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Technology policy for meeting net-zero carbon goals by 2050: Accelerating innovation in complementary technologies to decarbonize the electrical grid

Myriam Gregoire0Zawilski
Syracuse University

Abstract

In this dissertation, I examine the link between technology standards and innovation in green energy technologies. The first paper investigates the effects of compatibility standards on follow-on innovation at the firm-level in smart grid technology. Using data on the adoption of standards in 19 OECD countries and weights that capture the unique composition of each firm's country markets, we find that higher exposure to changes in standardization causes a decline in firms' patenting activity. This negative effect is concentrated in large incumbents and is partially offset by an increase in the quality of inventions. This suggests a tradeoff in the effects of standards on the quantity versus the quality of innovation, which might occur because standards help focus inventive activity onto high-quality pathways.

The second paper tests this technological focusing hypothesis more directly using an analysis of citations at the patent-level in three clean energy technologies: solar photovoltaic, wind turbines and smart grids. I leverage variation in standard counts across different cohorts of patents and technologies to estimate how standards affect patent citations. I find that standards cause an increase in patent citations, implying that they help inventors better utilize existing knowledge. Furthermore, when estimating the effects of standards across different quantiles of the patent quality distribution, I find that the increase in citations is concentrated in high-quality patents.

The third paper explores how standards affect knowledge transfers between different domains of smart grids technology. I use patent citation data to identify inventions that are highly influential within the citation network. Using this subsample of influential patents, I garner qualitative insights about the field's main knowledge trajectory. For example, influential patents appear to play an important role in transferring expertise across different sectors of smart grid technology. Findings from this exploratory analysis can help identify where important knowledge flows have occurred, with a view to informing future research on the causal effects of standards on knowledge transfers.

Technology policy for meeting net-zero carbon goals by 2050:
Accelerating innovation in complementary technologies to decarbonize the electrical grid

by

Myriam Grégoire-Zawilski

B.A. The University of British Columbia, 2011

M.Sc. Université de Montréal, 2015

Dissertation

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Introduction

The world is falling behind on its commitments to limit global warming to no more than 1.5 degrees Celsius above pre-industrial levels. Since the Paris Agreement was established, global emissions have continued to rise. The World Meteorological Organization now projects that global average temperatures will likely surpass the 1.5 degrees threshold for at least one year between now and 2027[1]. To have a realistic change of containing global warming to 1.5 degrees, some projections estimate that the transition to net-zero emissions will need to happen well before 2050, the target set by the Paris Agreement (Lamboll et al, 2023).

Amidst this crisis, the pivotal role of policy in accelerating decarbonization transitions cannot be overstated. In the past decades, policy has played a crucial role in driving down the costs of wind and solar generation to levels below those of fossil fuel generation. The creation of markets for these technologies was largely achieved through demand-pull policies such as customer subsidies and feed-in-tariffs (Reichardt and Rogge, 2016; Nemet, 2019; Gerarden, 2023). Despite these advancements, innovation remains insufficient in many areas necessary to advance decarbonization goals. According to the International Energy Agency, half of the technologies needed to achieve net-zero are not yet market-ready. In the electricity sector, these include enabling technologies to enhance grid flexibility and support the large-scale integration of variable electricity generation (IEA, 2021).

To advance the goals of the Paris Agreement, policies must address the dual externalities challenge causing an undersupply of R&D in green energy technologies (Popp, 2019). Market-based demand-pull interventions can help mitigate environmental externalities, while supply-side technology-push policies help address the public good nature of knowledge. On the demand-side, studies show that carbon pricing policies are effective at stimulating green innovation among regulated firms (Calel and Dechezleprêtre, 2016), and more generally, that increases in fossil fuel prices induce clean innovation (Popp, 2002) and cause firms to switch from

[1] https://wmo.int/news/media-centre/global-temperatures-set-reach-new-records-next-five-years

dirty to clean R&D (Aghion et al., 2016). On the supply-side, interventions such as research grants and fiscal incentives for R&D are also critical to address knowledge spillovers in markets for green inventions. Overall, a balanced and comprehensive mix of different policy instruments is needed to tackle the dual externalities problem (Costantini, et al., 2017).

Decision makers must also consider technology maturity when designing policy mixes to support green innovation. Broad-based price incentives are most effective for technologies nearing market-readiness, while technology-push instruments support innovation in earlier stages of the technology cycle (Johnstone et al., 2010). Looking ahead, policymakers face the complex task of accelerating the adoption of mature renewable generation technologies, while continuing to support technology development in nascent areas that will be critical to achieve net-zero in the long-term. Designing effective green innovation policy therefore requires leveraging a mix of instruments to address market failures at different stages of the technology cycle (Popp et al., 2024).

In recent years, policymakers in the United States have expanded the range of tools they use to support green innovation to address a broader set of market failures that include coordination failures and financial frictions, particularly during the pilot and demonstration stages of the technology cycle (Armitage et al., 2024). My dissertation advances understanding of these coordination bottlenecks, particularly technological uncertainty about compatibility requirements, that arise in networked and interdisciplinary emerging technologies like smart grids. It sheds light on technological trajectories within this field and on the role of technology standards, a policy instrument[2] largely overlooked in the green innovation literature, for addressing the above challenges.

In the first chapter, I investigate the effects of compatibility standards on follow-on innovation using an analysis of patenting activity at the firm-level. Using data on the adoption of smart grids

[2] In the green energy sector, standardization efforts have principally been initiated by public policy mandates directed at national and regional standardization bodies. Therefore, I argue that standard can serve as a public policy tool, despite traditionally being perceived as industry-led because of their voluntary nature and the high level of expertise and participation they require from industry.

standards in 19 OECD countries and weights that capture the unique composition of each firm's country markets, I estimate how exposure to changes in standardization affect firms' follow-on patenting levels. I find that standards lower inventive activity on average, but my analysis reveals important heterogeneity between large incumbent firms, mostly responsible for this negative effect, and new players, who are more likely to enter the market for smart grids inventions after the introduction of standards. A possible explanation is that standards lower the cost of acquiring information about the industry's best practices, helping new firms enter, while also providing valuable information to incumbents on where to focus their R&D efforts. In this case, the observed negative effect of standards is not necessarily a sign that standards are detrimental to innovation, but rather an artifact of technological focusing. Therefore, to understand more fully how standards affect follow-on inventions, we must look beyond their effects on patenting intensity to also consider how they alter the quality and direction of follow-on innovation.

I begin to unpack these questions in the first paper by using patent citations as a proxy for patent quality. I re-estimate my firm-level model using a citation-weighted count of patents as the dependent variable. These counts place greater weight on highly cited patents. When estimating this model, I find a smaller negative coefficient. While the quality effect is too small to completely offset the negative effect on patenting intensity, these results highlight a trade-off in the effects of standards on the quantity versus the quality of innovation: standards cause firms to pursue fewer inventions, but to produce higher-quality innovation. This may be because standards provide information that prompt firms to reallocate their R&D resources towards fewer, but more promising research directions.

I unpack this technological focusing hypothesis more fully in the second paper through an analysis of citations at the patent-level. The citation-weighted counts used for the firm-level analysis in the first chapter only provide a static snapshot of citations received within a 5-year window. Shifting the unit of analysis to the patent-level allows me to observe how standards alter patent citation trajectories over longer periods. I also expand the sample of patents to include solar photovoltaic and wind turbine technologies, in addition to smart grids inventions. This allows me to utilize variation in standard counts and compare how standards affect knowledge utilization and technological focusing across different types of technologies. I find that standards increase patent citations, particularly in smart grids. Furthermore, when estimating the effects of standards across different quantiles of the patent quality distribution, I find that the increase in citations is concentrated in-quality patents. This pattern is most striking in solar PV technology. Together, these results provide evidence that standards help follow-on inventors identify and utilize a high-quality knowledge base, focusing knowledge accumulation onto high-quality paths.

In the last chapter, I continue my investigation of how standards shape technological trajectories. An important part of supporting interoperability and the integration of complex interdisciplinary knowledge across a sector is ensuring that inventors who develop different components of a technology are learning from each other's expertise. The last paper begins to explore how standards affect knowledge transfers across different domains of smart grids technology. I use patent citation data to identify inventions that are highly influential within the citation network. Using this subsample of influential patents, I garner qualitative insights about the field's main knowledge trajectory. I find similarities with knowledge trajectories in other complex green energy technologies, like wind turbines. The core knowledge trajectory is diversified and evolves sequentially across different components. Innovation in core components – i.e., the information and communication layers of the smart grid architecture that have been the focus of standardization – seem to have propelled new innovation in already established areas such as home energy management, as well as in new areas such as storage and microgrids integration. I also find that influential patents have distinctive features: they span multiple domains of smart grid technology and build on more original knowledge. These patents appear to play an important role in transferring expertise across different sectors of smart grid technology. Findings from this exploratory analysis can help identify where important knowledge flows have occurred within the network of smart grid inventions, with a view to informing future research modelling the causal effects of standards on these knowledge transfers.

Finally, throughout this dissertation, I use data on standards and patents. There are measurement challenges associated with both. Those are well-acknowledged in extant literature, and I follow best available practice to measure standardization and innovation. Notably, standards and patents vary greatly in the breath, type, and quality of the information they contain, which can introduce inconsistency in the unit of analysis, such as giving equal weight to patented inventions that vary in quality or giving equal weight to standard that vary in breath and complexity. Below, I review these challenges and discuss the research decisions I made throughout the dissertation to manage these measurement issues.

Patent data

Patents grant intellectual property protection to the owner of an invention for a defined period within a given country jurisdiction. Patent assignees wishing to obtain intellectual property protection in multiple country markets must file for a patent in each country where they are seeking protection for their invention[3]. Through the Paris Convention, assignees are given priority to obtain protection for their invention in additional markets. If they file abroad within the 12-month priority period, signatories of the Convention will honor the date of the first filing[4]. Therefore, when counting inventions filed in multiple markets, it is critical to count patents at the family-level, and it is common practice to use the earliest filing to date the invention (De Rassenfosse et al, 2014). I follow standard practice when measuring patenting intensity (i.e. counts of patents) at the firm-level in multinational firms in Chapter 1.

Furthermore, the purpose of intellectual property (IP) protection is to exclude others from profiting commercially from an invention until the patent expires and this knowledge enters the public domain. This protection assures the IP owner that they will reap the benefits of any commercial success their invention achieves. It prevents others from using this knowledge without first entering into a licensing agreement with the IP owner. Since knowledge is non-excludable and non-rivalrous (i.e. a public good), without institutions to protect it, spillovers could lead to an underinvestment in R&D. To address this market failure, intellectual property protection provides individuals and organizations with reassurance that they will have a temporary monopoly over the commercialization of their ideas.

[3] Or they may obtain protection across multiple markets through filing for a patent with the World Intellectual Property Organization (WIPO) or the European Patent Office (EPO).
[4] https://www.wipo.int/pct/en/texts/ro/ro166.html, consulted on 29 July 2024.

Determining what constitutes novel knowledge is a central mandate of patent offices, as novelty is the main criteria for obtaining IP protection for an invention. Companies compete in a race to patent novel ideas and claim ownership over this space of technology. Working with patent data therefore requires understanding these competitive dynamics as well as the legal context within which patent data is recorded. While the patenting process occurs within a competitive market for ideas, knowledge nonetheless evolves in a cumulative way: different companies and individuals build upon the ideas of others. Patent citations provide a 'paper trail' that enables researchers to track the knowledge antecedents and descendants of inventions (Jaffe and De Rassenfosse, 2017; Jaffe and Trajtenberg, 1999). They differ from bibliometric citations, however, because they are recorded for legal reasons: the search for relevant prior art – areas of technology that are already protected and cannot be claimed - is part of assessing whether an invention is novel. In the United States, patent applicants are required to disclose prior relevant art, but they have no incentive to cite beyond what is directly relevant for defining the boundaries of the protected invention (Jaffe and De Rassenfosse, 2017).

Beyond this novelty requirement, patents vary greatly in their characteristics such as scope, quality, and nature of the invention. Patent databases like PATSTAT contain rich information that enable researchers to discern between inventions varying in such characteristics. For example, the number of claims provide information on an invention's breadth. Technology classes provide information about a patent's sector of technology at a highly granular level. Titles, abstracts, and claims contain textual data that allow researchers to capture the content of these inventions, for example, using keywords, topic models, or manual coding. Frequently, researchers also use citations to proxy for patent quality since multiple studies have shown that citations correlate with various measures of commercial success (Jaffe and De Rassenfosse, 2017). Throughout my dissertation, I leverage these data to account for differences across patented inventions. In Chapter 1, I start with simple counts of patents. However, these give equal weight to all inventions that meet a minimal threshold of patent quality. To account for differences in patent quality, later in this chapter I use citation-weighted patent counts. However, within my firm-level model it is not possible to control for other patent-level characteristics. I achieve this in Chapter 2 using a patent-level model that enables me to account for various characteristics of patented inventions. I use citations as the dependent variable to capture how standards change knowledge utilization and innovation trajectories, since these data allow me to track the knowledge descendants of inventions. Chapter 3 delves deeper into the content of patented inventions. I use citations data to identify inventions that are central within the patent citation network and then examine the content of these inventions in depth by coding their abstracts manually.

Standards data

While patents enable firms to claim ownership over some areas of technology, standards in contrast can be seen as a ceasefire between competing firms when an industry needs to solve common problems. Firms engage in standard development activities when they see value in cooperating to develop technical solutions for their industry - such as protocols, guidelines, product characteristics, etc. – which can help reduce technological uncertainty (Wiegmann et al., 2017, 2022). The specific ways in which firms input into standardization decisions depend on the institutional configurations of different standard-setting organizations (SSOs) and standards-development organizations (SDOs) (Baron and Spulber, 2018).

Standards developed by these organizations are open, meaning that their ownership is not held by any single firm. Once released, they can be used by any firm in the industry. However, implementing standards sometimes requires using technology whose intellectual property is owned by a private entity. When a standard endorses a specific patented technology, standardization organizations have rules and processes to limit the market advantage granted to the owner of the IP, for example by defining the conditions under which the technology may be licensed out. Because these practices have important implications for market competition, this issue has garnered significant attention in the industrial organization literature (Chiao et al, 2007; Lerner and Tirole, 2014, 2015).

Concerns about standards endorsing proprietary technology appear secondary in the context of my study, however. For example, I could not find declarations of standard-essential patents for the smart grid standards included in my analysis. In this industry, standards focus on establishing guidelines to ensure interoperability between devices – such as defining wireless data transmission protocols and common information models - rather than endorsing patentable technological artefacts. Also, because these standards focus on finding solutions to ensure that devices are compatible with each other across the entire electrical grid, they are typically not specific to any sub-domain of smart grid technology. For this reason, in Chapter 1, my model treats all standards as relevant to all patented inventions. In Chapter 2, I broaden my sample to include solar PV and wind turbine technologies. This enables me to incorporate variation in standard counts across the three technologies. For the same reasons as before, in the case of interoperability standards, and because of data limitations in the case of other types of standards like measurement and quality standards observed in solar PV and wind[5], I do not code standards at finer levels of granularity beyond the three technologies.

Another measurement challenge concerns uniformity in the unit of analysis. Like patents, standards vary in their coverage, making it challenging to assess whether each unit is comparable in scope. To mitigate this challenge, though imperfectly, I count standards at the part level. This approach ensures that the breadth of a standard addressing a wide range of issues, through the addition of different parts, is more accurately represented in the count of its individual components. There are other advantages to counting standards at the part level. It enables me to exclude standard parts that are not directly relevant to a given technology. For example, standard IEC 61400 concerning wind turbines encompasses several parts. Some parts concern the design of turbine components like the gearbox and the tower, while other parts concern communications between turbines and the grid. Counting at the part level allows me to assign the former to wind technology and the latter parts to smart grid technology. Furthermore, as technology matures and new technical challenges surface, standard development organizations sometimes incrementally add new parts to existing standards to resolve these emerging issues.

[5] I do not have access to sufficient textual data in the abstracts of standards documents (only abstracts are available freely in most cases) to code standards at a more granular level using keywords or topic models, such as identifying which standards are relevant to which sub-system of wind turbine technology or PV modules, like the power train or PV cell encapsulation. Also, at this level of granularity there might be insufficient variation in counts of standards and patents to estimate coefficients with precision.

Counting at the part level allows me to capture with greater precision when these renewed coordination efforts have occurred. Finally, to preserve uniformity in my unit of analysis, I only count first releases and exclude subsequent revisions. The initial release of a standard represents a significant coordination effort, whereas revisions are more akin to maintenance work to keep the standard up to date.

Standards not only vary in scope, but also in the types of information they contain. Extant literature proposes various typologies to classify standards according to the functions they perform and the types of market failures they help redress: information, quality, variety reduction, interoperability, measurement, etc. (Swann, 2000; Tassey, 1999; DeVries, 1999; Blind and Gauch, 2009). Accounting for differences in types of standards is therefore important when studying the outcomes from standardization, as different types of standards might produce different outcomes. In Chapter 1, the standards included in my sample are of a single type: interoperability. Any conclusions and recommendations drawn from the results from this chapter are therefore only relevant to other interoperability standards. Chapter 2 incorporates greater variety in types of standards. However, because different technologies encounter distinct technical challenges, they tend to align with specific types of standards. For example, in wind many standards concern the integrity and safety of wind turbine structures and materials. In solar, most standards concern measurement and performance testing. Therefore, there is no need to further code standards by type, as these would be collinear with the technologies. The results from Chapter 2 should however be interpreted as reflecting the types of standards predominant in each technology, given their respective technical challenges.

Chapter 1 Do technology standards induce innovation in environmental technologies when coordination is important?

Myriam Gregoire-Zawilski
David Popp

Abstract

A next generation of innovation in enabling and complementary green energy 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 governments may support the development and deployment of these technologies. 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 challenges. Using the case of smart grid technology, we investigate the effects of interoperability standards, an instrument that may facilitate coordination through establishing common technological frameworks, on inventive activity. Using firm-level analysis, we find that on average standards decrease firms' patenting activity. We further find that this negative effect is driven by firms with high patenting intensity, whereas standards enable the entry of new firms into the field. We further find suggestive evidence that standards improve innovation quality.

1.1 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 witnessed 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 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 decisions (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 with each other (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 this next wave of green energy innovation.

