R&D. Patents proxy for firms' accumulated knowledge. Assuming that knowledge stocks are shared across a firm's inventors requires counting all the patents held by the firms' various geographic branches, divisions, licensing units, etc.

However, identifying those patents is a challenge in the PATSTAT database. The same firm can be associated with more than one person identifier because there is no centralized system to track person identifiers for patents filed in various national patent offices, by different branches or even the same branches but overtime because assignees are not required to file under a standardized name or identifier every time they file a new patent application. The name listed in the database is what appears on the patent at the time of its publication (Arora et al., 2021). The same assignee may be associated with different names for various reasons: a change in the name of the company overtime (e.g., Minnesota Mining and Manufacturing and 3M), listing a subsidiary rather than the parent company (e.g., Google and Alphabet), listing a geographic branch, a licensing unit or a specific division instead of the parent company (Arora et al., 2021). Different spellings and typos also occur. Examples include *Alcatel USA* and *Alcatel Canada*; *Philips electronics North America corporation* and *Philips lighting North America corporation*, *ABB Research* and *ABB Patent*; *GM* and *General Motors*; *Siemen power transmission & distribution* (sic) and *Siemens power transmission and distribution*. We consider these to be the same firms.

To overcome these challenges, we cleaned firm names using a combination of keyword matching and manual verification. To select and clean our sample of firms, we use the variables psn_name and psn_id in PATSTAT. These names and identifiers have previously been partially cleaned using the University of Leuven harmonization procedure[29]. We use the variable psn_sector to select assignees that are companies. For assignees whose psn_sector is unknown, we first keep only those whose name is different from the name of the inventor to filter out individuals. We then conduct further manual cleaning to remove any remaining individuals, universities, non-profits, etc.

We then group the various assignee names that belong to the same company. We assume that different subsidiaries, country offices, and divisions of a same parent company share knowledge stocks and therefore assign them a common identifier. To do so we do keyword matching after removing words that commonly occur in our sample such as energy, automation, superconductor, electric, windpower, etc. We also include on the stop list mentions of companies' legal entity types such as ltd, limited, llc, s.p.a., ghmb, holding, inc, corp, and other frequently occurring geographic and division designations such as Korea, China, America, national, regional, global, corporate, technology, innovation, etc. We manually verify each match and confirm ambiguous ones using online searches.

To collect data on firms' internal knowledge stocks, the two challenges we seek to overcome when cleaning firm names are 1) including irrelevant company names and therefore irrelevant knowledge stocks, and 2) omitting relevant company names and failing to include

[29] This initiative harmonizes person identifiers using manual and automated cleaning. Details about this harmonization procedure may be found in the PATSTAT Data Catalogue ((https://documents.epo.org/projects/babylon/eponot.nsf/0/9440099DEF5C9067C125884600546C48/$File/patstat_data_catalog_global_5_19_en.pdf, p.295-297) and in WIPO documentation on name standardization efforts (https://www.wipo.int/edocs/mdocs/classifications/en/wipo_ip_cws_ns_ge_19/wipo_ip_cws_ns_part_1_callaert.pdf)

relevant knowledge stocks. To overcome this challenge, we further search for person identifiers that do not appear in our sample of smart grid patents. We do this to ensure that we do not overlook assignees that belong to the parent companies in our sample and have patents in CPC classes relevant for building the knowledge stocks variables and policy weights and would be missing from the sample if we only use applicant identifiers related to smart grid patents. We use wildcards to search the PATSTAT database for the brand name of the largest 325 companies in our sample. We limit our search to companies that have 5 or more smart grids patents because the likelihood that small firms have multiple identifiers is low. These searches sometimes return dozens and even hundreds of identifiers for large conglomerates such as Mitsubishi. Japanese and Korean conglomerates typically have a more decentralized corporate governance structure than European and North American conglomerates. For example, the different divisions of Mitsubishi operate as independent legal entities. For these, we further clean the search results to include only the ones containing keyword mentioned in the original sample of smart grid innovators. For example, we include Mitsubishi electric, Mitsubishi heavy industries and Mitsubishi semiconductors, but exclude patents by Mitsubishi metals and Mitsubishi materials from Mitsubishi's internal knowledge stocks.

Appendix B5: Assigning home country to firms

We need to assign a home country to each firm in our sample for two reasons: 1) our sample consists of firms that own granted patents in 19 OECD countries and whose home country is also in-sample, and 2) in robustness check 2.1, we also use information on firms' home countries to assign policy weights to new firms for which there is no pre-sample patents. To assign a country to a firm, we use information on the country of the applicant for the patents associated with that firm. We consider all the patents we collected in the period 1965-2020. These include patents in the cooperative patent classification sub-classes H (electricity), Y (environmental innovation), B60, F02C, F02B, F16D, F25B, F25D, G05, F21, B62D, and patents in the J-tag (ICTs) of the International Patent Classification. Fewer than a quarter of firms have more than one assignee country listed on their patents. For these, we use the country most frequently mentioned. In the case of a tie or when the applicant country is missing, we use information about priority patents to infer the missing values. We assume that the country where the firms' priority patents are filed is the home country.