Despite being one of few instruments promoted by governments to support grid integration technologies, interoperability standards are under-studied in the literature on green innovation. These establish a common technological framework for industry to build complementary follow-on technology. For example, specifying a connection-oriented transport layer for communication used on IP networks through standard EN 62056-4-7 may spur invention in smart meter technology. In this paper, we focus on the effect of standards on technology development in smart grids technologies. Investigation of the effects of standards on technology adoption and commercialization in downstream product markets is left to future research. Related to technology development, we hypothesize that technology standards have competing effects on patenting levels and might increase patenting activity in some firms but reduce levels in other firms. Furthermore, we hypothesize that any reduction in patenting activity is the result of a trade-off between the quantity and the quality of innovation, through a focusing of research activity in areas consistent with the technological framework endorsed by the standard. On average, we find that interoperability standards decrease firms' patenting activity. We further investigate heterogeneous effects and find that this negative effect is driven by firms with high patenting intensity, whereas we do not detect an effect for firms with low patenting intensity. We find that technology standards are associated with greater entry by firms without prior experience innovating in smart grids. We also provide preliminary evidence on the effect of standards on the quality of innovation. Together, these results suggest that standards provide know-how about accepted practices and technical specifications that would otherwise only be available to industry insiders. They provide clarity that potentially benefits all firms, but particularly new players, who become more likely to enter this sector of innovation after standards are adopted. The role of standards in providing guidance on a common technological framework appear particularly critical in a sector of technology, like smart grids, where interoperability is a chief concern, and that requires recombining knowledge from diverse fields, and therefore attracting diverse firms. Furthermore, our results provide exploratory evidence that endorsing a common technological framework enables some firms to focus follow-on research activity in high-value areas.

1.2 Motivation and context

1.2.1 Scaling-up renewables: challenges for the electrical grid

The integration of distributed renewable electricity generation poses novel challenges in the management of grid operations. Because intermittent sources are not as readily dispatchable as conventional electricity, matching the supply and demand for electricity requires improved flexibility (Martinot, 2016; NREL, 2015). The increased frequency and severity of weather shocks caused by climate change also aggravate grid stability challenges (Martinot, 2016; Palensky and

Kupzog, 2013; Stephens et al., 2013). The International Energy Agency estimates that hour-to-hour grid flexibility needs will quadruple to achieve decarbonization by 2050 (IEA, 2021).

Smart grid technologies will be instrumental for improving grid resilience in the face of these challenges (Brown et al., 2018). A smart grid could coordinate the activities of actors that participate in electricity markets, forecast the supply and demand for electricity, monitor grid conditions, detect faults and automate some grid management decisions (Brown et al., 2018; Palensky and Kupzog, 2013). Building a smarter grid implies developing and deploying hardware and software to collect and utilize more effectively granular power data (Colak et al., 2016; IEA, 2022; Lopes et al., 2019). Smart grids encompass a range of technologies that include smart meters, remote and automated sensing, smart switching, phasor measurement units, hierarchical or distributed control architectures and various big data analytics and artificial intelligence applications (Brown et al., 2018; Palenski and Kupzog, 2013; Lee et al., 2017; Syed et al., 2020). These will be essential for hosting other grid flexibility tools such as grid-integrated smart vehicle charging, responsive load, distributed energy storage, and microgrid islanding (Martinot, 2016), making smart grids a pivotal technology for the energy transition.

Large scale deployment of smart grid devices is needed to build a flexible and reliable electrical grid. Achieving this as power generation becomes increasingly decentralized requires coordinated investments by various actors participating in distributed electricity markets. Because smart grids are networked technologies, the usefulness of smart grid devices in collecting power data depends on whether these data can be exchanged and utilized by devices deployed at various locations on grid networks. These benefits can only be realized if smart grids technologies are compatible with one another with regards to wireless communication protocols, data architecture and data encryption protocols. The coordinated development and deployment of technologies sharing common protocols may in turn unlock important networks externalities (Katz and Shapiro, 1985). As more users adopt these technologies, more data will be exchanged, increasing the utility received by owners of smart grid devices. Coordination and reduced uncertainty about which technical specifications are selected by the market could enable further development of follow-on smart grid inventions[6].

1.2.2 Interoperability standards in smart grids technologies

These coordination dilemmas suggest that there is a role for policy to support technology development. Many of the policy tools that governments have incorporated in their renewable energy policy mix, such as taxes, R&D subsidies, cap-and-trade, and feed-in-tariffs help redress environmental externalities and knowledge spillovers market failures (Popp, 2019). However, they do not address the type of coordination dilemma described in the previous section. Interoperability challenges are ubiquitous in smart grids (Ho & O'Sullivan, 2017; Iqtiyanillham et al., 2017, Lin et al., 2013; Brown et al., 2018). In light of these challenges, some governments have assumed the role of a convener, promoting the development of interoperability standards for the smart grid in concert with industry. 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 other OECD countries have issued roadmaps to signal their commitment to advancing 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 literature. Even in other sectors of technology, there is a paucity of empirical studies on the relationship between standards and innovation. Our study contributes to two literatures: the literature on green energy innovation and the literature on standards.

[6] Examples of smart grid technologies at different levels of maturity, including possible future applications, are included in Appendix A1.

1.3 Related literature

1.3.1 Lessons from the literature on green energy innovation

Supporting clean energy innovation at requisite levels for meeting net-zero goals by mid-century will require a mix of policy instruments to address multiple market failures that suppress innovation. Widely studied market failures resulting in an under-provision of green energy innovation include environmental externalities and knowledge spillovers (Popp, 2019). The literature however rarely discusses coordination failures, nor does it consider how technology standards may be integrated in the policy mix to support the development and adoption of technologies facing high interoperability challenges. Our study uses smart grids as a case, but our results and discussion are relevant to a broader set of emerging and complementary energy technologies facing similar interoperability challenges, such as electric vehicle charging and hydrogen production (Cammeraat et al, 2022).

The green innovation literature classifies policy tools in two categories: policies that target the demand-side of innovation (demand-pull) and policies that target the supply-side of innovation (technology-push). Several studies find that pricing environmental externalities to expand market size for green energy technologies (e.g. demand-pull) triggers more innovation (Newell et al., 1999; Popp, 2002; Verdolini and Galeotti, 2011; Crabb and Johnson, 2010; Aghion et al., 2016, Calel and Dechezleprêtre, 2016). On the supply side, governments commonly support inventive activity through R&D subsidies to compensate inventors for the public good nature of the knowledge they create (Veugelers, 2012; Costantini et al, 2017). However, this literature offers few insights about the coordination challenges discussed previously, for which technology standards present a possible solution.

1.3.2 Lessons from the literature on standards and innovation

While the literature on green innovation says little about the role of technology standards, their impact on innovation has been studied in other sectors. Standards, like patents, are a vehicle for codifying technical knowledge. Firms use a combination of the two, along with scientific publishing, to disclose 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). Unlike command-and-control regulation such as fuel economy standards, technology standards do not make compliance compulsory unless specified otherwise in legislation or regulation (Baron and Spulber, 2018).

Instead, compliance arises because firms find value in observing these technical specifications and because standards perform important functions in markets. Different types of standards play different roles. For example, information and quality standards help in redressing asymmetries of information, and variety reduction standards help with enabling economies of scale (Swann, 2000; Tassey, 1999; DeVries, 1999). Compatibility standards coordinate market actors to achieve product or component compatibility and realize network externalities (Swann, 2000; Tassey, 1999; DeVries, 1999). It is these compatibility standards that are important for smart grids, and more generally for other complex manufactured products using networked technologies (Baron and Spulber, 2018). Given this, our study has implications for technology development in many areas facing high interoperability requirements, such as emerging information technologies like the Internet of Things and other networked green technologies, such as electric vehicle charging.

The standards we study are set through a formal process in standard-setting organizations. The importance of these organizations as venues for coordinating technology selection and development has grown in recent decades (Wiegmann et al, 2017; Baron and Spulber, 2018; Baron and Schmidt, 2019). Alongside this phenomenon, a core literature seeking to elucidate governance and decision-making patterns within these organizations has emerged (Chiao et al., 2007; Lerner and Tirole, 2015; Leiponen, 2008; Simcoe, Graham and Feldman, 2009; Simcoe, 2014; Bar and Leiponen, 2014; Kang and Bekker, 2015; Contreras, 2017; Wiegmann et al., 2022). It finds that standard-setting activities can help mitigate uncertainty (Aggarwal et al., 2011), shape expectations (Lerner and Tirole, 2015) and coordinate the implementation of new technological framework across an industry (Baron and Schmidt, 2019; Spulber 2008). As a result, most of the literature focusses on how firms strategically engage in these venues. Few large-N empirical studies investigate how standards conversely shape the inventive activities of firms in follow-on technologies after a standard has been released, including in firms that did not partake in standardization activities. Limited evidence shows that standards have beneficial effects on the quality of innovation of complementor firms (Wen et al, 2022), and on macroeconomic outcomes (Baron and Schmidt, 2019). Our paper contributes insights to this important gap in the literature. In the next section, we further expand on mechanisms through which standards may affect the level and quality of ensuing patenting.

1.4 Theory and hypotheses

We investigate the effects of technology standards on patenting levels and quality. Smart grid technology is cross-sectoral: it recombines knowledge from various technology fields. The composition of firms engaging in R&D in this area is therefore diverse. Those include large electricity sector incumbents, diversified IT conglomerates and green energy start-ups. These firms bring diversified knowledge and experiences into the smart grid innovation space. In this context, standards may clarify and establish a technological framework for firms from different backgrounds to build on. In the face of this diversity, standards might focus inventive efforts in the more valuable and promising research areas, with differentiated effects across types of firms. We posit two competing conjectures for the effects of standards on patenting levels, discuss when each is most likely to hold, and present our expectations on the effect of standards on innovation quality.

1.4.1 Effects of standards on patenting levels

H1. Greater exposure to standards causes a decrease in firms' patenting levels

Standards establish a technological framework that clarifies industry conventions (Tassey, 2000), and illuminate paths of technology development worth pursuing. As a result, they may remove incentives to test novel ideas that are not aligned with the endorsed conventions and focus research efforts on a narrower trajectory. As a result, fewer ideas may become worth pursuing.

H1.A. The negative effect of standards on patenting levels is strongest is large incumbent firms

We further hypothesize that the negative effect of standards is strongest in large incumbent firms. Standards often formalize existing practice (Wiegmann et al., 2022). When this is the case, large industry incumbents are more likely to have already acquired tacit knowledge of those conventions through learning-by-doing and industry experience. They may therefore have already tested and patented their most promising ideas. By the time a technological framework gets endorsed in a standard, the remaining ideas these firms have left to try may have low expected marginal value and not deemed worth pursuing, especially when they are not compatible with the endorsed framework.

H2. Greater exposure to standards causes an increase in firms' patenting levels

Conversely, standards make information about agreed-upon conventions explicit. This information contributes to reducing R&D uncertainty for inventors (Wen et al., 2022; Blind et al., 2017; Blind et al., 2018, Blind, 2004). Standards also help disseminate this information more widely. This may help some firms learn about best practices and the endorsed technological framework (Tassey, 2000). Both mechanisms would increase firms' patenting levels.

H2.A. The positive effect of standards on patenting levels is strongest is new entrants

While the knowledge disseminated by the standard can be used by any firm, we expect that the positive effect on patenting will be strongest in new entrants because they do not possess field-specific know-how otherwise acquired through industry experience. Therefore, the knowledge conveyed by standards may be most valuable to firms seeking guidance to enter this innovation space and who may bring in fresh ideas for new inventions complementary to the endorsed technological framework.

1.4.2 Effects of standards on innovation quality

H3. Greater exposure to standards increases patent quality

H3 is an expansion of H1 and highlights possible tradeoffs between the effects of standards on the quantity and the quality of innovation. By focusing experimentation on a narrower trajectory, standards may provide foundational knowledge that guides future experimentation and improve the quality of follow-on inventions. For example, standards may provide information that help inventors focus their research efforts in the most promising areas and avoid less promising research avenues. Or it may be that when inventors focus their resources on fewer projects, the smaller number of outputs they yield are more rigorous. Following convention in the literature, we observe patent quality through their forward citations (Jaffe and de Rassenfosse, 2017).

1.5 Empirical setting

1.5.1 Identification of causal effects

In the context of our study, most smart grids interoperability standards originated in international and regional standard-setting organizations (a list of standards included in our sample is available in Appendix A2) and were released at the country-level in different years. We leverage this variation in the timing of standards adoption across countries.[7] To translate country-level counts of standard to the firm level, we follow state-of-the-art methods from the literature on green innovation and obtain time-invariant country weights for each firm, based on the location of their patenting activities in the pre-sample period (Noailly and Smeets, 2015, 2022; Aghion et al., 2016; Lazkano et al., 2017; Rozendaal and Vollebergh, 2021). The weighted standard counts capture each firms' unique exposure to standards and other country-level variables. Following extant literature, we argue that where firms seek IP protection is a good indication of which are their important markets: obtaining patents is costly and a firm would not seek protection in a country unless it intended to commercialize its products in that market (Aghion et al, 2016).

These country weights allow to treat lagged values of our explanatory 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

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

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).

Also, using variation in the timing of country-level standards adoption further mitigates concerns of reverse causality. Technology endorsement by a standard has economic value and firms with large smart grid patent portfolios might seek to influence the standard-setting process to strategically position their inventions. This may in turn affect their inventive activities as well as the inventive activities of others. 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 voting on standards adoption in international standard-setting organizations do not allow direct participation by firms. To influence in their favor the drafting, comment-and-response and voting process in these international venues, firms would need to successfully influence a majority of member country organizations voting on the initial release of the international standard, which is unlikely. Furthermore, our identification of causal effects relies on variation in the timing of standard adoption at the country-level. For standards to be endogenously determined, firms would need to influence similar drafting, comment-and-response and voting processes occurring at the country-level across their different markets, which is highly unlikely. To further support this argument, we provide a more detailed description of the standard-setting process in these venues in Appendix A3.

Furthermore, concerns about firms engaging strategically in the standard setting process is greatest when firms can benefit from having their patents declared essential to the implementation of a standard, as this would require that downstream technology users wishing to comply with the standard enter into licensing agreements with the owners of the standard-essential patents (Lerner and Tirole, 2015). In such cases, firms have incentives to position their proprietary technology as “essential”, and this may in turn affect their own and others’ patenting levels. However, concerns about such strategic behaviors being a threat to identification appear secondary in our study context: we could not find any declarations of standard-essential patents for the smart grid standards included in our sample. A possible explanation is that firms engage collaboratively rather than strategically in standard-setting in the smart grid space – and other networked technologies facing high coordination issues - because they value the mutual benefits it provides, such as jointly shaping technology development, enabling information-sharing and legitimizing technical solutions. (see Wiegmann et al., 2022 who find evidence of this in the Internet of Things technology space).

1.5.2 Estimation

1.5.2.1 Dependent variable.

Our dependent variable is a count of successful smart grid patent applications filed by firm *i* in year *t*. To measure inventive activity, we retrieve firms' patents in technology classes that capture smart grids inventions related to electricity systems integration and efficiency, smart grids applications in buildings, information and communication technologies applications to smart grids, and smart grids applications for electricity end-users. Appendix B1 presents the full list of patent classes used to identify smart grids inventions. To avoid double-counting inventions granted IP protection in multiple countries, we count patents at the family-level and use the application date in the priority country to assign the year. We use the application date as this is closest to when the R&D activity took place. Furthermore, we only count patent applications subsequently granted by at least one patent office, as we want to only consider inventions that meet a minimum threshold of quality and are more likely to spawn marketable products.[8]

1.5.2.2 Model and explanatory variables.

Since our dependent variable is a weighted count of granted patents filed by firm *i* in year *t*, we use Poisson regression to estimate the effects of our explanatory variables. We use this specification when estimating effects for the whole sample and heterogeneous effects for firms with high and low patenting intensity. When investigating the effects of standards on new

[8] 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 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.

entrants, we use a Zero-Inflated Poisson model.[9] This model allows to decompose the effect into the extensive and intensive margins. Coefficients for the extensive margin show the probability that a firm will have zero patents. This more directly captures the concept of "entry". Furthermore, smart grid innovation is an emerging area of technology and 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 only the years in which each firm was active during this period.[10]

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 new standards introduced in year *t-2*.[11] We also control for the effects of other policies that affect firms' R&D investment decisions. These variables are denoted as *RG*, government R&D budgets in grid-related technologies, and *RR*, government R&D budgets in renewables. Data for these two policy variables come from the International Energy Agency and are expressed in 2015 US dollars. *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 relevant sectors. Similarly, *ES*, *EG*, *EE*, and *EI* represent external knowledge stocks for these same technologies. External knowledge stocks capture the knowledge firms are exposed to, based on

[9] We do not use the ZIP model for our estimation of effects on the full sample of firms and for the heterogeneity analysis because we gain little additional insights from the decomposition into the internal and external margins in these analysis at the cost of complicating our presentation and discussion of results. However, we present results for the ZIP model in appendix C4.

[10] 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 1B1. Patent classes used to identify green, electricity generation and information technology innovations are described in Table 3 of Appendix 1B1.

[11] In our main specification, we use a count of new standards adopted in year t-2 rather than a stock of standards. However, in tables 1C.2.5.1, 1C.2.5.2 and 1C2.5.3 in the Appendix, we show that our results are robust to using a stock of standards as the explanatory variable, but coefficients are smaller. This implies that firms are more responsive to the introduction of new standards rather than to incremental changes in stocks.

the location of their inventors.[12] Appendix B2 details how these 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* and include income (GDP per capita expressed in 2015 US dollar), household electricity prices expressed in 2015 US dollars, the share of renewables in the electricity mix, and the growth in electricity consumption. The data sources for these are the OECD/IEA and the US Energy Information Administration. The latter two control variables proxy for other energy policies that have supported the deployment of renewables, pulling demand for enabling grid technologies. Also, faster growth in electricity consumption may strain existing transmission infrastructure, also increasing market demand for technologies for better managing electricity transmission. When these country-level control variables are weighted and translated to the firm level, they also vary over time and across firms. A detailed description of these variables can be found in Appendix B3. All these right-hand side variables are lagged by two years to avoid reverse causality, and our results are robust to using different lags (robustness checks are included in Appendix C2).

Furthermore, 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 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 standard Poisson fixed effects model produces biased results. To control for unobserved confounding firm attributes, we instead control for firms' mean patenting activity in the pre-sample period, denoted as *α*.[13] This approach captures firms' baseline propensity to patent and is commonly used to approximate firm fixed effects when the assumptions of the Poisson fixed effects model

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

[13] 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 and use the same patent classes as we used to build the country weights.

are violated (e.g., Blundell et al., 1995; Noailly and Smeets, 2015, Rozendaal and Vollebergh 2021).[14] 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.

1.5.3 Sample and 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.

1.5.3.1 Sample

Our sample includes a mix of companies representative of the diversity of firms operating in global markets for smart grids technologies This group is comprised of large multinational conglomerates such as Panasonic, Toshiba and General Electric; information technologies firms such as IBM and Intel; traditional electricity sector players such as Asea Brown Boveri and Infineon, and clean technology firms that specialize in renewable energy, load management, or other grid services, such as Acciona, GridPoint, Voltalis and Solar City. The ten largest smart grids innovators in our sample period and countries, in order of importance, include: Panasonic, Mitsubishi, General Electric, Toshiba, Siemens, Hitachi, Asea Brown Boveri, Chugoku Electric Power, LG and Nippon Electric Corporation (See Appendix A4 for more information on these

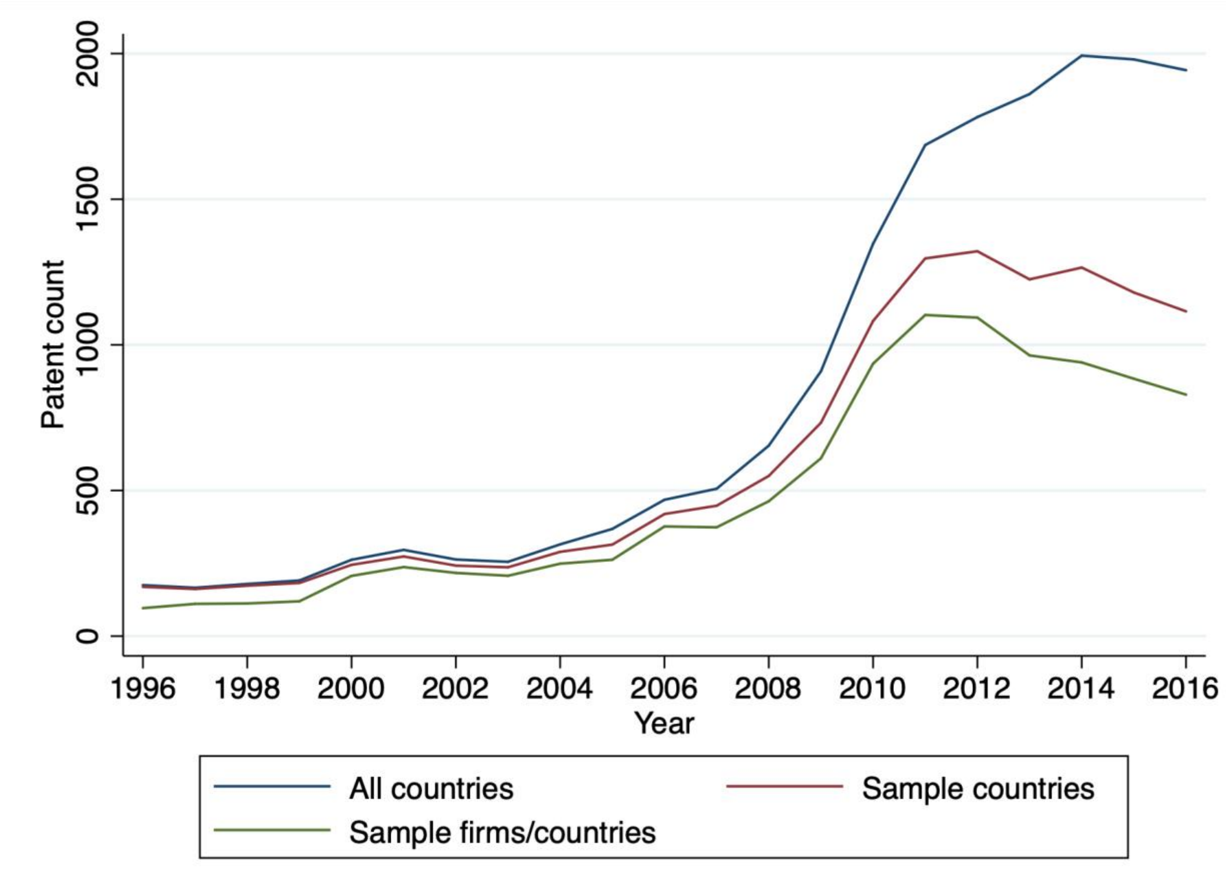
[14] In appendix C3, we compare results from our main specification using this pre-sample mean estimator approach with results for a standards Poisson fixed effects models. Our results suggest that, in our study context, the Poisson fixed effects model produces biased coefficients, supporting our decision to use the pre-sample mean estimator in our main specification.

firms). Firms were selected into the sample when 1) they had at least one granted smart grid patent in the 19 OECD countries covered in our analysis[15] during the period 2000-2016, and 2) their home country was one of these 19 countries (Appendix B5 details on how we assigned home countries to firms). We only include these 19 OECD countries due to limited data coverage for the standards and the electricity prices variables. Restricting our sample to firms whose home country is among these 19 countries also ensures that we are not leaving out important markets for those firms. Figure 1 shows that selecting firms based on these criteria does not compromise the representativeness of our sample. Most smart grids patents granted in these 19 OECD countries are assigned to our sample firms. Trends in smart grid patenting within our sample firms also tracks closely overall trends in patenting in these 19 countries, which also include inventions by non-firm inventors, such as universities and government laboratories not covered by our analysis.[16] Figure 1 also shows that patenting declines after 2011 in our sample countries and firms, while global smart grid patents continue to grow beyond this point. Patents granted in China mostly account for the difference between global patents and patents covered in our sample, which we purposely excluded from our analysis given the notable differences between IP policy in China and OECD countries.

[15] Austria, Australia, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Italy, Japan, Korea, Netherlands, Norway, Sweden, Turkey and the United States.

[16] We exclude patents by applicants that are not firms, such as universities, government agencies and non-governmental organizations because we cannot make the same assumptions about their global markets as we make for private firms using our identification strategy, because the nature of the R&D conducted by these other actors may be different (e.g. more basic, early-stage research) and because they may respond to different policy incentives which we are not testing for with our model. Appendix B4 details how we cleaned firm names and retrieved their knowledge stocks in areas beyond smart grids.

Figure 1.1 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.

1.5.3.2 Standards data

We find relevant standards 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). The full list of international standards included in our sample is included in Appendix A2. To identify country-level adoptions for these 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.[17] We count standards at the part level: 1) to avoid including standard parts that are irrelevant; 2) to capture coordination efforts in the face of novel technical challenges as technology evolves. Appendix A5 shows an example of an international standard whose different parts are added over time and adopted across countries in different years.

1.5.3.3 Patent data

We use patent data from the European Patent Office's PATSTAT database. While we date patents using their first application date, our sample only includes granted patents. Thus, 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).

1.5.4 Constructing weighted policy variables

Several control variables are collected at the country level. We follow state-of-the-art methods in the environmental innovation literature (e.g., Noailly and Smeets 2015, Aghion et al., 2016, Lazkano et al., 2017; 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 (Dechêzlepretre et al., 2021, Rozendaal and Vollebergh 2021).[18] Defining w_{ci}^{PAT} as the share of firm *i*'s pre-sample patents filed in country *c*, the weight becomes:

[17] 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.
[18] Dechezlepretre et al. (2021) suggest the exponent of 0.35, saying that it fits estimates of the elasticity of exports to GDP of the home country found by Eaton, Kortum, and Kramarz (2011). We include robustness checks using an exponent of 1, as in Aghion et al. (2016), in Appendix C2.

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

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 in excluded markets. 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. When conditioning on home country, we achieve a minimum coverage of 93% of firms' markets for 90% of the sample firms (descriptive statistics on country markets coverage for our sample firms are included in Appendix B6). 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 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.

1.5.5 Descriptive statistics

Finally, Table 1.1 shows descriptive statistics for the unweighted country-level variables, the firm-level variables as well as country-level variables after weighting.

Table 1.1 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

1.6 Results

1.6.1 Main model: Poisson regression on full sample

Table 1.2 shows results for our main Poisson model using a balanced and an unbalanced panel of firms.[19] Results are consistent across the two models, but the negative effect of standards is slightly stronger in our preferred specification, the unbalanced model. In this model, we only include firms in the analysis in the years they are known to be active in patenting. We discuss results pertaining to five 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.

We find that standards reduce firm's patenting levels by a magnitude of about 7.5% for each additional standard the firm is exposed to. This is consistent with our expectation that standards reduce incentives for firms to test out new ideas that are not compatible with the endorsed technological framework, but goes against the hypothesis that standards support inventive activity through diffusing information about industry conventions.

Our heterogeneity analysis presented next further unpacks this to show that effects go in different directions for different groups of firms. Regarding the other policy variables, we detect 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 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 suggests that knowledge from these sectors is relevant for innovating in smart grids, a cross-sectoral area of technology. However, firms with more experience in information technologies have fewer smart grids patents. This is counter to expectations, given the importance of information

[19] In Table 1.2, we focus on the main results of interest in our study. Appendix 1C1 shows results for the full model.

technologies in smart grids applications. We expected that firms with a background in information technologies would bring foundational knowledge into smart grids field. It could be that IT firms are new entrants in the electricity sector, or that their activities in this space are marginal relative to their patent portfolios in other sectors. Similar to our findings for the internal knowledge stocks, firms whose inventors are located in countries where more smart grid innovation takes place also are more likely 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 are associated with fewer patents. This result suggests similar tradeoffs as before between R&D in renewables and R&D in smart grids. We do not detect a statistically significant effect for the electricity and information technologies external stocks. Finally, an increase in the share of renewables in the electricity mix is associated with greater smart grids patenting activity. Greater renewables integration amplify grid management challenges and demand for these technologies, and also proxies for other renewable energy policies since much of the growth in renewable generation was policy driven during the time period covered in our analysis.

1.6.2 Heterogeneous effects across firms

We hypothesize that the direction of the effect of standards varies across firms, with standards increasing the entry of new innovators in this innovation space through providing information, but removing incentives to test out new ideas for large incumbents. To test these hypotheses, we propose two approaches.

First, we estimate our main model on a sub-sample of firms with high patenting intensity, and a sub-sample of firms with low patenting intensity. Estimating these models separately allows for all coefficients and intercepts to vary across the two groups. Because defining a cutoff between the two groups is arbitrary, we estimate these models for 3 different cutoffs: one at the median, one at 75th percentile of the distribution of firms' patenting intensity, and one at the 90th percentile. 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.

Table 1.2 Results from Poisson regressions

	Unbalanced	Balanced
Standards	-0.045***	-0.037***
	(0.012)	(0.011)
RD&D smart grid	0.094	0.039
	(0.064)	(0.063)
RD&D renewables	-0.198**	-0.145*
	(0.080)	(0.079)
Int. knowledge stocks - smart grids	0.938***	0.918***
	(0.041)	(0.041)
Int. knowledge stocks - green tech	0.130***	0.123***
	(0.033)	(0.032)
Int. knowledge stocks - electricity	0.261***	0.242***
	(0.034)	(0.034)
Int. knowledge stocks - ICTs	-0.122***	-0.133***
	(0.030)	(0.030)
Ext. knowledge stocks - smart grids	0.646***	0.529***
	(0.172)	(0.161)
Ext. knowledge stocks - green tech	-0.538***	-0.418***
	(0.156)	(0.157)
Ext. knowledge stocks - electricity	-0.268	-0.192
	(0.170)	(0.165)
Ext. knowledge stocks - ICTs	0.216	0.163
	(0.163)	(0.160)
Renewables share	1.330*	1.542**
	(0.757)	(0.743)
Marginal effect, standards	-0.078***	-0.045***
	(0.021)	(0.014)
Observations	30,628	44,370
Log-likelihood	-84109	-92700

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

Second, we interact a dummy variable for firms with no smart grid patents before year t with the standards variable. This measure identifies new entrants more precisely. Sample firms all eventually enter the smart grid space, so this model tests whether they are more likely to enter in response to standardization. For this analysis, we estimate a Zero-Inflated Poisson model. The first stage of this model – the extensive margin – captures the likelihood that a firm will have zero patents (i.e., that it will not enter in a given year). The second stage– the intensive margin – estimates the effects of standards on patenting levels given that a firm has patents that year. The interaction term at the extensive margin is therefore a more direct test of the effect of standards on entry for firms without prior smart grid experience.

Table 1.3 shows that the negative effect of standards is driven by large firms. For these firms, an additional standard decreases patenting by a magnitude ranging from 11-28%. These results support our hypothesis that standards stifle experimentation in large incumbent firms. The R&D investment decisions of firms with low patenting intensity 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. In particular, the tradeoff between R&D in smart grids and R&D in renewables is concentrated in these firms. This suggests that smaller, and presumably more resource constrained firms, do not have the capacity to do R&D in several areas at a time and may choose to innovate in renewables at the expense of smart grids when government funding opportunities are greater in this area. This crowding out effect is strongest in firms with low patenting activity when using the 75^{th} and 90^{th} percentiles cutoffs.

Results presented in Table 1.4 confirm that firms without prior smart grid experience are more likely to enter when exposed to more standards. The interaction of standards with the zero stocks dummy variable, as well as the joint significance of the standards variables and the interaction term are both negative and significant, indicating that firms are less likely to have zero patents. While there is a negative effect of standards on the level of smart grid patenting, this occurs for both new entrants and incumbents. The combined marginal effect of the extensive and intensives

Table 1.3 Regression results by firm size

Cutoff	Median		75th percentile		90th percentile	
Firm patenting intensity	High	Low	High	Low	High	Low
Standards	-0.051***	0.022	-0.058***	-0.005	-0.050***	-0.025*
	(0.013)	(0.023)	(0.014)	(0.017)	(0.016)	(0.014)
RD&D smart grid	0.070	-0.001	-0.038	0.105	-0.137	0.151***
	(0.071)	(0.101)	(0.103)	(0.065)	(0.144)	(0.056)
RD&D renewables	-0.198**	-0.070	-0.024	-0.313***	0.229	-0.349***
	(0.090)	(0.137)	(0.116)	(0.088)	(0.165)	(0.070)
Int. stocks - smart grids	0.937***	1.568***	0.941***	1.651***	0.900***	1.262***
	(0.039)	(0.475)	(0.037)	(0.220)	(0.043)	(0.067)
Int. stocks - green tech	0.126***	-0.049	0.118***	-0.221	0.102**	0.170***
	(0.033)	(0.323)	(0.034)	(0.207)	(0.044)	(0.060)
Int. stocks - electricity	0.197***	0.520*	0.218***	0.329***	0.339***	0.199***
	(0.035)	(0.312)	(0.042)	(0.078)	(0.057)	(0.051)
Int. stocks - ICTs	-0.117***	-0.273	-0.132***	-0.132	-0.198***	-0.089**
	(0.029)	(0.325)	(0.034)	(0.087)	(0.052)	(0.046)
Ext. stocks - smart grids	0.681***	0.289	0.440	0.385*	0.093	0.640***
	(0.220)	(0.254)	(0.330)	(0.207)	(0.416)	(0.183)
Ext. stocks - green tech	-0.583***	-0.298	-0.694***	-0.328	-1.062***	-0.322*
	(0.185)	(0.227)	(0.225)	(0.227)	(0.319)	(0.176)
Ext.stocks - electricity	-0.173	0.060	0.331	-0.336*	0.494	-0.229
	(0.222)	(0.255)	(0.305)	(0.173)	(0.390)	(0.149)
Ext. stocks - ICTs	0.178	-0.100	0.119	0.282	0.600*	-0.019
	(0.185)	(0.244)	(0.225)	(0.194)	(0.308)	(0.170)
Renewables share	0.826	-1.435	2.809***	-3.526***	3.307*	-0.683
	(0.888)	(2.018)	(0.926)	(1.345)	(1.691)	(0.988)
Marg. effect, standards	-0.120***	0.014	-0.206***	-0.004	-0.329***	-0.022*
	(0.032)	(0.015)	(0.052)	(0.013)	(0.110)	(0.013)
Observations	19,532	11,096	10,646	19,982	4,615	26,013
Pseudo R-squared	0.527	0.243	0.616	0.137	0.674	0.164

Note: These regressions use the same specification and control variables as the main model. Firms as classified as having high/low patenting intensity using different cutoffs in the distribution of patent counts (using total counts of patents assigned to the firm in the years 2000-2016 in the ICT, electricity, green innovation and smart grids patent classes). The first model uses the median observation (7 patents) as the cutoff between high and low patenting intensity. The second model uses the 75th percentile as a cutoff (57 patents). The third model uses the 90th percentile as a cutoff (512 patents). Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

margins is insignificant for new entrants. Standards increase the number of firms patenting in smart grids, but not the total number of smart grids patents. These results are 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.

1.6.3 Effect of standards on innovation quality

The models discussed in the previous sections estimate the effects of standards on the level of patenting activity, but provide limited insights into other possible effects of standards on the substance of innovation. It is possible that standards decrease patenting through focusing R&D in more promising areas, in which case inventors might be trading off quantity in exchange for higher quality. We test this hypothesis through estimating our model on citation-weighted patent counts.

To account for differences in citation behavior across patent offices, citation counts are normalized by dividing each patent's citation count by the average citation count received by all smart grid technology patents granted by the same national patent office. We add one to this normalized citation count so as to include patents without citations (Dechezleprêtre et al, 2021). The year fixed effects already included in our model control for the possibility that the likelihood of receiving citations changes over time, due to various unobservable factors. We counted citations received in the priority country within a five-year window from the patent's application date, with the exception of patent families granted by the European Patent Office, for which we used citations received from other European patents.

Results in Table 1.5 show that the negative marginal effect of standards on patenting is half as small when accounting for quality. While this is insufficient to completely offset the negative effect of standards, it indicates that standards affect forward citations. Results from the heterogeneity analysis suggest that standards have a positive effect on quality for firms with high patenting intensity, as the negative coefficient for this group is of smaller magnitude than in previous analyses. For these firms, standards reduce their overall patent count by 5.6%, but citations-weighted counts by just 3.6% (when using the 75th percentile as a cutoff), suggesting

Table 1.4 Effects of standards on new entrants (Zero-inflated Poisson)

	Intensive margin	Extensive margin
Standards	-0.033**	0.120***
	(0.015)	(0.013)
Interaction standards and zero stocks 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 for new entrants	-0.047***	-0.044***
	(0.011)	(0.009)
Marginal effect for new entrants	-0.014	
	(0.012)	
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 1.5 Effect of standards on citation-weighted patent counts

	All firms	High intensity	Low intensity	New entrants Int. margin	Ext. margin
Standards	-0.043***	-0.037**	-0.037***	-0.039***	0.109***
	(0.012)	(0.015)	(0.014)	(0.013)	(0.014)
Interaction				-0.010	-0.172***
				(0.013)	(0.013)
RD&D smart grid	0.092	-0.045	0.018	0.091	0.028
	(0.059)	(0.086)	(0.065)	(0.077)	(0.055)
RD&D renewables	-0.249***	-0.162	-0.096	-0.245**	-0.046
	(0.082)	(0.111)	(0.108)	(0.100)	(0.066)
Int. stocks - smart grids	0.960***	0.934***	1.608***	0.638***	-1.357***
	(0.039)	(0.036)	(0.224)	(0.034)	(0.052)
Int. stocks - green tech	0.091**	0.062	0.024	0.016	-0.188***
	(0.042)	(0.041)	(0.091)	(0.042)	(0.026)
Int. stocks - electricity	0.098**	0.043	0.222***	0.012	-0.153***
	(0.048)	(0.052)	(0.072)	(0.048)	(0.032)
Int. stocks - ICTs	0.088*	0.075	0.055	0.039	0.021
	(0.049)	(0.054)	(0.066)	(0.054)	(0.030)
Ext. stocks - smart grids	0.340**	0.020	0.240	-0.049	-0.333***
	(0.158)	(0.242)	(0.212)	(0.186)	(0.129)
Ext. stocks - green tech	0.047	-0.005	0.147	0.063	0.147
	(0.126)	(0.168)	(0.188)	(0.129)	(0.113)
Ext. stocks - electricity	-0.242*	0.090	0.030	0.083	0.010
	(0.146)	(0.221)	(0.173)	(0.165)	(0.122)
Ext. stocks - ICTs	0.152	0.307	-0.236	0.167	0.260**
	(0.164)	(0.207)	(0.168)	(0.152)	(0.125)
Renewables share	3.009***	3.500***	-0.951	0.518	-0.876
	(0.731)	(0.892)	(1.155)	(1.101)	(0.770)
Marginal effect	-0.034***	-0.061**	-0.013***	-0.040***	
	(0.009)	(0.025)	(0.005)	(0.008)	
Joint significance				-0.049***	-0.062***
				(0.012)	(0.012)
Observations	30,628	10,646	19,982	30,628	30,628
Pseudo R^2/log-likelihood	0.458	0.544	0.132	-28558	-28558

Note: The dependent variable in these regression analyses is a citation-weighted patent count. Patent counts are normalized as explained in the text. Firms with low patenting intensity and high patenting intensity are defined using the 75th percentile cutoff. New entrants are defined as before. Regressions are weighted by firm-level patent counts using importance weights. We use the same pre-sample mean Poisson estimator as before and include the same control variables as in our main specification. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

that the remaining patents are, on average, of higher quality. Also, the effect is now negative and significant for firms with low patenting intensity, suggesting that while standards had no effects on patenting levels, these firms' inventions received fewer citations after being exposed to standards. For new entrants, the interaction term coefficient at the extensive margin is of larger magnitude, suggesting that standards increase both entry and quality. The effect is not strong enough to offset the reduction in patenting level at the intensive margin and the combined marginal effect for new entrants remains negative. Together these results suggest that if anything, the standards help firms with high patenting intensity in producing more influential knowledge, and through codifying and making widely available the knowledge embedded in the standard, help new entrants produce valuable complementary innovations, but firms with low patenting intensity do not appear to benefit from standards in the same way.