Appendix B6: Firms in sample countries

We use countries where firms obtained patents as an indication of where their markets are located. Applying for patents is a costly process and it is reasonable to expect that firms only file in countries where they intent to sell their products (Aghion et al., 2016). When considering firms' markets, we are limited to 19 OECD countries for which we have complete data for our explanatory variables. However, many firms operate in markets beyond these 19 countries and might therefore be influenced by economic and policy conditions in markets for which we do not have data. To avoid spurious associations, it is important that we only include firms that have high exposure to explanatory variables in our sample countries and are therefore less likely to be influenced by conditions in out-of-sample countries.

Given this, we built the policy weights using information on all countries where firms have granted patents in relevant patent classes. In our main specification, we use the following Cooperative Patent Classification sub-classes: H (electricity), Y (environmental innovation), B60, F02C, F02B, F16D, F25B, F25D, G05, F21, B62D, and the J-tag (ICTs) of the International Patent Classification. To ensure sufficient exposure to the policies included in the explanatory variables, in the sample we only include firms located in these 19 countries. With this strategy, the sample is composed of firms who conduct a large share of their business in the 19 countries for which we have complete policy data. Using this strategy, 90% of the sample firms have at least 93% of their granted patents in those 19 countries. Table 2 shows further descriptive statistics about the coverage of the policy weights.

Table B6. Market coverage of sample countries for sample firms

Percentile	Sum of weights	Percentile	Sum of Weights
1%	0.5865056	75%	0.987733
5%	0.6550884	90%	0.9896584
10%	0.935672	95%	0.9946694
25%	0.9611475	99%	1
50%	0.9764343		
Min: 0.3174534	Mean: 0.953985	Max: 1	

Appendix B7: Assigning country to patent family

To build external knowledge stocks, we assign countries to patents. To identify where a patent originated, we use information on the location of its inventor(s). This implies that what matters for invention are spillover in the countries where the firm's R&D activities take place. However, the person country is often missing for inventors in PATSTAT (for methods to infer missing values, see: Pasimeni, 2019; Rassenfosse and Seliger, 2021). To infer those missing values, we use the following strategy:

- For patents that always have inventor country available, but for which this information is inconsistent within the patent family, we assign the inventor country that is most frequently listed. When there are ties, we use information contained in the most recent publication of the patent family.
- For patents that are sometimes missing inventor country data, we use the inventor country listed in the publication that contains complete information.
- When inventor information is always incomplete, we retrieve inventor country information from other patents that have the same inventor(s). This assumes that inventors are not mobile. When there are multiple countries, we assign the most frequently listed on other patents.
- In the case of patents for which we cannot infer inventor country information using the steps above, we assign the country of the applicant.

Appendix B8: Summary statistics

Table B8. Summary statistics

	Count	Mean	SD	Min	Max
Country-level variables					
Standards	323	4.07	7.07	0.00	97
Standards (cumulative)	323	37.70	37.81	0.00	215
RD&D renewables	323	6,928.16	27,038.30	0.46	187,898
RD&D grid	323	3,129.54	12,999.40	0.00	87,114
Household electricity prices	323	204.62	114.03	76.76	1,228.07
Renewables share	323	0.30	0.26	0.01	1
GDP per capita	323	41,386.57	10,043.86	11,891.63	68,787.47
Growth electricity consumption	323	1.19	3.26	-6.85	22.41
Firm-level variables					
Patent count	30628	1.74	12.16	0.00	650.00
Internal stocks - smart grids	30628	1.65	8.51	0.00	234.47
Internal stocks - green tech	30628	43.35	294.52	0.00	10,104.26
Internal stocks - electricity	30628	168.16	1,065.04	0.00	34,488.09
Internal stocks - ICTs	30628	281.41	1,723.34	0.00	41,705.38
Pre-sample mean of patents	30628	31.13	197.94	0.00	3,310.04
Country-level variables, weighted at the firm-level					
Standards	30628	5.72	3.92	0.00	33.97
Standards (cumulative)	30628	48.77	30.23	0.00	141.96
RD&D renewables	30628	16,974.02	28,507.93	13.13	187,898
RD&D grid	30628	7,248.33	13,591.65	0.00	87,114
Household electricity prices	30628	169.36	35.59	106.20	379.33
Renewables share	30628	0.16	0.07	0.01	0.77
GDP per capita	30628	45,841.91	4,741.09	24,860.99	57,459.40
Growth electricity consumption	30628	0.79	2.32	-6.85	22.41
External stocks - smart grids	30628	810.91	724.55	0.00	2,537.94
External stocks - green tech	30628	32,160.91	22,099.83	27.79	86,991.48
External stocks - electricity	30628	106,588.7	59,810.06	76.55	206,606.6
External stocks - ICTs	30628	167,952.7	104,892	120.54	327,427.2

APPENDIX C: ROBUSTNESS CHECKS AND OTHER RESULTS

Appendix C1: Full results for main model

Table C1. Regression results from Zero-Inflated Poisson regressions (full results)

Variables	Intensive margin	Extensive margin
Standards	-0.038***	0.016*
	(0.012)	(0.008)
RD&D smart grid	0.116	0.019
	(0.074)	(0.039)
RD&D renewables	-0.197**	-0.033
	(0.091)	(0.050)
Int. knowledge stocks - smart grids	0.598***	-1.436***
	(0.032)	(0.050)
Int. knowledge stocks - green tech	0.075**	-0.180***
	(0.032)	(0.022)
Int. knowledge stocks - electricity	0.137***	-0.147***
	(0.034)	(0.029)
Int. knowledge stocks - ICTs	-0.165***	-0.012
	(0.029)	(0.025)
Ext. knowledge stocks - smart grids	0.454**	-0.414***
	(0.185)	(0.098)
Ext. knowledge stocks - green tech	-0.565***	0.078
	(0.151)	(0.096)
Ext. knowledge stocks - electricity	-0.010	0.013
	(0.177)	(0.094)
Ext. knowledge stocks - ICTs	0.108	0.290***
	(0.151)	(0.101)
Renewables share	-1.077	-1.146**
	(0.887)	(0.564)
Elect. consumption growth	0.018	0.016
	(0.028)	(0.016)
Household elect. prices	0.530	0.280
	(0.418)	(0.304)
GDP per capita	0.857	1.083**
	(0.593)	(0.453)
Average patents /year in pre-sample	0.000***	-0.001***
	(0.000)	(0.000)
New firm	-0.054	-0.060
	(0.104)	(0.049)
Zero stock - smart grids	0.192**	-2.013***
	(0.092)	(0.065)
Zero stock - green tech	0.225**	-0.195***
	(0.102)	(0.051)
Zero stock - electricity	-0.015	-0.693***
	(0.100)	(0.054)
Zero stock - ICTs	0.051	-0.437***
	(0.093)	(0.050)
Marginal effect, standards (combined)	-0.076***	
	(0.021)	
Observations	30,628	30,628
Log-likelihood	-47022	-47022

Note: Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix C2: Robustness checks

We verify that our results are robust to making different research decisions and assumptions concerning 1) the home markets of firms with no pre-sample patent data, 2) the patent classes used to build the policy weights, 3) the rate at which knowledge stocks depreciate, 4) GDP weighting to account for market size in the policy weights, 5) the number of lagged periods it takes for standards to have an effect on patents, and 6) the choice of measure for the standards variable. We find that our results are robust to making these different research decisions.

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

C2.1 Policy weights, assumptions for new firms

We constructed policy weights using information on the countries where firms obtained patents during the pre-sample period. Applying for patents is costly, and firms seek intellectual property protection only in markets where they intend to sell their products (Aghion et al., 2016). We use this information as an indication of where their relevant markets are located. Because smart grids are an emerging area of technology with few patents in the pre-sample period, we use firms' patents in green innovation, electricity, and information technologies more broadly to construct those weights. It is also a feature of this sector that several firms are too new to have patents prior to 2000. For these firms, in the main specification we weight their exposure to international markets using the average market share 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 are relevant. In other words, we assign a weight of one to these companies' home country. Table C2.1 shows results for this robustness check. We lose significance on the standards and the renewables share variables at the extensive margin, and the smart grid external knowledge stocks at the intensive margin. Other key results remain unchanged with coefficients of similar magnitude and significance.

Table C.2.1.2 shows results for this robustness checks for large and small firms. As noted in the text, assuming that firms without any pre-sample data only operate domestically is more likely to hold for small firms. In this table, the key finding that the negative effect of standards is driven by large firms and that small firms are more responsive to government R&D support remains unchanged. However, government R&D support to smart grids has the effect of reducing the inventive activities of large firms at the extensive margin. Some of the results for the external knowledge stocks are also sensitive to assigning these different policy weights to new firms, as this robustness check changes firms' exposure to these variables. For small firms, we lose significance for the green and electricity external knowledge stocks at the intensive margin, but external smart grids stocks matter at both margins for these firms. For these firms, higher renewables share now dampen patenting at the extensive margin rather than the intensive margin. For large firm, external knowledge stocks in electricity now encourage entry, but external smart grids stocks do not. Other key results remain unchanged.

Table C2.1.1 Alternative weights for firms with no pre-sample patents – main model

Variables	Intensive margin	Extensive margin
Standards	-0.023***	0.004
	(0.007)	(0.004)
RD&D smart grid	0.055	-0.002
	(0.047)	(0.019)
RD&D renewables	-0.125**	0.016
	(0.053)	(0.025)
Int. knowledge stocks - smart grids	0.603***	-1.450***
	(0.032)	(0.050)
Int. knowledge stocks - green tech	0.071**	-0.188***
	(0.032)	(0.022)
Int. knowledge stocks - electricity	0.134***	-0.138***
	(0.033)	(0.028)
Int. knowledge stocks - ICTs	-0.163***	-0.011
	(0.030)	(0.024)
Ext. knowledge stocks - smart grids	0.271	-0.278***
	(0.205)	(0.098)
Ext. knowledge stocks - green tech	-0.446***	-0.044
	(0.163)	(0.099)
Ext. knowledge stocks - electricity	0.127	-0.004
	(0.192)	(0.095)
Ext. knowledge stocks - ICTs	0.056	0.304***
	(0.148)	(0.102)
Renewables share	-0.432	0.240
	(0.290)	(0.185)
Marginal effect, standards (combined)	-0.042***	
	(0.012)	
Observations	30,628	30,628
Log-likelihood	-47022	-47022