1.6.4 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 measurement of the standards variable. Results for these robustness checks are presented in Appendix C2.

1.7 Discussion

Our analysis reveals heterogeneous effects of technology standards on firms' inventive activities and suggests important tradeoffs, with implications for policy. A first consideration is that standards affect differentially the R&D decisions of incumbent firms, new entrants, firms with high patenting intensity and firms with low patenting intensity. Depending on the goals they are pursuing – such as stimulating competition in the market for smart grid technologies or strengthening incumbent champions – policy makers should consider these differential effects.

Second, our analysis of citation-weighted counts suggests a tradeoff between the quantity and quality of innovation. One purpose of standards is to elect a technological framework that will become the convention within an industry. Our results show that this causes a decline in patenting. A tenable explanation is that standards remove incentives to test out-of-box ideas and narrow the scope of ideas pursued by inventors. This is not necessarily an undesirable outcome. By giving more clarity to inventors about which research avenues are worth pursuing, standards likely help focus research efforts in areas that produce the highest expected value and establish foundational knowledge for future research. Our results provide suggestive evidence of this. While counts of citation-weighted patents also fall with additional exposure to standards, the percentage decrease is smaller for large firms particularly, from a 5.6% to a 3.6% reduction after accounting for patent quality, suggesting that the remaining patents are of higher quality than those no longer invented. Our findings are consistent with limited evidence in the literature, including work by Rysman and Simcoe (2008) who find that standard-setting organizations are effective at selecting high-quality technology and by Wen and colleagues (2022) who find that standards help complementor firms produce high-impact innovation through lowering technological and legal uncertainty. This aligns with our findings that standards facilitate the entry of new players in the smart grid innovation space, conceivably through providing information that lowers uncertainty.

Finally, both policy makers and future research should carefully consider the timing of standard adoption. Policy makers should assess when the timing is ripe for transitioning from broad experimentation to a narrower path of inventive activity. This in part depends on how much experimentation has already occurred, on technology maturity and on how promising alternative research avenues appear. Considering the timing of standards adoption is also relevant given possible tradeoffs in the effects of standards on technology development versus diffusion. More substantial benefits from standardization may occur in downstream product markets where standards facilitate the deployment of technologies through reducing technical uncertainty for new adopters. Testing this hypothesis is beyond the scope of this paper, but remains an important question for future research.

1.8 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. Through the case of smart grids technology, we draw attention on the importance of considering technology standards within the literature on green energy innovation, especially because coordination and compatibility challenges are poised to become prominent in enabling and complementary energy technologies. We add to the literature on standards by contributing needed empirical evidence to further knowledge of the relationship between standards and innovation. In particular, we advance understanding of the heterogeneous effects standards have on the inventive activities of different types of firms. We find that standards reduce the number of patents produced by firms with high patenting intensity, but help new players penetrate this sector of innovation. We further find preliminary evidence of tradeoffs between the effect of standards on the quantity versus the quality of patents. Future research should test the latter hypothesis more directly using patent-level models to analyze the effect of standards on citation patterns and other patent characteristics.

Appendix 1.A Background on smart grids and standards

Appendix 1.A.1 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[20]. 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).

Synchrophasors. Another technology that has been widely adopted by utilities is the phasor measurement unit[21]. 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

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

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

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 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 1.A.2 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 1.A.3 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[22]. Individuals and firms can only 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,

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

the United States National Committee[23] 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[24]. 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[25]. 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).

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

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

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[26].

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

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

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 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[27]. 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.

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

Table 1.6 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 1.6 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 1.A.4 Large 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.

Table 1.7 List of largest smart grid innovators

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 1.A.5 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.

Table 1.8 Example of wind turbines standard

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 1.B Data Construction

Appendix 1.B.1 Definition of smart grids technologies included in sample, policy weights and knowledge stocks

Table 1.9. 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

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.

Table 1.10 Patent classes used for policy weights

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[28]: 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[29]	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)

[28] 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.

[29] 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).

Table 1.11 Patent classes used to build 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 1.B.2 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).[30] 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 inventors on firm *i*'s patents located in country *c*, w_{ic}^{K}. This gives us the stock of external knowledge:

[30] 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.

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

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 1.B.3 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 1.B.4 Cleaning firm names and retrieving their 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[31]. We use the variable psn_sector to select

[31] This initiative harmonizes person identifiers using manual and automated cleaning. Details about this harmonization procedure may be found in the PATSTAT Data Catalogue

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 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

((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) 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 1.B.5 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 1.B.6 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 1.12 shows further descriptive statistics about the coverage of the policy weights.

Table 1.12 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 1.B.7 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 1.C Robustness checks

Appendix 1.C.1 Full results

Table 1.13 Regression results from Poisson model (full results)

Standards	-0.045***
	(0.012)
RD&D smart grids	0.094
	(0.064)
RD&D renewables	-0.198**
	(0.080)
Int. knowledge stocks - smart grids	0.938***
	(0.041)
Int. knowledge stocks - green tech	0.130***
	(0.033)
Int. knowledge stocks - electricity	0.261***
	(0.034)
Int. knowledge stocks - ICTs	-0.122***
	(0.030)
Ext. knowledge stocks - smart grids	0.646***
	(0.172)
Ext. knowledge stocks - green tech	-0.538***
	(0.156)
Ext. knowledge stocks - electricity	-0.268
	(0.170)
Ext. knowledge stocks - ICTs	0.216
	(0.163)
Renewables share	1.330*
	(0.757)
Elect. consumption growth	-0.001
	(0.028)
Household elect. prices	-0.266
	(0.436)
GDP per capita	-1.267**
	(0.578)
New firm	-0.036
	(0.095)
Average patents/year in pre-sample	0.000
	(0.000)
Zero stock - smart grids	0.785***
	(0.075)
Zero stock - green tech	0.053
	(0.091)
Zero stock - electricity	0.734***
	(0.077)
Zero stock - ICTs	0.364***
	(0.074)
Marginal effect, standards	-0.0781***
	(0.021)
Observations	30,628
Log-likelihood	-84109

*** p<0.01, ** p<0.05, * p<0.1

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.

Appendix 1.C.2 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 1.14 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 1.15 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 1.14 Alternative weights for firms with no pre-sample patents – main model

Standards	-0.022***
	(0.008)
RD&D smart grid	0.019
	(0.027)
RD&D renewables	-0.136***
	(0.039)
Int. knowledge stocks - smart grids	0.946***
	(0.042)
Int. knowledge stocks - green tech	0.118***
	(0.034)
Int. knowledge stocks - electricity	0.268***
	(0.035)
Int. knowledge stocks - ICTs	-0.131***
	(0.032)
Ext. knowledge stocks - smart grids	0.258
	(0.195)
Ext. knowledge stocks - green tech	-0.342**
	(0.163)
Ext. knowledge stocks - electricity	-0.047
	(0.187)
Ext. knowledge stocks - ICTs	0.202
	(0.158)
Renewables share	-0.347
	(0.295)
Marginal effect, standards	-0.038***
	(0.014)
Observations	30,628
Log-likelihood	-84157

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 1.15 Alternative weights for firms with no pre-sample patents - heterogeneity

	High patenting intensity	Low patenting intensity
Standards	-0.051***	-0.007
	(0.012)	(0.008)
RD&D smart grid	-0.015	0.054*
	(0.072)	(0.029)
RD&D renewables	0.003	-0.166***
	(0.083)	(0.046)
Int. knowledge stocks - smart grids	0.942***	1.644***
	(0.037)	(0.217)
Int. knowledge stocks - green tech	0.112***	-0.221
	(0.034)	(0.204)
Int. knowledge stocks - electricity	0.228***	0.342***
	(0.040)	(0.077)
Int. knowledge stocks - ICTs	-0.141***	-0.142*
	(0.034)	(0.086)
Ext. knowledge stocks - smart grids	0.291	0.414**
	(0.318)	(0.199)
Ext. knowledge stocks - green tech	-0.665***	-0.246
	(0.215)	(0.252)
Ext. knowledge stocks - electricity	0.477*	-0.304*
	(0.288)	(0.174)
Ext. knowledge stocks - ICTs	0.055	0.169
	(0.222)	(0.208)
Renewables share	1.599**	-0.705**
	(0.700)	(0.336)
Marginal effect, standards	-0.180***	-0.005
	(0.044)	(0.006)
Observations	10,646	19,982
Log-likelihood	-39996	-40924

Note: In this model, firms with no pre-sample patents and for which it is not possible to build pre-sample weights are assigned their home country as their main market. Firms with high patenting intensity are defined as firms that are in the upper 25 percentile of total patents assigned in the ICT, electricity and green innovation patent classes during the period 2000-2016. Firms with low patenting intensity are defined as firms in the lower 75th percentile in the same patent classes and years. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 1.C.3 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 1.16, we allow knowledge stocks to depreciate faster, at a rate of 20%. Both rates are commonly used in the literature. Using one or the other does not substantively alter our results.

Table 1.16. 20% depreciation rate for knowledge stocks

Standards	-0.045***
	(0.012)
RD&D smart grid	0.092
	(0.064)
RD&D renewables	-0.204**
	(0.080)
Int. knowledge stocks - green tech	0.131***
	(0.034)
Int. knowledge stocks - electricity	0.268***
	(0.035)
Int. knowledge stocks - ICTs	-0.121***
	(0.031)
Ext. knowledge stocks - smart grids	0.587***
	(0.170)
Ext. knowledge stocks - green tech	-0.511***
	(0.151)
Ext. knowledge stocks - electricity	-0.264
	(0.173)
Ext. knowledge stocks - ICTs	0.239
	(0.165)
Renewables share	1.436*
	(0.741)
Marginal effect, standards	-0.077***
	(0.021)
Observations	30,628
Log-likelihood	-84231

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

Appendix 1.C.4 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 1.17, 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.

Table 1.17 Alternative GDP weighting of the policy weights

Standards	-0.057***
	(0.016)
RD&D smart grid	0.169**
	(0.074)
RD&D renewables	-0.272***
	(0.101)
Int. knowledge stocks - smart grids	0.946***
	(0.041)
Int. knowledge stocks - green tech	0.126***
	(0.033)
Int. knowledge stocks - electricity	0.279***
	(0.035)
Int. knowledge stocks - ICTs	-0.135***
	(0.030)
Ext. knowledge stocks - smart grids	0.704***
	(0.151)
Ext. knowledge stocks - green tech	-0.597***
	(0.157)
Ext. knowledge stocks - electricity	-0.293*
	(0.174)
Ext. knowledge stocks - ICTs	0.186
	(0.168)
Renewables share	0.024
	(1.300)
Marginal effect, standards	-0.010***
	0.029
Observations	30,628
Log-likelihood	-84317

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

Appendix 1.C.5 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 1.18 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 1.18 Regression results for alternative lags

	1-year lag	2-year lag	3-year lag	4-year lag
Standards	-0.043***	-0.045***	-0.031*	-0.043***
	(0.013)	(0.012)	(0.017)	(0.014)
RD&D smart grid	0.099	0.094	0.151**	0.140**
	(0.063)	(0.064)	(0.064)	(0.054)
RD&D renewables	-0.180*	-0.198**	-0.253***	-0.215***
	(0.092)	(0.080)	(0.078)	(0.069)
Int. knowledge stocks - smart grids	1.017***	0.938***	0.890***	0.877***
	(0.039)	(0.041)	(0.044)	(0.048)
Int. knowledge stocks - green tech	0.084***	0.130***	0.171***	0.195***
	(0.032)	(0.033)	(0.033)	(0.034)
Int. knowledge stocks - electricity	0.272***	0.261***	0.241***	0.253***
	(0.034)	(0.034)	(0.036)	(0.038)
Int. knowledge stocks - ICTs	-0.125***	-0.122***	-0.117***	-0.128***
	(0.030)	(0.030)	(0.031)	(0.031)
Ext. knowledge stocks - smart grids	0.800***	0.646***	0.702***	0.800***
	(0.154)	(0.172)	(0.166)	(0.160)
Ext. knowledge stocks - green tech	-0.546***	-0.538***	-0.551***	-0.572***
	(0.158)	(0.156)	(0.160)	(0.166)
Ext. knowledge stocks - electricity	-0.376**	-0.268	-0.231	-0.142
	(0.148)	(0.170)	(0.161)	(0.152)
Ext. knowledge stocks - ICTs	0.162	0.216	0.162	0.017
	(0.165)	(0.163)	(0.160)	(0.166)
Share of renewables	1.630**	1.330*	1.093	1.460*
	(0.782)	(0.757)	(0.756)	(0.763)
Marginal effect, standards	-0.075***	-0.078***	-0.054*	-0.075**
	(0.023)	(0.021)	(0.029)	(0.025)
Observations	30,628	30,628	30,623	30,618
Log-likelihood	-79805	-84109	-86962	-88626
AIC	159686	168294	174000	177327

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 1.19 Short and long run effects of standards

Standards (1 year lag)	-0.027**
	(0.014)
Standards (2 year lag)	-0.031**
	(0.013)
Standards (3 year lag)	-0.018
	(0.014)
Standards (4 year lag)	-0.043***
	(0.014)
Joint significance	-0.119***
	(0.025)
RD&D smart grid (1 year lag)	-0.087
	(0.090)
RD&D smart grid (2 year lag)	-0.028
	(0.118)
RD&D smart grid (3 year lag)	0.085
	(0.116)
RD&D smart grid (4 year lag)	0.084
	(0.080)
Joint significance	0.054
	(0.065)
RD&D renewables (1 year lag)	-0.019
	(0.199)
RD&D renewables (2 year lag)	0.049
	(0.250)
RD&D renewables (3 year lag)	-0.424*
	(0.218)
RD&D renewables (4 year lag)	0.183
	(0.173)
Joint significance	-0.211**
	(0.089)
Observations	30,618
Log-likelihood	-88331

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 1.19, 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.

Appendix 1.C.6 Cumulative stock of standards

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 standards. 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 1.20, 1.21and .1.22 replicate our main results tables (Tables 1.2, 1.3 and 1.4) 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 marg

Table 1.20 Main model on cumulative count of standards

Standards	-0.017***
	(0.004)
RD&D smart grid	0.109*
	(0.062)
RD&D renewables	-0.299***
	(0.075)
Int. knowledge stocks - smart grids	0.936***
	(0.042)
Int. knowledge stocks - green tech	0.132***
	(0.034)
Int. knowledge stocks - electricity	0.268***
	(0.035)
Int. knowledge stocks - ICTs	-0.125***
	(0.030)
Ext. knowledge stocks - smart grids	0.481***
	(0.170)
Ext. knowledge stocks - green tech	-0.339**
	(0.161)
Ext. knowledge stocks - electricity	-0.144
	(0.172)
Ext. knowledge stocks - ICTs	0.066
	(0.168)
Renewables share	1.270*
	(0.733)
Marginal effect, standards	-0.030***
	(0.008)
Observations	30,628
Log-likelihood	-84056

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

Table 1.21 Results by firm patenting intensity using cumulative count of standards

	High patenting intensity	Low patenting intensity
Standards	-0.028***	-0.000
	(0.005)	(0.005)
RD&D smart grid	0.003	0.106
	(0.098)	(0.066)
RD&D renewables	-0.226**	-0.313***
	(0.108)	(0.087)
Int. knowledge stocks - smart grids	0.945***	1.651***
	(0.037)	(0.220)
Int. knowledge stocks - green tech	0.119***	-0.221
	(0.034)	(0.207)
Int. knowledge stocks - electricity	0.235***	0.329***
	(0.043)	(0.078)
Int. knowledge stocks - ICTs	-0.139***	-0.132
	(0.034)	(0.087)
Ext. knowledge stocks - smart grids	0.126	0.382*
	(0.318)	(0.206)
Ext. knowledge stocks - green tech	-0.331	-0.324
	(0.236)	(0.226)
Ext. knowledge stocks - electricity	0.540*	-0.338*
	(0.302)	(0.181)
Ext. knowledge stocks - ICTs	-0.143	0.283
	(0.228)	(0.199)
Renewables share	2.703***	-3.530***
	(0.832)	(1.304)
Marginal effect, standards	-0.101***	-0.000
	(0.020)	0.004
Observations	10,646	19,982
Log-likelihood	-39535	-40889

Note: These regressions use the same specification and control variables as the main model, with the exception that the standard variable is a cumulative count of standards (stock) rather than a simple count (flow). Firms with high patenting intensity are defined as firms that are in the upper 25 percentile of total patents assigned in the ICT, electricity and green innovation patent classes during the period 2000-2016. This corresponds to more than 57 assigned patents. Firms with low patenting intensity are defined as having a total of 57 or fewer patents in these same technology classes and years. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 1.22 Effect on new entrants using cumulative count of standards

	Intensive margin	Extensive margin
Standards	-0.022***	0.015***
	(0.004)	(0.003)
Interaction standards and zero stock dummy	0.004	-0.034***
	(.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 1.21 are more sensitive to using the cumulative count of standards 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 1.22 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.