Note: In this model, firms with no pre-sample patents and for which it is not possible to build weights are assigned their home country as their main market. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.2.1.2 Alternative weights for firms with no pre-sample patents - heterogeneity

	Large firms		Small firms	
Variables	Intensive m.	Extensive m.	Intensive m.	Extensive m.
Standards	-0.048***	0.021*	-0.005	0.002
	(0.012)	(0.012)	(0.007)	(0.005)
RD&D smart grid	0.023	0.074**	0.083**	-0.013
	(0.119)	(0.036)	(0.040)	(0.023)
RD&D renewables	0.002	-0.015	-0.190***	0.014
	(0.127)	(0.054)	(0.051)	(0.031)
Int. knowledge stocks - smart grids	0.638***	-1.246***	0.399**	-1.533***
	(0.033)	(0.056)	(0.188)	(0.095)
Int. knowledge stocks - green tech	0.072*	-0.156***	-0.205	-0.068
	(0.037)	(0.025)	(0.150)	(0.061)
Int. knowledge stocks - electricity	0.218***	0.013	0.007	-0.290***
	(0.044)	(0.035)	(0.063)	(0.052)
Int. knowledge stocks - ICTs	-0.210***	-0.078**	-0.099	-0.008
	(0.036)	(0.031)	(0.069)	(0.049)
Ext. knowledge stocks - smart grids	0.396	-0.086	0.335*	-0.215*
	(0.362)	(0.179)	(0.192)	(0.122)
Ext. knowledge stocks - green tech	-0.685***	0.115	-0.241	-0.161
	(0.231)	(0.156)	(0.214)	(0.133)
Ext. knowledge stocks - electricity	0.344	-0.367*	-0.203	0.059
	(0.301)	(0.188)	(0.165)	(0.115)
Ext. knowledge stocks - ICTs	0.012	0.286	0.166	0.309**
	(0.211)	(0.190)	(0.191)	(0.126)
Renewables share	0.281	-0.620	-0.322	0.429**
	(0.983)	(0.647)	(0.284)	(0.207)
Marginal effect, standards (combined)	-0.205***		-0.005	
	(0.050)		(0.005)	
Number of firms	597	597	2,154	2,154
Observations	9,523	9,523	21,105	21,105
Log-likelihood	-23751	-23751	-21315	-21315

Note: In this model, firms with no pre-sample patents and for which it is not possible to build weights are assigned their home country as their main market. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

C2.2 Knowledge stocks depreciation rate

Another research decision pertains to the choice of the depreciation rate applied to the external and internal knowledge stocks variables (see Appendix B2, which details how these stocks were constructed). In our main specification, we use a 15% depreciation rate. In Table C2.2, 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.

Table C2.2 20% depreciation rate for knowledge stocks

Variables	Extensive margin	Intensive margin
Standards, collapse(mean)	-0.037***	0.017*
	(0.012)	(0.008)
RD&D smart grid, collapse(mean)	0.116	0.022
	(0.074)	(0.039)
RD&D renewables, collapse(mean)	-0.201**	-0.034
	(0.091)	(0.050)
Int. knowledge stocks - green tech	0.075**	-0.185***
	(0.032)	(0.022)
Int. knowledge stocks - electricity	0.139***	-0.152***
	(0.034)	(0.029)
Int. knowledge stocks - ICTs	-0.164***	-0.013
	(0.029)	(0.025)
Ext. knowledge stocks - smart grids	0.417**	-0.410***
	(0.181)	(0.095)
Ext. knowledge stocks - green tech	-0.563***	0.080
	(0.146)	(0.093)
Ext. knowledge stocks - electricity	-0.009	0.023
	(0.180)	(0.094)
Ext. knowledge stocks - ICTs	0.138	0.275***
	(0.153)	(0.101)
Renewables share	-0.959	-1.221**
	(0.876)	(0.561)
Marginal effect, standards (combined)	-0.076***	
	(0.020)	
Observations	30,628	30,628
Log-likelihood	-46971	-46971

Note: This model uses the same specification and control variables as our main model with the exception that the knowledge stocks variables depreciate 20% annually instead of 15%. Robust standard errors are in included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

C2.3 *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 C2.3, 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. The effect of standards at the extensive margin is estimated less precisely and becomes insignificant, but the effect of government support to R&D in grid-related technologies becomes significant at the intensive margin. Other key results are unchanged.

C2.4 Lagged variables

We also check the effects of standards on patents using different lags, as it is unclear how many years it takes for standards to affect patenting levels. Table C2.4.1 shows results from regressions that use different lags in separate models. For each of these models we lag all the time-varying explanatory and control variables by 1 year, 2 years (main model), 3 years and 4 years respectively. Results for the standards variable are generally robust, with the exception of the effect of standards at the extensive margin which is only significant in the short run. Across all models, the combined marginal effect of standards is of similar magnitude and significance. Given this, we chose the model with the second lag as our preferred specification because it has a better goodness of fit than the models that include the 3rd and 4th lags. The model with the first lag has better goodness of fit but does not leave enough time for government R&D support to take effect. Government R&D only start becoming significant after two years have passed and becomes stronger and more significant thereafter. Choosing the model with the second lag as our main specification allows to balance the effect of standards acting quickly than government R&D.

Table C2.3 Alternative GDP weighting of the policy weights

Variables	Intensive margin	Extensive margin
Standards, collapse(mean)	-0.056***	0.013
	(0.016)	(0.011)
RD&D smart grid, collapse(mean)	0.177*	0.042
	(0.092)	(0.049)
RD&D renewables, collapse(mean)	-0.285**	-0.082
	(0.126)	(0.066)
Int. knowledge stocks - smart grids	0.600***	-1.442***
	(0.032)	(0.050)
Int. knowledge stocks - green tech	0.072**	-0.174***
	(0.032)	(0.022)
Int. knowledge stocks - electricity	0.146***	-0.159***
	(0.037)	(0.029)
Int. knowledge stocks - ICTs	-0.171***	-0.004
	(0.029)	(0.025)
Ext. knowledge stocks - smart grids	0.515***	-0.451***
	(0.164)	(0.079)
Ext. knowledge stocks - green tech	-0.508***	0.175*
	(0.153)	(0.092)
Ext. knowledge stocks - electricity	-0.142	-0.054
	(0.177)	(0.090)
Ext. knowledge stocks - ICTs	0.100	0.323***
	(0.158)	(0.104)
Renewables share	-3.576*	-0.210
	(1.912)	(1.105)
Marginal effect, standards (combined)	-0.106***	
	(0.029)	
Observations	30,628	30,628
Log-likelihood	-46934	-46934

Note: This model uses the same specification and control variables as our main model with the exception that the policy weights are weighted by GDP instead of GDP to the power of 0.35. *** p<0.01, ** p<0.05, * p<0.1

Table C2.4.1 Regression results for alternative lags

	1 year lag		2 year lag		3 year lag		4 year lag	
Variables	Intensive m.	Extensive m.	Intensive m.	Extensive m.	Intensive m.	Extensive m.	Intensive m.	Extensive m.
Standards	-0.030**	0.039***	-0.038***	0.016*	-0.037**	-0.002	-0.049***	-0.003
	(0.013)	(0.009)	(0.012)	(0.008)	(0.015)	(0.009)	(0.013)	(0.009)
RD&D smart grid	0.061	-0.042	0.116	0.019	0.172**	0.004	0.184***	0.006
	(0.070)	(0.045)	(0.074)	(0.039)	(0.074)	(0.038)	(0.065)	(0.034)
RD&D renewables	-0.098	0.042	-0.197**	-0.033	-0.267***	-0.021	-0.260***	-0.035
	(0.098)	(0.059)	(0.091)	(0.050)	(0.087)	(0.047)	(0.074)	(0.044)
Int. knowledge stocks - smart grids	0.652***	-1.596***	0.598***	-1.436***	0.566***	-1.333***	0.561***	-1.250***
	(0.031)	(0.051)	(0.032)	(0.050)	(0.033)	(0.051)	(0.036)	(0.053)
Int. knowledge stocks - green tech	0.048	-0.168***	0.075**	-0.180***	0.102***	-0.196***	0.113***	-0.206***
	(0.031)	(0.022)	(0.032)	(0.022)	(0.032)	(0.021)	(0.033)	(0.021)
Int. knowledge stocks - electricity	0.140***	-0.177***	0.137***	-0.147***	0.122***	-0.127***	0.136***	-0.127***
	(0.034)	(0.029)	(0.034)	(0.029)	(0.036)	(0.029)	(0.039)	(0.029)
Int. knowledge stocks - ICTs	-0.167***	-0.007	-0.165***	-0.012	-0.162***	-0.023	-0.171***	-0.018
	(0.029)	(0.025)	(0.029)	(0.025)	(0.030)	(0.025)	(0.030)	(0.025)
Ext. knowledge stocks - smart grids	0.525***	-0.590***	0.454**	-0.414***	0.503***	-0.370***	0.587***	-0.344***
	(0.165)	(0.103)	(0.185)	(0.098)	(0.176)	(0.095)	(0.159)	(0.092)
Ext. knowledge stocks - green tech	-0.621***	0.065	-0.565***	0.078	-0.521***	0.098	-0.461***	0.131
	(0.152)	(0.099)	(0.151)	(0.096)	(0.152)	(0.094)	(0.156)	(0.094)
Ext. knowledge stocks - electricity	-0.015	0.068	-0.010	0.013	0.028	0.022	0.106	-0.023
	(0.154)	(0.098)	(0.177)	(0.094)	(0.167)	(0.091)	(0.147)	(0.090)
Ext. knowledge stocks - ICTs	0.080	0.429***	0.108	0.290***	0.004	0.206**	-0.193	0.187*
	(0.162)	(0.104)	(0.151)	(0.101)	(0.143)	(0.099)	(0.152)	(0.098)
Share of renewables	-0.596	-1.289**	-1.077	-1.146**	-1.435*	-1.225**	-1.091	-1.691***
	(0.946)	(0.574)	(0.887)	(0.564)	(0.872)	(0.556)	(0.901)	(0.536)
Marginal effect, standards (comb.)	-0.076***		-0.076***		-0.062**		-0.082***	
	(0.022)		(0.021)		(0.025)		(0.229)	
Observations	30,628	30,628	30,628	30,628	30,623	30,623	30,618	30,618
Log-likelihood	-45292	-45292	-47022	-47022	-47918	-47918	-48430	-48430
AIC	90735	90735	94195	94195	95988	95988	97011	97011