Appendix 1.C.7 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 1.23, 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 1.23 Alternative cut-off year for building policy weights (1977-2004)

Standards	-0.042***
	(0.012)
RD&D smart grid	0.086
	(0.113)
RD&D renewables	-0.336***
	(0.125)
Int. knowledge stocks - smart grids	0.941***
	(0.045)
Int. knowledge stocks - green tech	0.106***
	(0.034)
Int. knowledge stocks - electricity	0.203***
	(0.035)
Int. knowledge stocks - ICTs	-0.065**
	(0.031)
Ext. knowledge stocks - smart grids	0.586***
	(0.210)
Ext. knowledge stocks - green tech	-0.661***
	(0.169)
Ext. knowledge stocks - electricity	-0.492**
	(0.202)
Ext. knowledge stocks - ICTs	0.628***
	(0.175)
Renewables share	0.348
	(0.848)
Marginal effect, standards	-0.080***
	(0.023)
Observations	24,774
Log-likelihood	-70167

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 1.C.8 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 exogenenity 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 1.24 presents results from a fixed effect Poisson model, side-by-side with our main pre-sample mean Poisson model. Table 1C.8 shows that the coefficients in the fixed effects Poisson model are biased, especially for the smart grid knowledge stocks variables, whose direction, flips between the two models. This model also estimates the effect of standards and government R&D variables imprecisely.

Table 1.24 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

Appendix 1.C.9 Zero-inflated Poisson model

We further decompose the effects of standards on patenting levels into the extensive and intensive margins. This approach models excess zeros arising from the large number of small firms that rarely patent, through modelling the decision of whether to patent separately from the decision of how much to patent. In the first stage, this model estimates the effect on the probability that a firm will have zero patents using a logit regression. In the second stage, it estimates the effect on patenting levels using Poisson regression. The results from the ZIP model are similar to those from our main specification, and do not provide additional information. In particular, the combined marginal effect for the extensive and intensive margins in the ZIP model is nearly identical to the marginal effect in Table 1.2.

Table 1.25 Results from ZIP model

	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)
Combined marginal effect, standards		-0.076***	
		(0.020)	
Observations	30,628		30,628
Log-likelihood	-47022		-47022

Note: The Zero-Inflated Poisson model includes the same explanatory variables as the main model. *** p<0.01, ** p<0.05, * p<0.1

Chapter 2 The effects of standards on technological change in the green energy sector: an analysis of patent citations

Myriam Gregoire-Zawilski

Abstract

Addressing grand societal challenges, such as climate mitigation and adaptation, requires focusing research efforts in areas most likely to deliver impactful solutions fast. The unprecedented scale and speed at which the research community must devise solutions probes many questions about the role of public policy in directing technological trajectories towards promising areas. This paper investigates the effects of technology standards in shaping technological trajectories. Standards disseminate information and expertise that can support R&D coordination, technology compatibility, and knowledge translation across fields. These functions may be particularly impactful in industries experiencing increased technological complexity, such as those undergoing digital transformations. Using the green energy technology sector (solar PV, wind turbine and smart grid technologies) as an empirical application, this paper models the effects of technology standards on follow-on patent citation trajectories using a cohort approach. It presents evidence that standards support knowledge accumulation and convergence onto high-quality trajectories. These effects are strongest in technologies that have a complex architecture, draw on a diversified knowledge base, and require little customization to be scaled across different manufacturing and user environments.

2.1 Introduction

Addressing grand societal challenges, such as climate mitigation and adaptation, requires focusing research efforts in areas most likely to deliver impactful solutions fast. The unprecedented scale and speed at which the research community must devise solutions probes many questions about the role of public policy in directing technological trajectories towards promising areas. Acknowledging that conventional technology policy instruments such as research grants and R&D fiscal incentives are insufficient to achieve these goals, policy makers are expressing renewed interest in leveraging a broader mix of policy tools - often presented under the label “green industrial policy” - to supply the research infrastructure and public goods that innovation systems need to deliver solutions to wicked societal problems. This paper investigates the effects of one such tool, technology standards, in shaping follow-on technological trajectories. It extends work presented in Gregoire-Zawilski and Popp (2024) in which we find that technical standards cause a decline in firms’ patenting activity in smart grids technology. These results require further contextualization to determine if this decline is necessarily a sign that standards are detrimental to innovation. Standards shape follow-on innovation in many ways beyond R&D intensity and it may be that their impacts on other dimensions of innovation outweigh concerns raised by a slowdown in R&D. In Gregoire-Zawilski and Popp (2024), we provide preliminary evidence that standards improve patent quality, a result aligned with findings from other studies (Wenn et al, 2022). However, to the best of my knowledge, the literature provides limited insights for understanding trade-offs associated with standardization to guide decision-making in the planning and management of standards (see Ho and O’Sullivan, 2018 and Featherson et al., 2016 for an overview). In particular, we know little about how standards shape follow-on knowledge trajectories.

Using an analysis of patent citations, this paper unpacks how standards shape technological trajectories through investigating the following questions: 1) do standards increase knowledge utilization by follow-on inventive activity, 2) is this increase concentrated in high-value areas of technology, and 3) do the effects of standards on citations trajectories vary across different technologies? I find that standards generally increase patent citations and that this effect is greater in high-quality inventions. Together, these results provide evidence that standards steer innovation onto high-quality pathways. I also find that the positive effect of standards is strongest in inventions that recombine knowledge from diverse fields: this shows that standards help follow-on inventors utilize knowledge that is particularly complex. There is notable heterogeneity across technologies that vary in their design complexity, knowledge base attributes, and scalability. In smart grids, standards support knowledge utilization across the whole distribution of patent quality, whereas technological focusing is strongest in solar photovoltaic technology. In wind, standards cause a decline in citations.

Together these results provide important insights for practitioners to weight the advantages and disadvantages of standards at different stages of the technology cycle and across different industries. While standardization may be advisable to accelerate knowledge accumulation onto common foundations in areas where technical solutions are urgently needed, they might reallocate R&D resources away from research directions that have more uncertain horizons. Policy makers may also want to concentrate their standardization efforts in areas that will yield the greatest impacts. My findings show that standards are most effective at supporting knowledge utilization in technologies that have intricate design architectures, related interoperability needs, and that build on a diverse knowledge base.

Drawing on insights from the innovation systems literature, my findings also have important implications for advancing theory. Innovation systems are comprised of a complex web of interactions across a constellation of individuals, organizations, and institutions (Nelson, 1993; Edquist and Johnson, 1997). Within these systems, technical change is defined as a process of knowledge accumulation and recombination intermediated by a multiplicity of factors such as the characteristics of different technologies and markets (Dosi, 1982; Nelson and Winter, 1982). Technical standards are important institutions intermediating these processes of technical change, for example supporting the transition from a technological paradigm to another (Bergek et al, 2008; Tassey, 2017). But their role within innovation systems remains under-investigated. My study provides further evidence that standards can help manage technological complexity by providing common foundations that support technological stability and focus (Tassey, 2000; 2017).

The rest of the paper is structured as follows: section 2.2 reviews relevant insights from the standards and technical innovation systems literature; section 2.3 develops theoretical propositions; section 2.4 presents the data and empirical model; section 2.5 presents results; and section 2.6 discusses the implications of these results for policy and future research.

2.2 Theoretical framework

This paper combines insights from the standards literature with lessons from studies in the technological innovation systems literature that map the characteristics and knowledge trajectories of green energy technologies. Below, I summarize key findings from these two literatures. I then formulate new theoretical propositions about how standards and knowledge trajectories interact.

2.2.1 Defining and characterizing standards

Standards and innovation influence each other in myriad ways that can encourage or hinder innovation (Swann, 2000). Existing research offers various typologies to categorize standards and describe their roles in markets and innovation systems (Swan, 2000; Tassey, 2000; Blind and Gauch, 2009). However, scholars have paid less attention to how standards shape subsequent technological trajectories.

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). These documents are typically developed in standard-setting organizations, with the input of technical experts from industry and other potential standard users (Wiegmann et al., 2017; Baron and Spulber, 2018). These organizations coordinate standardization activities with the goal of “establishing and recording a limited set of solutions…intending and expecting that these solutions will be repeatedly or continuously used… by a substantial number of parties for whom they are meant" (de Vries, 1999, p.19).

As institutions, standards play a crucial role in disclosing, codifying, and disseminating technical knowledge (Blind et al., 2023), but they vary in the type of information they contain and the functions they perform in markets and innovation systems. Different types of standards address different market failures. Quality standards reduce information asymmetries, information standards lower transaction costs, variety reduction standards support economies of scale, and compatibility standards foster network externalities (Swann, 2000). Standards also clarify various types of technical information, responding to knowledge needs surfacing at different stages of the technology lifecycle (Blind and Gauch, 2009). In the early stages, terminology standards foster common understanding of concepts and testing standards provide guidance on measurement. Both support the translation of basic science into applied research. In later stages, variety reduction and compatibility standards support the development and commercialization of new technology applications (Blind and Gauch, 2009). Understanding how standardization needs evolve over the course of a technology's lifecycle is therefore also critical for managing standard-setting activities strategically (Ho and O'Sullivan, 2018; Featherson et al., 2016; Blind and Gauch, 2009).

2.2.2 Interplay between standards and innovation

Standards serve as both inputs and outputs in the innovation process: they draw on an industry's state-of-the-art knowledge and make this information widely accessible, informing subsequent technology development. Past research has mainly focused on standards as an output, for example, of the governance structure of standard-setting organizations (Chiao et al., 2007.). A growing body of literature, to which this paper contributes, has however recently begun to consider standards as an input to follow-on innovation. These studies shed light on 1) how standards affect firms' innovation outputs, productivity, and overall industry growth, 2) how standards shape the attributes of subsequent inventions, and 3) how standards guide technological change within and across industries.

Extant literature shows that standards affect innovation in intricate ways. At the firm-level, Gregoire-Zawilski and Popp (2024) find that standards cause a decline in patenting. At the industry-level, Baron and Schmidt (2019) find a similar decline in total factor productivity, but only in the short-run as firms adapt to new a technological paradigm. In the long run, the authors find that standards help industries grow. These average effects mask important heterogeneity, however. Gregoire-Zawilski and Popp (2024) find that the decline in patenting is concentrated in incumbents, whereas standards promote greater entry by new players. Bergeaud and colleagues find that standards initially boost the R&D investments of firms closest to the technological frontier, but that they eventually help less productive firms catch-up (2022). Other studies similarly find that standards support innovation by complementor firms further downstream in value chains (Funk and Luo, 2015; Wenn et al, 2022). Together these findings underscore the role of standards in establishing a common technological framework across an industry, helping various actors – including less productive firms and new entrants – innovate and transition to a new technological paradigm.

Standards not only affect who partakes in inventive activities, but also the nature of subsequent innovation. Recent studies find that standards lead to higher-quality follow-on innovation (Wen et al., 2022; Gregoire-Zawilski and Popp, 2024, Rysman and Simcoe, 2006), but steer innovation onto more incremental paths, especially amongst less R&D intensive firms (Brem, Nylund and Schuster, 2016; Foucard and Li, 2021, Clugherty and Grajek, 2023). Together these finding help contextualize the effects of standards on patenting intensity previously discussed. Standards improve the quality and cumulativeness of knowledge. Declines in patenting therefore do not necessarily signal that standards are detrimental to innovation, but rather a natural consequence of this change on the characteristics of follow-on innovation.

Finally, through consolidating a common technological framework (Swann, 2000), standards shape the rate and direction of technical change and industry growth (Tassey, 2017 p.267-268). When industries experience technological breakthroughs, standards help firms in the industry transition to this new technological paradigm, facilitating the creative destruction process and encouraging knowledge accumulation in these new directions (Tassey, 2017). Furthermore, standards can also accelerate technological convergence not only within, but also across industries producing complementary products (Blind and Gauch, 2015). The literature on technological innovation systems, which I review next, provides useful lenses for understanding these processes of technological change in greater depth.

2.2.3 Understanding knowledge trajectories

Technology evolves through a series of generalizable stages (Murmann and Frenken, 2006). In the early stages, competition across different designs causes high technological uncertainty, until a dominant design takes root. When consensus is achieved, the focus of inventive efforts moves downstream the design architecture in a way that is ordered by the technology's design hierarchy (Murmann and Frenken, 2006; Huenteler et al., 2016; Malhotra et al., 2021). A product's architecture defines the different components of a system and their interfaces, enabling the prioritization and sequencing of subsequent R&D activities. Some technical problems have greater incidence on the design of other parts of the system and are therefore tackled first. These considerations give form to a technology's design hierarchy – the organization of its various nested parts – and are instrumental in ordering knowledge trajectories (Huenteler et al., 2016; Malhotra et al., 2019).

The case of wind turbine technology provides a useful demonstration of these stages. From the mid-1980s onwards, the industry adopted the 'Danish design', consisting of a 3-blade upwind rotor. Getting clarity and consensus on the dominant design for the rotor enabled further innovation down the product design hierarchy: in power train technology, then in mounting and encapsulation, and finally, in grid connectivity technology. Data on patent citations show clear progression across these sub-system elements overtime and knowledge accumulation along the dominant trajectories (Huenteler, et al., 2016). Similarly, in solar photovoltaic technology, getting consensus on wafer-based crystalline silicon cells as a dominant design has enabled subsequent technology development – and related standardization – in PV modules, followed by off-grid standalone applications, and large-scale grid-connected power systems (Ho and O'Sullivan, 2018). The stages model therefore provides a useful heuristic for theorizing about the direction of technological trajectories. In empirical applications, however, the foci of inventive activities do not always follow such an orderly linear progression. External shocks, such as shifting needs and demand in the use environment or unexpected scientific breakthroughs might alter these paths. For example, in lithium-ion batteries, booming demand from the automobile industry prompted innovation back into product architecture to develop lighter non-stationary applications better suited to needs of this new use environment (Malhotra et al., 2021).

2.2.4 Standards and knowledge trajectories

The Murmann-Franken's nested hierarchy model is useful to reflect on how standards intervene in processes of technical change and knowledge accumulation. For example, standards may help consolidate a dominant design and focus subsequent inventive activity along the downstream product hierarchy, enabling specialization in component development (Vakili, 2016). Standards also lower the cost of searching and utilizing relevant high-quality knowledge. This may be particularly helpful when developing components that require interdisciplinary knowledge. Because technologies differ in their product architectures and knowledge bases, their knowledge trajectories also differ (Malhotra et al., 2019). In the green energy sector, these differences have been thoroughly analyzed, including using the Murmann-Franken model, by Malhotra and Schmidt (2020), Malhotra and colleagues (2019), and Huenteler and colleagues (2016). Drawing on insights from these studies, Table 1 summarizes the key characteristics of smart grids, wind turbine and solar photovoltaic technologies. Considering variation in these characteristics is essential for understanding the heterogeneous effects of standards on knowledge trajectories.

In Table 1, design complexity refers to a technology's product architecture. Complex designs have several components and interactions amongst them (Murmann and Frenken, 2006). The knowledge base refers to the scientific and technical knowledge one needs to acquire to innovate in this technology. When the knowledge base is highly specific, inventors cannot readily use general purpose technology. They require specialized expertise to adapt scientific discoveries to applications in their sector. Technology complexity refers to the diversity of the knowledge needed to innovate in a technology. Technologies building on interdisciplinary knowledge have highly complex knowledge bases. Finally, the need for customization refers to the scalability of technical solutions across different manufacturing contexts and user environments.

Standardized technical solutions will be most helpful in technologies that require low customization to be implemented in different manufacturing and user environments, and whose technical challenges can be simulated, tested, and resolved in laboratory environments (Malhotra et al., 2019).

Table 2.1 Technology characteristics and types of standards.

	Wind	**Solar**	**Smart grids**
Design complexity	High	Low	High
Knowledge base			
Specificity	Low	High	High
Complexity	Low	Low	High
Customization needs	High	Low	Low
Standard types	Safety	Testing, Measurement	Interoperability

Note: Adapted from Malhotra et al. (2019), and Malhotra and Schmidt (2020).

The characteristics presented in Table 1 have different implications for how standards shape innovation. Below, I posit different ways in which these characteristics moderate follow-on knowledge trajectories.

2.2.4.1 Design complexity

The tuning of different product components is a chief concern in complex product architectures. Standards can clarify this architecture, the compatibility requirements between its different components, and map the sequence of innovation needs across the system. In doing so, standards provide guidance on where inventors should focus their efforts, and in which order of priority. Strong uncertainty and lack of guidance about the dominant architecture and compatibility across its different components might cripple innovation altogether in the absence of standards, especially when designs are highly intricate and when a constellation of decentralized inventors are developing technology for different components. When the industry is more vertically integrated, learning how to tune and integrate different components may be done through means other than standards, such as close collaboration between the providers and users of various components. In sum, the complexity of a technology's design and how R&D actors in the value chain have organized in response to this complexity are both important factors mediating the relationship between standards and innovation. These are also related to the characteristics of a technology’s knowledge base, which I discuss next.

2.2.4.2 Knowledge base specificity

When inventors need highly specialized expertise, standards might help them identify relevant scientific foundations for their inventions and provide guidance on translating this knowledge into technology-specific applications. In this case, standards can help disseminate and facilitate the utilization of relevant scientific knowledge and state-of-the-art solutions. However, when developing new components builds on general purpose technology, standards may not add much value because the knowledge base is more readily usable without making sector-specific adaptations. When the knowledge base is general, manufacturers may be able to design components in-house without needing to acquire highly specialized expertise, in which case standards would add little benefit.

2.2.4.3 Knowledge base complexity

Finally, when the knowledge base required for innovating in a sector of technology draws on a limited number of fields, or from fields the industry possesses core expertise in, standards might similarly add little value. In this case, firms may be able to develop components in-house with their existing R&D capabilities. However, when firms need to pool knowledge from different domains, especially those outside of their industry’s core expertise, standards may help summarize and translate technical information. For example, standards might define common concepts and identify areas of synergies. This may be particularly important when actors from varied backgrounds and possessing distinct core expertise are developing different components of a technology.

2.2.4.4 Customization needs

Finally, technologies differ in their levels of replicability and scalability. Some technologies are readily deployable and scalable across different manufacturing and user environments. In this case, standards may help inventors replicate and improve upon state-of-the-art solutions across different contexts. However, when technology requires a high degree of customization to work in different environments, local solutions may be too idiosyncratic for standards to support knowledge utilization and accumulation upon common trajectories.

2.2.5 Standards and knowledge trajectories in green energy technologies

Table 1 summarizes the characteristics described above for wind, solar and smart grid technology. Below, I elaborate on each and further highlight the types of standards that are prevalent in those technologies. The hypotheses formally developed in Section 3 then expand on how standards moderate knowledge trajectories, given these technologies' respective characteristics.