Note: These regressions include the same control variables as the main model. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C2.4.2 Short and long run effects of standards

Variables	Intensive margin	Extensive margin
Standards (1 year lag)	-0.012	0.029***
	(0.013)	(0.008)
Standards (2 year lag)	-0.023*	0.014*
	(0.012)	(0.008)
Standards (3 year lag)	-0.027**	-0.004
	(0.013)	(0.008)
Standards (4 year lag)	-0.047***	-0.002
	(0.012)	(0.008)
Joint significance	-0.110***	0.037**
	(0.024)	(0.015)
RD&D smart grid (1 year lag)	-0.145	-0.024
	(0.116)	(0.071)
RD&D smart grid (2 year lag)	-0.003	0.049
	(0.139)	(0.078)
RD&D smart grid (3 year lag)	0.088	0.028
	(0.120)	(0.080)
RD&D smart grid (4 year lag)	0.129	-0.034
	(0.088)	(0.063)
Joint significance	0.068	0.019
	(0.075)	(0.043)
RD&D renewables (1 year lag)	0.105	0.163
	(0.211)	(0.117)
RD&D renewables (2 year lag)	-0.011	-0.066
	(0.257)	(0.142)
RD&D renewables (3 year lag)	-0.335	0.139
	(0.225)	(0.136)
RD&D renewables (4 year lag)	0.039	-0.236**
	(0.175)	(0.106)
Joint significance	-0.202**	0.001
	(0.095)	(0.057)
Observations	30,618	30,618
Log-likelihood	-48118	-48118

Note: This regression adds the first, third and fourth lags to the main model. The internal and external knowledge stocks variables and zero stock dummies are lagged by 4 periods instead of two. The variables share of renewables, electricity consumption growth, household electricity prices and GDP per capita are lagged by two periods, as in the main model. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

We also investigate the short and long-run effects of standards by including these 4 lags in a single model, and testing whether the effect of standards over the four years that follow the introduction of a standard is jointly significant. Result from this model, included in Table C2.4.2, show that the effect of standards at the intensive margin becomes stronger and more significant overtime and that the effect for the four years is jointly significant at both the extensive and intensive margins.

C2.5 Cumulative stock of patents

We also conduct robustness checks using an alternative measure of the standards variable, as it is unclear which measure is most appropriate. In our main model, we use a simple count of patents. Results using this variable can be interpreted as an event-study approach – how does the accreditation of a new standard in a firm's market affect innovation. In these robustness checks, we use a cumulative count of all smart grids standards that have been accredited in country *c* up to and including year *t*. This count can be interpreted as a proxy for the overall level of standardization each firm is exposed to in its markets. Tables C2.5.1, C2.5.2 and C2.5.3 replicates our main results tables (Tables 1, 2 and 3) using this cumulative count of standards as the main explanatory variable. Overall, using this measure allows to estimate the effects of the RD&D variables more precisely, and our results on the standards variables are generally robust at the intensive margin.

Table C2.5.1 Main model on cumulative count of standards

Variables	Intensive margin	Extensive margin
Standards	-0.021***	-0.002
	(0.004)	(0.003)
RD&D smart grid	0.124*	0.009
	(0.071)	(0.039)
RD&D renewables	-0.325***	-0.053
	(0.084)	(0.053)
Int. knowledge stocks - smart grids	0.596***	-1.433***
	(0.032)	(0.050)
Int. knowledge stocks - green tech	0.078**	-0.179***
	(0.032)	(0.022)
Int. knowledge stocks - electricity	0.149***	-0.144***
	(0.035)	(0.029)
Int. knowledge stocks - ICTs	-0.171***	-0.014
	(0.029)	(0.025)
Ext. knowledge stocks - smart grids	0.233	-0.438***
	(0.180)	(0.099)
Ext. knowledge stocks - green tech	-0.327**	0.096
	(0.155)	(0.099)
Ext. knowledge stocks - electricity	0.149	0.049
	(0.175)	(0.096)
Ext. knowledge stocks - ICTs	-0.059	0.261**
	(0.153)	(0.104)
Renewables share	-0.947	-1.143**
	(0.854)	(0.567)
Marginal effect, standards (combined)	-0.034***	
	(0.007)	
Observations	30,628	30,628
Log-likelihood	-46771	-46771

Note: This model uses the same specification and control variables as our main model with the exception that the main explanatory variable is a cumulative count of standards. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In Table C2.5.1 using the cumulative count of standards slightly attenuates the effect of standards at the intensive margin, and the coefficient is estimated with less precision at the extensive margin. Conversely, it makes the results on the RD&D variables stronger and more significant at the intensive margin. The results for the knowledge stocks variables remain generally unchanged, with the exception of the smart grids external knowledge stocks, which is estimated less precisely at the intensive margin.