2.2.5.1 Wind turbine technology

Wind turbines encompass 4 key subsystems – rotor, powertrain, mounting and encapsulation, and system integration - which are in turn composed of dozens of components (see Huenteler et al., 2016, and Malhotra et al., 2019, for a detailed description of wind turbines' product architecture). These interdependent parts combine in intricate ways to affect the overall performance of turbines, making their design highly complex. Tuning these moving parts to optimize the overall performance of the finished product is a chief concern of turbine manufacturers, and a central focus of technology development (Huenteler et al., 2016; Malhotra et al., 2019). Components that are vital to overall system performance, such as rotor blades, drive trains and control electronics, are typically developed and manufactured in-house (Malhotra et al., 2019). However, several of the inputs and components used in wind turbines, as well as the manufacturing processes employed in their assembly, rely on general purpose technology such as steel- and iron-making, welding, and forging (Malhotra et al., 2019). For this reason, I describe the wind knowledge base as having low specificity: it generally requires few adaptations to be transposed to the wind turbine manufacturing context. When components rely on specialized knowledge from external fields, the turbine manufacturer maintains close relationships with suppliers to iteratively develop and test those products. This is limited to the procurement of generators and gearboxes. For this reason, I describe the knowledge base as having low complexity. These attributes of the knowledge base have translated into a vertically integrated sector, where most components can be produced and assembled in-house, with a reliance on a small number of suppliers to procure specialized components (Malhotra et al., 2019). Knowledge is acquired internally, through learning-by-doing for system optimization, or through these close interactions with select suppliers of specialized inputs, rather than being translated and disseminated through industry standards. This may explain why, as major technological leaps were being achieved, for example in increasing the size of rotors which has drastically improved the performance of wind turbines since the early 2000s, the industry has featured high rates of learning-by-doing at the firm-level, but low rates of knowledge spillovers within the industry (Sweeney et al., 2022; Anderson et al., 2019). Finally, the weather conditions in which wind turbines are deployed are impossible to re-create in laboratory and vary greatly across different user locations. Therefore, wind manufacturers also maintain close relationships with wind farm developers to gather feedback about turbine performance in real-world settings when developing their products (Malhotra et al., 2019). The need for customization in the user environment is high, limiting opportunities to replicate and apply lessons from one user environment to another (Malhotra and Schmidt, 2020). The standardization activity that I observe in the wind sector reflects the industry's limited needs and opportunities to standardize. Despite being the most mature of the sampled technologies, wind features the fewest standards. The standards that have been deployed are predominantly concerned with limiting the potential hazards and nuisances from wind turbines, with fewer standards providing guidance on measurement or design issues (see Appendix C1 for a full list of wind standards included in the analysis). For example, standard IEC 61400-5 outlines requirements for ensuring the engineering integrity and operational safety of wind turbine blades overtime and standard IEEE 2400 defines techniques for measuring the level of aero acoustic noise generated by wind turbines.

2.2.5.2 Solar photovoltaic technology

The core of solar photovoltaic technology consists of wafer-based crystalline silicon and thin-film cells. After the polysilicon is cast into ingots, sliced into wafers, etched, polished, printed and coated to form cells, the resulting PV cells are assembled into modules (Malhotra et al., 2019; Zhang et Gallagher, 2016). These modules exhibit relatively simple product design compared to wind turbines (Malhotra et al., 2019). There are not as many distinct and interdependent components to calibrate, as they mainly consist of an array of PV cells encapsulated together.

The challenge in developing solar has instead been in achieving scientific breakthroughs in PV cell technology, followed by efficiency gains in the use of materials (reduction in wafer thickness to cut the use of polysilicon), and in achieving economies of scale in manufacturing (Malhotra et al., 2019; Nemet, 2019; IRENA, 2022). Solar PV technology builds on basic science, in areas such as materials science and photonics, developed specifically for this sector of technology. Its scientific foundations are therefore highly specific to the industry and have required high levels of initial R&D and iterative learning across materials suppliers and PV cell manufacturers (Malhotra et al., 2019). However, once these scientific foundations were established and a dominant design for PV cells had taken root, sector-specific knowledge – such as the properties of materials developed for PV cell manufacturing – was standardizable and replicable across many manufacturing contexts (Malhotra et al., 2019). Furthermore, when the sector draws on knowledge outside of its core competencies, such as innovations in encapsulation materials and metal pastes coming from the chemicals sectors, these materials can easily be procured and incorporated into manufacturing without making adaptations that require sector-specific R&D (Malhotra et al., 2019). Therefore, the complexity of the knowledge base for solar is relatively low, while its specificity is high. These properties of the sector's knowledge base have enabled the replication and massive take-up of PV technology. This has afforded ample opportunities for different actors to innovate simultaneously to further improve manufacturing processes, bringing solar onto a steep experience curve (Nemet, 2019; Malhotra et al., 2019). This has occurred despite the high complexity of PV cell manufacturing processes, which involves multiple steps and the tuning of hundreds of parameters (Malhotra et al., 2019). Because solar is modular, scalable and replicable across various contexts, the sector experienced a rapid take-up of lessons and technical solutions for optimizing manufacturing processes. Finally, when customization needs have surfaced across different user environments and applications – such as rooftop, ground-mounted, off-grid, or building-integrated systems, etc. – required adaptations have concerned peripheral components such as mounting equipment or inverter design, rather than core PV cell technology. Therefore, it has been possible to massively produce PV modules across different manufacturing locations for these different uses, and to simulate various user environments in the lab rather than requiring costly real-world applications and infrastructure investments to test and improve PV technology (Malhotra and Schmidt, 2020; Malhotra et al., 2019). With these technology characteristics, standardization activity has been abundant in solar and focused on providing industry-wide guidance for consistently measuring, assessing, and reporting on the performance of PV materials, cells, and modules (see Appendix C1 for a full list of solar standards included in the analysis). These may help, for example, with calibrating various parameters on production lines and measuring the specifications and quality of various materials and outputs. Examples of solar standards include ASTM E927-04A, which concerns the classification of solar simulators used for testing photovoltaic devices indoors; ISO 9847, which provides guidance on calibrating pyranometers which are instruments used in solar manufacturing to test solar radiation levels that PV modules are exposed to; and IEC 72788-1-6, which define terminology and testing guidelines for measuring the degree of cure of Ethylene-Vinyl Acetate encapsulation sheets used in photovoltaic modules.

2.2.5.3 Smart grid technology

Finally, smart grid technology differs vastly from the two technologies previously discussed as it is an umbrella term designating innovation in an amalgam of different hardware and software applications, rather than a single physical product. These technologies aim to digitalize or automate different parts of the electrical grid. Working together, they could enable two-way real-time communication across the grid system to improve the flexibility and resilience of grid operations (Brown et al., 2018; Colak et al., 2016; Martinot, 2016). A smart grid would have a highly complex product architecture, with millions of 'smart' components such as sensors, phasor measurement units, invertors, and metering equipment, all collecting, exchanging, and analyzing data in various subsystems, such as residential electricity consumption, behind-the-meter generation, distributed energy generation, electricity markets, power transmission and power distribution (NIST, 2021). Conducting R&D to develop various components of this decentralized system requires highly specialized knowledge about the industry's state-of-the-art practices and requirements, for example regarding data transmission and security protocols. Standards can help clarify which specific data architectures, data encryption and transmission protocols apply to grid communications. Innovating in this area also requires proficiency in various emerging and fast-moving areas of technology that include artificial intelligence, information and communication technologies, cloud computing, control engineering, information engineering, in addition to the industry's core expertise in electrical engineering, (Ghiani et al., 2018; IEA, 2021; Syed et al., 2020). Smart grid innovation therefore draws on a highly complex and diversified knowledge base. Standards may add value through translating knowledge from these different fields that is relevant to develop smart grids applications, thereby supporting knowledge accumulation and technological focusing. Finally, companies innovating in this area develop products targeted at various niche uses and clients, such as automated demand response, building energy management, smart home appliances, smart electricity metering, smart electricity billing, microgrids, substation automation, etc. Despite the diversity of user environments, these technologies all have in common that to be useful, they need to communicate with the rest of the system and operate as part of a network. Therefore, standardization and interoperability needs are high in smart grids (Brown et al., 2018). Given this, most standards observed in smart grids are concerned with defining a common smart grid architecture, along with terminology and compatibility guidelines. Examples include the IEC 61850 series which clarifies communications procedures between intelligent devices within power utility automation systems; ANSI/CTA-2045, which specifies a modular communications interface for residential energy management devices; and NIST IR 7761, which defines wireless communication standards for various smart grid applications.

2.3 Hypotheses

Building on the theoretical framework presented in section 2.4. and using an empirical model that estimates how standards change citations over the course of patents' life, this paper tests hypotheses about 1) the effects of standards on patent citation intensity, 2) the effects of standards on reorienting knowledge utilization towards high-quality inventions, and 3) the heterogeneous effects of standards across the 3 technologies.

H1. Increases in standards cause an increase in patent citations.

H1 tests whether standards help follow-on inventors better utilize existing relevant knowledge, thereby supporting the dissemination of state-of-the-art technical solutions (Swann, 2000;

Tassey, 2000). If standards facilitate knowledge accumulation onto common paths, we should observe that patents exposed to greater standardization receive more citations, compared to similar patents exposed to lower standardization levels at similar stages of their citation lifecycle. H1 builds on findings from Gregoire-Zawilski and Popp (2024) and Wen and colleagues (2022) who estimate that standards cause patents to be more highly cited. However, these two studies estimate the effects of standard on patent quality at the firm-level using a static citation window, which does not allow to capture how standards change citations trajectories[32]. The contribution of this paper is to use an empirical model that allows to estimate how standards change citations over the course of patents' lifetime.

H2. The positive effect of standards on patent citations is concentrated in high-value patents.

H2 provides a more direct test of the posited technological focusing effect of standards (Swann, 2000; Tassey, 2000). As evidence of technological focusing, we should observe that standards reallocate citations away from low-quality inventions and towards high-quality patents. Such effect would suggest that standards help inventors identify a relevant and high-quality knowledge base upon which to build (Gregoire-Zawilski and Popp, 2024). To test H2, I estimate the effects of standards on patents at different quantiles of the conditional distribution function.

H3. The effect of standards on patent citations varies across different technologies.

Finally, I posit that standards have heterogeneous effects across technologies exhibiting different features. The positive effect on citations will be highest in technologies that have a complex design, require complex and domain-specific knowledge, and present opportunities to replicate standardized solutions across many different user and manufacturing environments (Table 1).

[32] Gregoire-Zawilski and Popp (2024) use citation-weighted patent counts, using 5-year citation windows. Wenn and colleagues (2022) use a dummy variable that indicates whether a complementor firm had any high impact patent, defined as a patent in the top 5th percent of their cohort for the number of 10-year forward citations received.

H3a. In wind technology, standards have no effect, or a negligible effect, on patent citations.

In wind turbine technology, a highly complex product architecture combined with a relatively general and simple knowledge base has allowed wind manufacturers to develop most components in-house or through close interactions with select suppliers. The focus is on optimizing complex interactions between different components of the product architecture, including as they interact with climatic elements in various user environments, requiring customized solutions. For these reasons, I posit that standards will be of little use for supporting knowledge accumulation and technological focusing, as most technical solutions are too idiosyncratic to build on knowledge acquired in other contexts.

H3b. In solar technology, standards have a positive effect on patent citations.

Solar PV technology is characterized by a relatively simple product architecture whose manufacturing is highly replicable across various contexts. I posit that standards make sector-specific scientific knowledge more widely accessible and translate requisite lessons from other fields for use in the solar PV sector, enabling follow-on inventors to build on the industry's accumulated knowledge and focus inventive activities towards common knowledge pathways that advance high-quality technical solutions widely applicable across the field.

H3c. In smart grid technology, standards have a positive effect on patent citations.

Smart grids have a highly intricate product architecture, comprising a constellation of interdependent components. These have high interoperability needs, as the different component are intended to be deployed across decentralized grid networks. The value of these inventions will come from their ability to collect, exchange, and use data in real time to digitalize and automate various grid operations. Developing these applications requires bringing knowledge from fast-moving high-tech fields into the electricity sector: areas of technology that are outside of the traditional expertise of this sector. It also requires developing common agreement on the industry's vision for the smart grid data architecture and on protocols needed to ensure compatibility between devices. In this context, standards can clarify a common knowledge base for the field and make relevant external and sector-specific knowledge more readily accessible and usable to follow-on inventors. I posit that standards strongly support knowledge accumulation and technological focusing onto high-quality knowledge pathways in this sector. This should be evidenced by a strong positive effect of standards on patent citations, concentrated in the upper end of the patent quality distribution.

2.4 Data and methods

This paper uses data on citations between pairs of citing-cited patents as the outcome variable. Citation data provides information on patent quality and knowledge utilization. I combine these with data on the release of standard documents to measure standardization levels as the independent variable.

2.4.1 Data on patent citations

I use data on forward patent citations as an indicator of patents' quality. Patent citations are useful for documenting trajectories of technological change and trends in innovative activity (Huenteler et al., 2016). With these data, we can track the knowledge antecedents and descendants of individual patents, as well as technological trajectories building upon important inventions (Jaffe and de Rassenfosse, 2017). Extant literature shows that these data are a reliable indicator of a patent's quality, both in terms of an inventions' contribution to advancing knowledge as well as its economic value (Hall et al, 2005; Trajtenberg, 1990; Jaffe and Rassenfosse, 2017). Studies find that patent citations correlate with various measures of technological performance, such as declines in technology costs (Benson and Magee, 2015), assessments of an invention's value by experts (Albert et al, 1991), and other indicators of commercial success (Jaffe and de Rassenfosse, 2017).

I collect patent data using the European Patent Office's PATSTAT database. I use the Cooperative Patent Classification, which identifies green technologies at a high degree of granularity, to sample cited patents granted in the United States in three areas of technology: smart grids (excluding electric vehicle grid connectivity), solar photovoltaic, and wind energy generation. The technology classes used to identify relevant patents are presented in Appendix C3.

I then track the forward citations received by these patents. These inform us on how this knowledge is utilized by follow-on innovation. For example, the absence of forward citations indicates a technological dead end, whereas forward citations across diverse technology classes may signal a general-purpose technology (Jaffe and de Rassenfosse, 2017). When sampling patent citations, I restrict the technology classes of the citing patents to the same classes as the cited patents because the focus of the analysis is on how standards help accumulate knowledge within an industry. This also controls for differences in citations within and between technologies, as patents in the same classes are more likely to cite each other (Jaffe and Trajtenberg, 1999) Additionally, I only count citations between patents that have at least one inventor located in the United States. This controls for home bias in citations (Jaffe and Trajtenberg, 1999) and is also motivated by the expectation that domestic standards are only relevant to citing patents developed within the United States. Appendix Table B1 nevertheless shows that results are robust to also counting citations between all patents granted in the United States. I further exclude self-citations from the counts because patents sharing the same assignee are more likely to cite each other, which could create self-citation bias in the more prolific assignees (Jaffe and Trajtenberg, 1999)

Finally, to assemble the data on forward citations, I begin by tracking citations across pairs of cited and citing patents. I use the filing year to date these patents, because it is closest to when the R&D activity took place, but only include cited and citing patents that were eventually granted. I then compute the count of citations received by each cited patent in each subsequent year after the filing year until 2019. Finally, patents classified under multiple technologies are assigned different counts, for citations received in each of the technology they belong to.

2.4.2 Data on standards

I collect data on standards from multiple sources. For solar and wind standards, I used keyword[33] searches in the webstore search engines of the American National Standards Institute[34] (ANSI) and the International Electrotechnical Commission (IEC). Most standards included in the analysis were retrieved from these two sources, but I also searched for additional standards on the websites of the following ANSI-accredited standard developers: CSA America, the National Electrical Manufacturers Association (NEMA), the American Society of Mechanical Engineers (ASME), the American Society for Testing and Materials (ASTM), and the Institute of Electrical and Electronics Engineers (IEEE). Smart grids standards were retrieved from the Catalogue of Standards curated by the Smart Electric Power Alliance[35]. Further information on decision rules used for sampling standards, as well as the full list of sampled standards are available in Appendix C1 and C2.

For the independent variable, I compute a stock of standards in each year/technology. I use a stock instead of a flow of standards because inventors likely consider the universe of existing standards when ascertaining which prior knowledge to build upon, and not just newly released standards. The cumulative counts include standards developed by US-based and by international standard-setting organizations (SSOs). The two do not usually overlap and international standards are globally relevant, including to inventors located in the United States. Appendix Table B2 shows that results are similar when only counting standards developed by US-based SSOs. Following Grégoire-Zawilski and Popp (2024), I count standards at the part-level. Furthermore, because standard-setting organizations maintain and update standards periodically, I assume that the sampled standards remain relevant unless explicitly withdrawn. Therefore, no depreciation rate is applied to the standards stocks. Additionally, in the main specification, standard parts are counted only in the year of their first iteration. This approach

[33] Keywords used include the following: wind energy, wind turbines, offshore wind, eolian, solar photovoltaic, solar PV, solar energy, solar power, solar panel. Standards pertaining to solar thermal collectors and solar concentrators were excluded from the sample.

[34] ANSI also has a directory of relevant standards by energy sector: https://webstore.ansi.org/industry/energy

[35] https://sepapower.org/knowledge/catalog-of-standards/

was preferred because subsequent revisions generally consist of minor updates to maintain and keep the standards current and should therefore not be counted as equivalent to first releases. Appendix Table B2 nevertheless shows that results are robust to counting revisions[36]. Finally, I assign the year of the standard release, rather than the year the technical committee initiated the project, because this is the date closest to when the knowledge comprised in the standard document became broadly available.

2.4.3 Sample

The sample comprises 18,044 individual patents that have at least 1 inventor located in the United States, for which it was possible to obtain a measure of patent originality[37], to observe at least 3 duration years, and whose application filing year is between 2000 and 2017. These patents may be cited between the years 2001-2019[38]. The unit of analysis is a cited patent, in a given technology and citing year. The number of years that a patent is represented in the sample varies by filing year[39]. Overall, the sample comprises 116,927 patent-technology-year observations. The standard count varies by technology and year. By 2019, the last year covered in the analysis, the stock of standards tallied up to 218 across the 3 technologies.

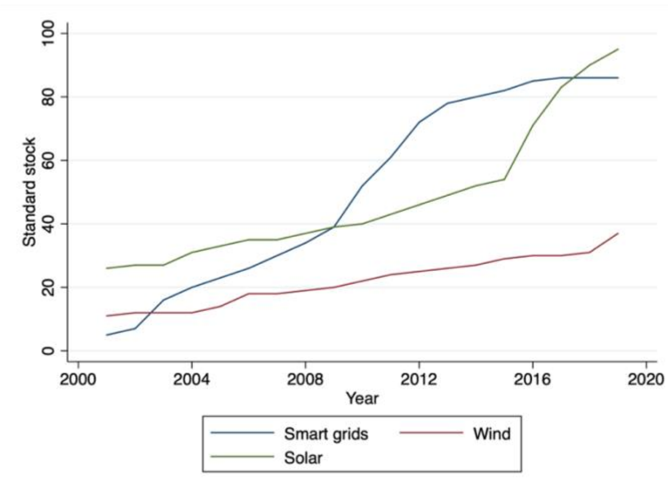
Figures 2.1 and 2.2 show standard stocks and patent counts[40] by year across the three technologies in the United States over the course of the sample period. These figures show important variation in the growth in standardization and in patenting activity across the three technologies over the sample period.