Table C2.5.2 Regression results by firm size using cumulative count of patents

	Large firms		Small firms	
Variables	Intensive m.	Extensive m.	Intensive m.	Extensive m.
Standards	-0.031***	-0.001	-0.001	-0.004
	(0.005)	(0.004)	(0.005)	(0.004)
RD&D smart grid	0.013	0.062	0.233***	0.061
	(0.111)	(0.068)	(0.082)	(0.050)
RD&D renewables	-0.202*	-0.001	-0.449***	-0.134*
	(0.116)	(0.086)	(0.100)	(0.072)
Int. knowledge stocks - smart grids	0.640***	-1.219***	0.389**	-1.536***
	(0.033)	(0.056)	(0.190)	(0.095)
Int. knowledge stocks - green tech	0.076**	-0.145***	-0.197	-0.067
	(0.037)	(0.025)	(0.154)	(0.062)
Int. knowledge stocks - electricity	0.231***	0.020	-0.017	-0.300***
	(0.048)	(0.036)	(0.064)	(0.052)
Int. knowledge stocks - ICTs	-0.211***	-0.089***	-0.089	-0.005
	(0.036)	(0.032)	(0.072)	(0.049)
Ext. knowledge stocks - smart grids	-0.115	-0.411**	0.335	-0.263**
	(0.347)	(0.202)	(0.208)	(0.121)
Ext. knowledge stocks - green tech	-0.220	0.249	-0.345*	-0.065
	(0.249)	(0.164)	(0.198)	(0.128)
Ext. knowledge stocks - electricity	0.619**	-0.145	-0.281*	0.055
	(0.305)	(0.195)	(0.171)	(0.121)
Ext. knowledge stocks - ICTs	-0.216	0.210	0.306	0.260**
	(0.212)	(0.197)	(0.186)	(0.128)
Renewables share	0.873	-1.391*	-2.244**	0.230
	(1.032)	(0.816)	(1.014)	(0.903)
Marginal effect, standards	-0.119***		0.001	
	(0.021)		(0.004)	
Observations	9,523	9,523	21,105	21,105
Log-likelihood	-23413	-23413	-21227	-21227

Note: These regressions use the same specification and control variables as the main model. Large firms are defined as firms that had more than 100 patents in the ICT, electricity and green innovation patent classes durin the period 1977-2016. Small firms are defined as firms that 100 or fewer patents in the same patents class and period. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C2.5.3 Effect on new entrants using cumulative count of standards

Variables	Intensive margin	Extensive margin
Standards	-0.022***	0.015***
	(0.004)	(0.003)
Interaction standards and zero stock dummy	0.004	-0.034***
	(0.003)	(0.002)
RD&D smart grid	0.132*	-0.019
	(0.071)	(0.041)
RD&D renewables	-0.336***	0.020
	(0.084)	(0.055)
Int. knowledge stocks - smart grids	0.603***	-1.436***
	(0.032)	(0.049)
Int. knowledge stocks - green tech	0.079**	-0.174***
	(0.032)	(0.021)
Int. knowledge stocks - electricity	0.153***	-0.147***
	(0.035)	(0.028)
Int. knowledge stocks - ICTs	-0.175***	0.002
	(0.029)	(0.025)
Ext. knowledge stocks - smart grids	0.230	-0.260**
	(0.181)	(0.101)
Ext. knowledge stocks - green tech	-0.331**	0.076
	(0.156)	(0.102)
Ext. knowledge stocks - electricity	0.172	-0.074
	(0.180)	(0.100)
Ext. knowledge stocks - ICTs	-0.073	0.218**
	(0.154)	(0.106)
Renewables share	-0.984	-0.991*
	(0.858)	(0.571)
Joint significance	-0.018***	-0.019***
	(0.004)	(0.003)
Observations	30,628	30,628
Log-likelihood	-46493	-46493

Note: This regression uses the same specification and control variables as the main model. This model interacts the standards variables with a dummy variable that indicates whether the firm had any internal knowledge stocks in past periods. As with other variables, we use the second lag. Robust standard errors are included in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Our results for large firms, shown in table C.2.5.2 are more sensitive to using the cumulative count of patents than the results for small firms. This being said, key results remain robust to using this alternative measure. For large firms, the coefficients on the standard variables and the combined marginal effect is smaller, which is consistent with one new standard being a smaller percentage increase in the cumulative count. , Moreover, the effect of standards on large firms loses significance at the extensive margin. Conversely, the RD&D renewables variable becomes significant at the extensive margin. The external knowledge stocks are more sensitive to changing our measure of the standard variable with the green stocks losing significance and the electricity stocks gaining significance. Our results are substantively unchanged for small firms with the exception that the external ICT knowledge stocks variables is estimated less precisely at the intensive margin.

Finally, table C.2.5.3 shows again that using a cumulative count attenuates the effect of standards, but the sign and significance of these coefficient corroborate our main findings. Again, the effects of the RD&D variables are estimated with greater precision and other key results remain unchanged.