Technologies that stand to benefit the most from standardization – smart grids and solar – have distinctly higher standards stocks than wind. Also, there does not appear to have strong

[36] Revisions were counted when these amendments were substantive: corrections and the re-publication of consolidated versions were not counted.
[37] Some 305 patents drop from the analysis because their originality score is missing because the CPC classes of the patents they cited are missing in the PATSTAT database.
[38] I stop in 2019 to avoid truncation bias, while allowing for patents filed in 2017 to have at least 1 cited year included in the analysis (given the 2-year lag used in the model).
[39] Patents filed in different years, have different duration. Therefore, the number of times patent appears in the sample is unbalanced.
[40] Those include all patents eventually granted in the United States, sorted by application year.

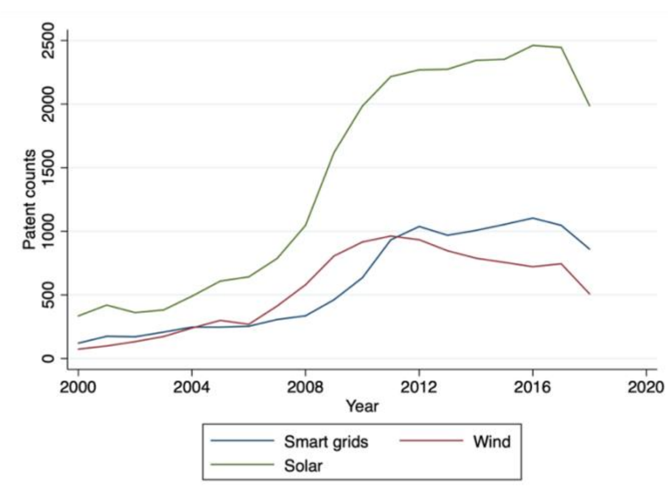
association between patenting levels and standardization levels. Smart grid technology has the highest stock of standards for the better part of the 2010s, despite having much lower patenting activity than solar. In contrast, solar experienced a boom in patenting from the late 2000s onwards, but slow standardization activity until the mid-2015. Relative to these two technologies, wind has low patenting and standardization levels throughout the sample period.

Figure 2.1 Standards stock by technology and year



Note: Figure 2.1 shows cumulative counts of standards in respective technologies by year. Cumulative counts represent stocks of standards available in each year. Standards are added to the count in the year they were released.

Figure 2.2 Patent counts by technology and year



Note: Figure 2.2 shows counts of patents in respective technology categories, sorted by application year. These counts only include patent applications that were eventually granted in the United States. Some patents are counted in more than one technology category. Counts show applications filed in each year and not cumulative counts.

2.4.4 Empirical strategy

I model the citation lifecycle using a cohort model that controls for observable and unobservable confounders that affect the likelihood of receiving citations over the course of a patent's life. Patents with different characteristics undergo different trajectories. For example, citations to patents by different types of assignees grow at different rates (Popp, 2017) and some sectors experience faster rates of technological change and knowledge decay, translating into shorter citation spans (Jaffe and de Rassenfosse, 2017). The model isolates those factors from the effects of standards, allowing to treat changes in standardization levels as plausibly exogenous. It leverages variation in the timing of standards across cohorts and technologies. Cohorts are differentially exposed to standards over the course of their life. The year-to-year change in standard stocks can therefore be treated as a series of exogenous shocks affecting the future likelihood of receiving citations. This is because the knowledge contained in a patent and its latent quality are fixed attributes of this invention. They are determined at the onset of a patent's lifecycle and do not transform in response to changes in standardization. Only the utilization of this knowledge in follow-on R&D may be affected by changes in standardization. Because the duration year varies across different cohorts experiencing a common shock in a given calendar year, the model captures how these shocks cause a departure from the citation trajectory compared to similar patents that experience this shock in a different duration year.

Risks of selection bias are also minimal. As we argue in Gregoire-Zawilski and Popp (2024), it is unlikely that a single assignee would capture the standard-setting process to position its proprietary technology as the industry's standard, translating into higher citation counts. First, standards in the technology areas covered by this study don't typically endorse single inventions, but rather provide guidelines for inter-device compatibility, measurement, and quality control. This is evidenced by the lack of standard-essential patents in these industries. Secondly, most standards included in the analysis were developed by standards-setting organizations whose voting members are national governments, making it unlikely that a single assignee would succeed at influencing the outcome of the vote (see Appendix in Gregoire-Zawilski and Popp, 2024, for a detailed description of voting processes in these SSOs).

2.4.4.1 Baseline model

I use Poisson regression to estimate the effects of standards on patent citations. I use a cohort model that leverages variation in the stock of standards over time and across technologies to isolate the effects of standards from other factors that affect citations. Patents sharing similar characteristics but belonging to different cohorts are differentially exposed to changes in standardization over the course of their life, providing the identifying variation.

I estimate a model that controls for different characteristics of 1) the cohort, 2) the technology, 3) the cited patent and 4) time trends affecting all patent citations. I write the baseline model as follows:

$$\begin{aligned} Y_{ijt_{ctd}t_{ctg}} = \exp\,(&\beta_0 + \beta_1 logS_{jt_{ctg-2}} + \beta_2 D_{t_{ctg}-t_{ctd}} + \beta_3 D^2_{t_{ctg}-t_{ctd}} \\ &+ \beta_4 P_{jt_{ctd}} + \beta_5 O_{t_{ctg}} + \beta_6 logM_{jt_{ctg}} + \beta_7 Z_i + T_{ctg} \\ &+ T^2_{ctg} + T^3_{ctg} + T^4_{ctg} + \alpha_j + u_{ijt_{ctd},t_{ctg}}) \end{aligned}$$

In this model the subscripts *ctd* and *ctg* indicate the years in which the cited patent *ctd* and the citing patent, *ctg*, were respectively filed. Cited patents enter the analysis in the year they were filed. Then then become eligible to receive citations the next year.

The dependent variable Y designates the number of citations received by cited patent *i* belonging to the cohort of patents filed in year t_{ctd} and in technology *j*. These citations are received in citing year t_{ctg}.

The independent variables are indexed as follows:

<u>Main variable of interest</u>

- **S** designates the stock of standards in technology *j* and citing year t_{ctg-2}. I use the log to normalize across different technologies and years and to interpret coefficients as an elasticity. Table B3 in the Appendix shows that results are robust to using the raw stocks instead of their logged transformation. I also lag this variable to avoid simultaneity bias, using the second lag in the main specification [41]. Appendix Table B4 shows that the results are robust to using the first, third and fourth lags.

Controlling for factors affecting patent citations across different cohorts

- **D** is a duration variable that designates the time that has elapsed since the patent was filed. It is the difference between the year of the citing patents, *ctg*, and the year of the cited patent, *ctd*, and represents how far along the patent is in its citation lifecycle. I enter this variable in the model also as a quadratic. This assumes that the baseline citation trajectory follows an inverse u-shape.
- **P** designates the supply of patents that were filed in the same year, *ctd*, and technology class, *j*, as the cited patent. Following Popp (2006) and Popp and colleagues (2013), I include this variable to control for opportunities to be cited, which in part depend on competition for citations amongst patents belonging to the same cohort.
- Opportunities to be cited also depend on the demand for knowledge. I therefore control for **O**, the number of green patents filed in citing year, *ctg*. These represent the supply of all potentially citing patents (Popp et al., 2013).

Controlling for factors affecting patent citations across different technologies

- I control for unobservable factors that affect the likelihood of citations across different technologies using fixed effects, denoted as $\boldsymbol{\alpha_j}$. The fixed effects control for each technology's baseline citation propensity.
- The likelihood of receiving citations also changes as technologies mature. To control for differences in the rates of technology maturation, I include **M**, the stock of patents in each technology *j* and citing year *ctg*. Stocks represent the cumulative sum of patents granted in the United States since 1977 after applying a yearly 15% depreciation rate. In the main specification, I model technology maturation non-linearly using the log transformation of

[41] I use the second lag because it allows sufficient time for the standards variable to take effect, while also maximizing the number of observations included in the analysis

this variable, but Table B5 in the Appendix shows that results are robust to using simple stocks.

Controlling for characteristics of the patent

- Vector **Z** denotes time-invariant attributes of the cited patent *i* that affect its likelihood of receiving citations. These include:
  - The patent's number of claims. This proxies for the patent's technological breadth. Patents with greater breadth are more likely to receive citations because they make a wider contribution to the advancement of knowledge and have greater technological and economic value (Squicciarini et al., 2013).
  - The patent's originality. This indicates the technological diversity of the knowledge base used by the patent. Patents that draw on more original combinations of antecedents may have greater technological value and be more likely to receive citations. Also, standards may be most helpful to translate knowledge from patents drawing on a complex and original base. I build a diversity measure using the technology classes comprised in the cited patents' backwards citations following the methodology proposed in Squicciarini and colleagues (2013, p.49-52, see Appendix C4 for a description).
  - The assignee type. The sample comprises patents filed by different types of assignees, such as private companies, universities and government research laboratories. Studies show that assignee types differ in their propensity to receive citations, making it an important factor to account for (Jaffe and Trajtenberg, 1996; Trajtenberg et al, 1997; Popp, 2017).
  - Finally, in the preferred specification, I do not control for unobserved patent characteristics. However, the results presented in Table B7 of the Appendix show that using a random effects model yields results similar to those from my preferred specification, providing reassurance that no important confounding factor has been omitted.

Controlling for factors affecting patent citations in different calendar years

- To account for broad patterns in citations trends common to all patents and technologies over time, I model time non-parametrically using 4 polynomials, denoted as **T** (starting with citing year 2000=0). Table B6 in the Appendix further shows that results are robust to using 3-year fixed effects to model time trends [42].

2.4.4.2 Quantile regressions

The baseline Poisson model presented in the previous section estimates the conditional mean effect of the explanatory variables. It does not provide insights into how standards affect citations across different regions of the conditional distribution. Patent data are highly skewed, as most patents are never cited (Trajtenberg, 2000; Egger et al., 2016). Therefore, conditional mean estimates provide a poor representation of the effects of standards on patents located at the extremes of the distribution (Koenker and Hallock, 2001; Hao and Naiman, 2007). These regions are of core interest to my analysis: if standards lead to technological focusing, we should observe that increases in citations are concentrated in the upper quantiles, where high-value patents are located.

To garner evidence of technological focusing (H2), I use quantile regressions to obtain estimates for different quantiles of the conditional distribution[43]. Quantile regressions sort patents into different regions of the distribution of regression residuals. In the context of citations data, I interpret residuals as providing information on the latent quality of these patents. Patents that have a high positive residual receive many more citations than predicted based on their observed characteristics (Popp et al., 2013). To accommodate count data, I employ a jittering approach

[42] Three-year fixed effects are used, because single-year fixed effects are collinear with the other market trend variables included in the model, which are preferred because they provide more information and cross-technology variation than single-year fixed effects would.
[43] Quantile analysis obtains regressions estimates using OLS, but through centering the solution of the minimization problem around a specified quantile rather than the mean (Koenker and Hallock, 2001). Because observations located on either side of a quantile are unbalanced (other than for the median), minimization is performed after weighting the sum of squared errors to accommodate this imbalance (Koenker and Hallock, 2001).

proposed by Machado and Santos Silva (2005, also used with citations data in Popp et al., 2013, and Kelchtermans and Veugelers, 2011)[44].

Quantile regression analysis presents many advantages when working with skewed patent citations data: estimation is more robust to the presence of outliers, it better accommodates heteroskedasticity and it is useful for investigating (re)-distributive issues, such as the technological focusing phenomenon investigated in this paper (Koenker and Hallock, 2001; Hao and Naiman, 2007). Previous studies using similar data have leveraged this method to investigate the returns to R&D in the green energy innovation sector (Popp et al., 2013), the determinants of scientific productivity in highly prolific researchers (Kelchtermans and Veugelers, 2011) and the effects of R&D on firms' innovation performance (Ebersberger et al., 2010).

2.5 Results

In this section, I only discuss the main coefficients of interest. Tables A1-A3 in the Appendix display the full results, showing that coefficients for the control variables behave as expected. Summary statistics are presented in Table 2.2 and results from the regression analyses are presented in Tables 2.3-2.5.

Table 2.3 first presents results for the baseline model, which estimates effects on the full sample, alongside results from a model that interacts the standards stocks with the technology variable[45]. Results from the baseline model show that an increase of 10% in the stock of standards increases citations by 6% on average. This confirms that standards increase knowledge utilization by follow-on invention (H1). When including interactions in the model, I find important heterogeneity across the different technologies, as hypothesized in H3. The positive effect of standards is driven

[44] This approach generates a random variable, uncorrelated with the dependent and independent variables, that is uniformly distributed between 0 and 1. This random variable is then added to the discrete citations counts, to artificially smooth the dependent variable and lend it to quantile estimation. This approach draws the random variable 100 times to create an average of the "jittered" sample. Other studies using patent citations to analyse the value of green energy patents and scientific production have also used this jittering method (Popp et al., 2013; Kelchtermans and Veugelers, 2011).

[45] This allows to estimate the heterogeneous effects of standards across the different technologies, while also continuing to leverage cross-technology and cross-cohort variation to estimate the parameters.

by smart grids patents, whose citations increase by 4.3% when the stock of standard increases by 10%, while the effect is negative in solar and wind patents, with declines of 4.5% and 13% respectively.

These heterogeneous effects accord with the theoretical expectations outlined in Section 2.3 about differences in these technologies' attributes and their respective needs for standardization. Smart grid technology has an intricate product architecture and draws on a highly specific and complex knowledge base outside of the traditional expertise of the electricity sector. For smart grids, standards clarify a common technological framework and help identify and translate relevant knowledge for the industry. Results in Table 2.4 further show that, in this technology, standards have a strong positive effect across all quantiles of the distribution, with the largest coefficient at the 90th quantile. These results confirm that in this technology standards broadly help follow-on inventors build on existing knowledge, while also focusing inventive activity onto high-value trajectories.

The technological focusing effect is starkest in solar PV patents. While the effect of standards on citations in solar PV patents is negative in the pooled model, the quantile regression analysis reveals notable differences across the distribution, with statistically insignificant effects of lower magnitudes in the bottom quantiles and a strong and statistically significant effect in the top quantile. This provides evidence that standards reallocate the bulk of the increase in citations towards high-quality patents. These results align with theoretical expectations for the characteristics of solar PV technology. The relatively simple product architecture and low customization needs enable the replicability of technical solutions. Standards support the widescale uptake of high-quality solutions. As the industry converges on adopting these solutions, it may also abandon *en masse* other technological paths. In addition to Table 2.4, Figure 2.3 visualizes the distribution of regression coefficients across the different technologies and quantiles. It shows a steeper upward curve in solar technology, illustrating that the bulk of the increase in citation is occurring in these upper quantiles

Table 2.2 Summary statistics

	Mean	Std. Dev.	Min.	Max.	Obs.		Obs.
All technologies							
Citation count	0.37	1.37	0	35	116,927	Assignee type	
Standards stock	63.12	24.59	12	95	116,927	Academic	8,359
Duration	6.88	3.46	3	19	116,927	Company	89,273
Patent originality	0.87	0.13	0	1	116,927	Company-univ.	623
Number of claims	20.11	13.23	0	170	116,927	Government	1,690
Tech. maturity	7,553.14	3,851.24	538	12,739	116,927	Individual	13,662
Opp. to be cited (*ctd*)	1,021.55	742.99	74	2,462	116,927	Other partnership	246
Opp. to be cited (*ctg*)	23,061.29	5,195.13	10,562	28,211	116,927	Unknown	3,074
Smart grids							
Citation count	0.44	1.68	0	35	33,672	Assignee type	
Standards stock	76.45	16.81	16	86	33,672	Academic	551
Duration	6.97	3.59	3	19	33,672	Company	30,016
Patent originality	0.90	0.11	0	1	33,672	Company-univ.	56
Number of claims	22.52	14.32	1	170	33,672	Government	430
Tech. maturity	4,362.73	1,303.53	841	5,411	33,672	Individual	2,064
Opp. to be cited (*ctd*)	554.95	351.22	121	1,105	33,672	Other partnership	17
Opp. to be cited (*ctg*)	22,832.27	5,266.35	10,562	28,211	33,672	Unknown	538
Solar photovoltaic							
Citation count	0.37	1.33	0	33	60,689	Assignee type	
Standards stock	68.44	20.91	27	95	60,689	Academic	7,324
Duration	6.83	3.42	3	19	60,689	Company	45,128
Patent originality	0.85	0.13	0	1	60,689	Company-univ.	562
Number of claims	19.71	13.49	0	169	60,689	Government	1,130
Tech. maturity	10,658.44	2,704.75	1,952	12,739	60,689	Individual	5,214
Opp. to be cited *(ctd)*	1,435.09	777.14	338	2,462	60,689	Other partnership	226
Opp. to be cited (*ctg*)	23,117.33	5,186.84	10,562	28,211	60,689	Unknown	1,105
Wind turbines							
Citation count	0.28	0.81	0	24	22,566	Assignee type	
Standards stock	28.90	4.95	12	37	22,566	Academic	484
Duration	6.88	3.37	3	19	22,566	Company	14,129
Patent originality	0.86	0.13	0	1	22,566	Company-univ.	5
Number of claims	17.58	9.76	1	127	22,566	Government	130
Tech. maturity	3,962.34	791.91	538	4,515	22,566	Individual	6,384
Opp. to be cited (*ctd*)	605.61	307.07	74	964	22,566	Other partnership	3
Opp. to be cited (*ctg*)	23,252.33	5,097.85	10,562	28,211	22,566	Unknown	1,431

Table 2.3 Average effect of standards and effects by technology

	Baseline	Tech. effects
Standard	0.600***	
	(0.095)	
Smart grids # standards		0.429***
		(0.100)
Solar # standards		-0.445***
		(0.123)
Wind # Standards		-1.333***
		(0.172)
Observations	116,927	116,927
Pseudo R-squared	0.0991	0.102

Note: Robust standard errors are clustered at the patent level. The reference category for the technology fixed effects is smart grids. The reference category for the assignee fixed effect is private companies. *** p<0.01, ** p<0.05, * p<0.1