C2.6 Alternative cut-off years

We also verify that the cutoff year we use for building the policy weights is not driving the results. In the main specification, we build policy weights using firms' patents in the years 1977-1999 and begin the regression analysis in 2000. In Table 14, we use patent data for the years 1977-2004 to build the policy weights and begin the regression analysis in 2005. While the effects of external knowledge are somewhat sensitive to when the stocks are constructed, our main results on standards and R&D are not affected by changing the years of the sample.

Table C2.6 Alternative cut-off year for building policy weights (1977-2004)

Variables	Intensive margin	Extensive margin
Standards	-0.035***	0.016*
	(0.012)	(0.009)
RD&D smart grid	0.091	0.051
	(0.122)	(0.075)
RD&D renewables	-0.254*	0.045
	(0.136)	(0.084)
Int. knowledge stocks - smart grids	0.601***	-1.417***
	(0.035)	(0.054)
Int. knowledge stocks - green tech	0.061*	-0.191***
	(0.033)	(0.024)
Int. knowledge stocks - electricity	0.101***	-0.105***
	(0.035)	(0.032)
Int. knowledge stocks - ICTs	-0.127***	-0.040
	(0.031)	(0.027)
Ext. knowledge stocks - smart grids	0.149	-0.557***
	(0.211)	(0.112)
Ext. knowledge stocks - green tech	-0.580***	0.179*
	(0.159)	(0.107)
Ext. knowledge stocks - electricity	-0.037	0.190*
	(0.208)	(0.110)
Ext. knowledge stocks - ICTs	0.443***	0.137
	(0.157)	(0.121)
Renewables share	-1.380	-0.293
	(1.030)	(0.662)
Marginal effect, standards (combined)	-0.077***	
	(0.023)	
Observations	24,798	24,798
Log-likelihood	-39949	-39949

Note: This model uses the same specification and control variables as our main model with the exception that the policy weights were constructed using firms patents in the 1977-2004 period. Regression starts in 2005 and ends in 2016. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix C3: Fixed effects Poisson model

To control for a firm's overall propensity to patent, our preferred specification uses the average number of patents each firm had during pre-sample years, combined with a dummy that identifies new firms. This way of de-meaning to control for unobserved firm heterogenenity presents the advantage of producing consistent estimates under weak exogenenity, which is not possible with a fixed effects Poisson model, because the latter requires strict exogenenity. Strict exogenenit requires that these variables be orthogonal to error terms in all past, present and future periods. The strict exogeneity assumption is violated by our smart grid knowledge stocks variables, which by constrution are correlatd with past error terms since they carry forward patent counts from previous years. For these variables, weak exogenity only requires that shocks in period t are not correlated with lagged knowledge stocks, which is a more reasonable assumption.

To demonstrate this bias, Table C3 presents results from a fixed effect Poisson model, as well as a Poisson model using the pre-sample mean estimator for comparison. Table C3 clearly shows that the coefficients in the fixed effects Poisson model are biased, especially for the smart grid knowledge stocks variables, whose direction, magnitude and significance are diametrically different from the coefficients from the Pre-sample mean Poisson model. This model also estimates the effect of standards and RD&D variables imprecisely. The Pre-sample mean Poisson model included in Table C3 produces results that are much more similar to the coefficients from our main Zero-Inflated Poisson (ZIP) model since both address the biases of the Fixed Effects Poisson model. While the pre-sample mean estimator provides similar resutls to the ZIP model, we focus on the ZIP model in the main text as it better handles the high number of zeros in our data by rescaling the estimates in the second stage of the model to account for the probability of having any patents.

Table C3. Regression results from pre-sample mean estimator and fixed-effects Poisson

Variable	Pre-sample mean Poisson	Fixed Effects Poisson
Standards	-0.045***	-0.019
	(0.012)	(0.013)
RD&D smart grid	0.094	0.015
	(0.064)	(0.093)
RD&D renewables	-0.198**	-0.029
	(0.080)	(0.180)
Int. knowledge stocks - smart grids	0.938***	-0.324***
	(0.041)	(0.114)
Int. knowledge stocks - green tech	0.130***	0.213
	(0.033)	(0.139)
Int. knowledge stocks - electricity	0.261***	0.440***
	(0.034)	(0.117)
Int. knowledge stocks - ICTs	-0.122***	0.070
	(0.030)	(0.098)
Ext. knowledge stocks - smart grids	0.646***	0.248
	(0.172)	(0.375)
Ext. knowledge stocks - green tech	-0.538***	-1.637***
	(0.156)	(0.563)
Ext. knowledge stocks - electricity	-0.268	3.885***
	(0.170)	(0.818)
Ext. knowledge stocks - ICTs	0.216	-1.517
	(0.163)	(0.937)
Renewables share	1.330*	-4.336
	(0.757)	(4.101)
Observations	30,628	30,426
Pseudo R-squared	0.492	
Log-likelihood		-50701

Note: The pre-sample mean estimator model includes firms' average yearly patents in the pre-sample period and a complete set of year dummies. The fixed effect Poisson model includes firm and year fixed effects. Both include the same control variables as the Zero-Inflated Poisson regression (main model). Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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