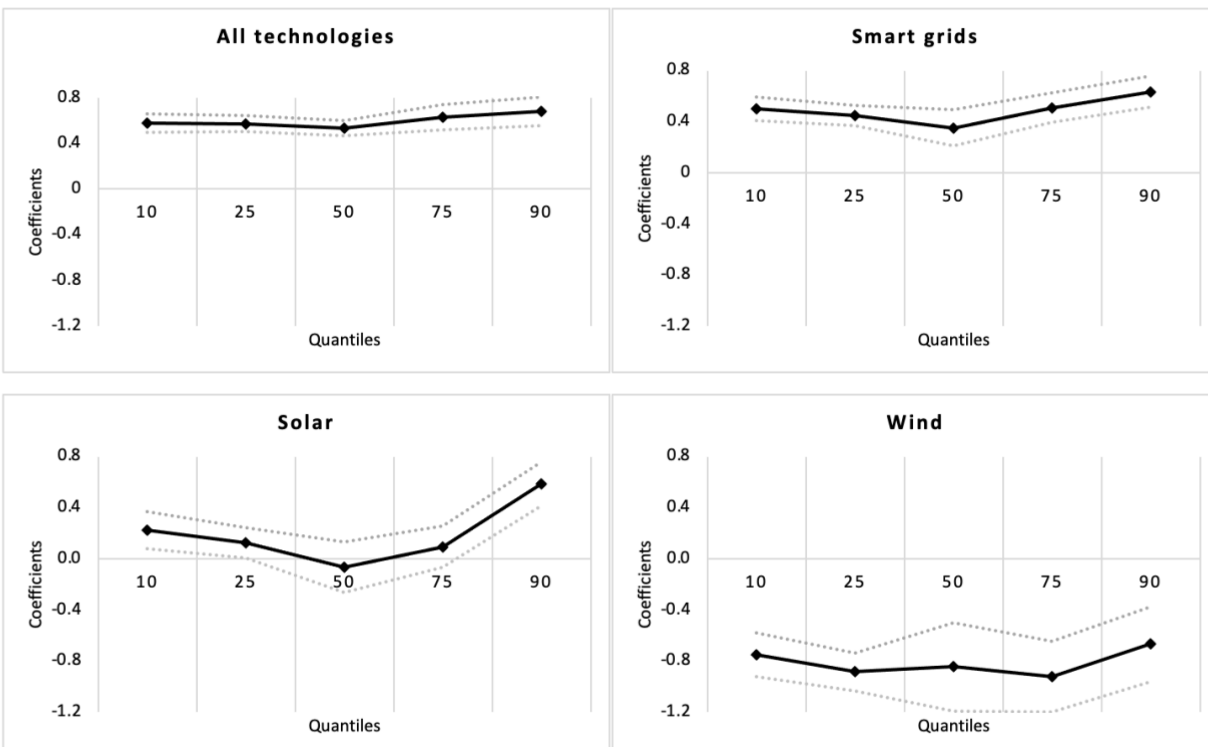
Finally, I find a consistently strong negative effect in wind patents, suggesting that standards slow down knowledge accumulation. While the strength and significance of this result is surprising – H3 predicted that the effect in wind would be negligible – it may be explained by the type of standardization activity pursued in this sector. Wind technology is more mature and has lower standardization needs, given its relatively simple product architecture and knowledge base (Malhotra and Schmidt, 2020). Component compatibility and calibration has been achieved through other means such as vertical integration and close interaction with suppliers (Hueneter al et al, 2016a; Malhotra et al, 2019). It may be that in these later stages of technology maturation, standards address issues – such as safety, engineering integrity and noise externalities - that require looking inwards to innovate incrementally and develop customized solutions, rather than building on technology developed by others. While there is a discernable slowdown in R&D activity in this sector during the sample period, as wind technology matures (Fig. 2.2), results show that after controlling for technology-specific time trends, standards cause a generalized decline in citations in wind patents.

Table 2.4 Effect by quantile, tech. effects model

	Mean	Q10	Q25	Q50	Q75	Q90
Smart grids # std	0.429***	0.502***	0.449***	0.352**	0.511***	0.636***
	(0.100)	(0.092)	(0.077)	(0.142)	(0.116)	(0.124)
Solar # std	-0.445***	0.225	0.125	-0.063	0.095	0.586***
	(0.123)	(0.145)	(0.118)	(0.198)	(0.161)	(0.173)
Wind # std	-1.333***	-0.752***	-0.885***	-0.845**	-0.920***	-0.667**
	(0.172)	(0.17)	(0.146)	(0.347)	(0.276)	(0.293)
Observations	116927	116927	116927	116927	116927	116927

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

Figure 2.3 Quantile results, baseline and tech. effects models



In a final analysis, I interact the standards variable with the originality variable. This enables me to test if standards have a stronger positive effect in patents that draw on a more complex knowledge base. The originality measure is constructed using the technology classes of the cited patents' backward citations: patents that are more original recombine knowledge from diverse fields. Results presented in Table 2.5 confirm that the effect of standards increases as patent originality rises. This provides strong evidence that standards facilitate knowledge utilization when the knowledge base is complex. Furthermore, results from the pooled model show that this effect is concentrated in smart grid technology, aligning with expectations for this technology as it is characterized by a relatively complex and interdisciplinary knowledge base.

Table 2.5 Effect of interaction of standards and patent originality

	Baseline (orig.)	Pooled (orig.)
Standards # originality	0.729***	
	(0.123)	
Standards # orig. (smart grids)		0.538***
		(0.104)
Standards # orig. (solar)		-0.265
		(0.271)
Standards # orig. (wind)		-0.222
		(0.337)
Observations	116,927	116,927
Pseudo R-squared	0.0996	0.104

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

Results presented in Tables 2.3, 2.4, 2.5 and in Figure 2.3 show that standards increase forward patent citations overall, but these effects vary across technologies. Standards are most helpful in facilitating knowledge utilization when technologies have intricate design architectures, draw on a complex knowledge base, or have greater opportunities to utilize standardized solutions across the industry. Results from the quantile regressions unambiguously show that standards cause technological focusing in solar PV technology, and to a lesser extent, in smart grids. Coefficients for the interaction between standards and patent originality provide strong evidence that standards are most useful in aiding knowledge translation and utilization when this knowledge is complex.

Furthermore, these results are robust to using different model specifications and measurement of the main variables, providing reassurance that my findings are not driven by arbitrary research decisions. Tables 2.B1-2.B7 in the Appendix show results 1) when including citing patents by all inventors, 2) when including revisions in the stock of standards and when excluding international standards from this variable, 3) when estimating the effects of standards as a semi-elasticity, 4) when using the first, third and fourth lag of the standards variable, 5) when modelling technology maturity using the stock of standards instead of its logged transformation, 6) when using 3-year fixed effects to control for time trends, and 7) when controlling for potential unobserved confounding factors using a random effects model.

2.6 Discussion and conclusion

Overall, my results show that standards help inventors better utilize pre-existing knowledge: not only do patent citations increase, but this increase is greater in high-quality inventions. I find that standards have a stronger positive effect on citations in inventions that recombine knowledge from diverse fields: this shows that standards help follow-on inventors utilize knowledge that is particularly complex. My analysis also reveals important heterogeneity across technologies that differ greatly in generalizable characteristics such as design and knowledge base complexity, providing important insights about when standards are most helpful to steer innovation towards common high-quality trajectories. In short, while knowledge is a public good, there are important barriers to accessing and using it. My findings show that standards help overcome those.

These findings nuance contentious debates in the literature about the benefits and drawbacks of standards. They show that to understand the full scope of their impacts, we must look beyond their effects on patenting levels. That standards cause a decline in patenting, as we find in Gregoire-Zawilski and Popp (2024), is not necessarily deleterious to innovation. I find that this drop occurs in concert with a shift towards more focused and high-quality innovation trajectories. As far as I am aware, this study is the first to offer a detailed investigation into how standards shape patent citation trajectories, complementing findings that standards steer innovation onto more incremental pathways (Foucard and Li, 2021; Clougherty and Grajet, 2023) and support technological convergence across industries (Blind and Gauch, 2015). My study therefore contributes rich insights for advancing understanding of the complex interplay between standards and innovation, and cautions against hastily concluding that drops in inventive activity are a symptom of technology lock-in. Overusing examples of "locked-in" inferior technologies, such as the QWERTY keyboard and the VHS videotape, detracts from more constructive discussions on understanding tradeoffs when designing standardization policy. Given the urgency of addressing complex wicked problems in the climate arena and beyond, focusing the research community's efforts on promising solutions and accelerating knowledge accumulation in those directions may outweigh concerns of technology lock-in, even when it means abandoning research avenues that could eventually yield valuable scientific breakthroughs but under more uncertain time horizons.

Answering calls to advance understanding of the relationship between standards and innovation to inform the planning and management of standards (Ho and O'Sullivan, 2018; Tassey, 2015; Featherston et al., 2016), this study more specifically provides insights for practitioners on two themes: 1) considering the stage of technology maturity, and 2) considering the attributes of different technologies.

Considering technology maturity is a chief concern for informing policy decisions about standardization. Extant literature suggests that standards play an important role in the technology maturation and creative destruction process (Tassey, 2015). For example, building on the typology offered by Sherif (2001), Ho and O'Sullivan (2018) examine how standards in the solar PV sector have evolved through recurring cycles of anticipatory-participatory-responsive standards as the industry sequentially tackled different technical challenges, from improving the efficiency of solar cells, to that of solar modules, and later, the performance of PV systems. This reinforces evidence that different types of standards are needed at different stages of technology maturation (Blind and Gauch, 2009). My study contributes complementary evidence by highlighting how standards give directionality and focus to technological change, further stressing the need to consider technology maturity since this narrowing of inventive activities may not be desirable in the early stages.

Finally, different standardization strategies should not only consider the stage of technology development, but also the attributes of the technologies themselves. My study illuminates heterogeneity in the effects of standards across technologies that differ appreciably in their characteristics. I find that standards have a strong positive effect across all quantiles of the smart grid distribution, a technology characterized by cross-disciplinarity and a complex decentralized architecture. This adds complementary evidence to extant literature, about the benefits of standards for mitigating technological and market uncertainty, especially in complex technological platforms and networked technologies (Blind, Peterson and Riillo, 2016). Findings for the smart grid case, in particular, have high generalizability and broad relevance in a context where major sectors of our economies are undergoing similar digital transformations that require integrating external knowledge of digital technologies to develop industry-specific applications. My findings also provide important insights for many emerging areas of green technologies that combine interdisciplinary knowledge and are in need to coordinate the R&D efforts of suppliers developing different components. In many cases, coordination is unlikely to occur through markets or vertical integration fast enough to confront the climate emergency. Policy makers should consider prioritizing standardization in those areas. Examples of such technologies include bioplastics and hydrogen. Bioplastics require specific advances in fundamental science in fields that include chemistry, materials sciences, and bioengineering, as well as the development of complex manufacturing processes. Hydrogen has similar features, it draws on knowledge from multiple fields that include chemical engineering, materials sciences, and electrical engineering and face similar interoperability challenges in developing infrastructure and processes for blending, storing, and distributing hydrogen (Cammeraat et al, 2022). Bioplastics and hydrogen therefore exhibit similar characteristics to smart grids, and lessons from my study may therefore generalize to these technologies.

A final aspect that is critical for informing sound standardization policy but is left to future research due to the data limitations of this study, is discerning between the effects of standards on technology development and technology adoption. It may be that the strongest effects of standards are in supporting the deployment of technologies. The potential for standards to help technologies reach markets faster is of high interest to policy makers (European Commission, 2011), and future research should bridge this gap in knowledge though studying the effects of standards in the commercialization and deployment stages of innovation.

Appendix 2.A Full Results

Table 2.6 Average effect of standards and effects by technology

	Baseline	Pooled
Standard	0.600***	
	(0.095)	
Smart grids # standards		0.429***
		(0.100)
Solar # standards		-0.445***
		(0.123)
Wind # Standards		-1.333***
		(0.172)
Duration	0.244***	0.259***
	(0.016)	(0.017)
Duration squared	-0.006***	-0.006***
	(0.001)	(0.001)
Patent originality	0.187	0.204
	(0.260)	(0.261)
Patent claims	0.006***	0.006***
	(0.002)	(0.002)
Assignee: academic	-1.000***	-1.001***
	(0.097)	(0.097)
Assignee: company university	-0.142	-0.143
	(0.695)	(0.695)
Assignee : government	0.124	0.123
	(0.189)	(0.189)
Assignee: individual	0.211***	0.202**
	(0.080)	(0.080)
Assignee : other partnerships	-1.787***	-1.793***
	(0.422)	(0.421)
Assignee : unknown	0.417***	0.420***
	(0.106)	(0.107)
Technology: solar	-1.913***	2.408***
	(0.176)	(0.429)
Technology : wind	0.093	5.510***
	(0.106)	(0.480)
Technology maturity	2.215***	1.109***
	(0.183)	(0.191)
Patents in cited year	0.000	0.000
	(0.000)	(0.000)
Patents in citing year	0.000	0.000
	(0.000)	(0.000)
Time	2.739***	2.066***
	(0.341)	(0.301)
Time^2	-0.417***	-0.277***
	(0.050)	(0.044)
Time^3	0.022***	0.013***
	(0.003)	(0.003)
Time^4	-0.000***	-0.000***
	(0.000)	(0.000)
Observations	116,927	116,927
Pseudo R-squared	0.0991	0.102

Robust standard errors are clustered at the patent level. *** p<0.01, ** p<0.05, * p<0.1

Table 2.7 Effect by quantile, baseline model

	Baseline	Q10	Q25	Q50	Q75	Q90
Standard	0.600***	0.576***	0.574***	0.536***	0.627***	0.681***
	(0.095)	(0.080)	(0.070)	(0.066)	(0.110)	(0.123)
Duration	0.244***	0.221***	0.234***	0.217***	0.289***	0.258***
	(0.016)	(0.013)	(0.012)	(0.011)	(0.018)	(0.020)
Duration squared	-0.006***	-0.006***	-0.006***	-0.005***	-0.008***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patent originality	0.187	0.398***	0.363***	0.375***	0.266**	0.802***
	(0.260)	(0.078)	(0.069)	(0.066)	(0.108)	(0.124)
Patent claims	0.006***	0.005***	0.006***	0.005***	0.008***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Assignee: academic	-1.000***	-0.787	-0.678***	-0.648***	-0.898***	-1.131***
	(0.097)	(60861.207)	(0.046)	(0.041)	(0.053)	(0.061)
Assignee: company university	-0.142	-4.483	-2.909	-1.276	-0.426**	-1.343***
	(0.695)	(3417172.747)	(4080368.932)	(3572886.025)	(0.183)	(0.208)
Assignee : government	0.124	0.101	0.076	0.100	0.006	-0.049
	(0.189)	(0.077)	(0.068)	(0.062)	(0.112)	(0.127)
Assignee: individual	0.211***	0.251***	0.251***	0.236***	0.303***	0.361***
	(0.080)	(0.027)	(0.026)	(0.025)	(0.043)	(0.049)
Assignee : other partnerships	-1.787***	-5.834	-5.170	-4.414	-1.197***	-1.485***
	(0.422)	(5277882.674)	(7734533.373)	(8324294.572)	(0.290)	(0.327)
Assignee : unknown	0.417***	0.612***	0.624***	0.547***	0.656***	0.512***
	(0.106)	(0.040)	(0.039)	(0.039)	(0.085)	(0.097)
Technology: solar	-1.913***	-1.290***	-1.389***	-1.252***	-1.883***	-1.385***
	(0.176)	(0.160)	(0.144)	(0.136)	(0.227)	(0.259)
Technology : wind	0.093	0.753***	0.742***	0.666***	0.677***	0.373***
	(0.106)	(0.076)	(0.067)	(0.063)	(0.106)	(0.120)
Technology maturity	2.215***	1.619***	1.718***	1.561***	2.250***	1.885***
	(0.183)	(0.169)	(0.153)	(0.145)	(0.243)	(0.279)
Patents in cited year	0.000	0.000***	0.000***	0.000***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patents in citing year	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time	2.739***	1.564***	1.656***	1.537***	2.043***	1.858***
	(0.341)	(0.327)	(0.276)	(0.259)	(0.405)	(0.476)
Time^2	-0.417***	-0.257***	-0.277***	-0.258***	-0.343***	-0.305***
	(0.050)	(0.048)	(0.041)	(0.039)	(0.062)	(0.073)
Time^3	0.022***	0.013***	0.015***	0.014***	0.018***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Time^4	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	116,927	116,927	116,927	116,927	116,927	116,927

Table 2.8 Effect by quantile, pooled model

	Pooled	Q10	Q25	Q50	Q75	Q90
Smart grids # standards	0.429***	0.502***	0.449***	0.352**	0.511***	0.636***
	(0.100)	(0.092)	(0.077)	(0.142)	(0.116)	(0.124)
Solar # standards	-0.445***	0.225	0.125	-0.063	0.095	0.586***
	(0.123)	(0.145)	(0.118)	(0.198)	(0.161)	(0.173)
Wind # Standards	-1.333***	-0.752***	-0.885***	-0.845**	-0.920***	-0.667**
	(0.172)	(0.170)	(0.146)	(0.347)	(0.276)	(0.293)
Duration	0.259***	0.233***	0.232***	0.190***	0.279***	0.274***
	(0.017)	(0.014)	(0.012)	(0.023)	(0.018)	(0.020)
Duration squared	-0.006***	-0.006***	-0.006***	-0.004***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patent originality	0.204	0.421***	0.355***	0.694***	0.259**	0.870***
	(0.261)	(0.080)	(0.068)	(0.139)	(0.111)	(0.123)
Patent claims	0.006***	0.006***	0.006***	0.005***	0.008***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Assignee: academic	-1.001***	-0.808	-0.670***	-0.634***	-0.743***	-1.144***
	(0.097)	(66036.614)	(0.046)	(0.068)	(0.055)	(0.060)
Assignee: company university	-0.143	-4.854	-2.899	-0.213	-1.254***	-1.391***
	(0.695)	(3463597.589)	(3860667.575)	(0.234)	(0.189)	(0.205)
Assignee : government	0.123	0.118	0.087	0.201	0.141	0.006
	(0.189)	(0.077)	(0.067)	(0.143)	(0.116)	(0.125)
Assignee: individual	0.202**	0.255***	0.242***	0.235***	0.265***	0.296***
	(0.080)	(0.028)	(0.026)	(0.056)	(0.045)	(0.049)
Assignee : other partnerships	-1.793***	-6.373	-4.986	-19.109***	-1.199***	-0.924***
	(0.421)	(5575598.524)	(7436307.504)	(0.372)	(0.300)	(0.322)
Assignee : unknown	0.420***	0.631***	0.609***	0.532***	0.654***	0.429***
	(0.107)	(0.041)	(0.039)	(0.109)	(0.088)	(0.096)
Technology: solar	2.408***	0.445	0.610*	1.160*	0.888*	-0.108
	(0.429)	(0.416)	(0.343)	(0.652)	(0.528)	(0.572)
Technology : wind	5.510***	4.658***	4.843***	4.282***	5.139***	4.427***
	(0.480)	(0.426)	(0.361)	(0.934)	(0.743)	(0.790)
Technology maturity	1.109***	0.888***	0.887***	0.650*	0.941***	0.715**
	(0.191)	(0.197)	(0.168)	(0.366)	(0.296)	(0.329)
Patents in cited year	0.000	0.000***	0.000***	0.000	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patents in citing year	0.000	0.000*	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time	2.066***	1.331***	1.214***	1.153**	0.788*	1.347***
	(0.301)	(0.338)	(0.262)	(0.504)	(0.419)	(0.479)
Time^2	-0.277***	-0.191***	-0.180***	-0.168**	-0.111*	-0.193***
	(0.044)	(0.049)	(0.039)	(0.079)	(0.065)	(0.074)
Time^3	0.013***	0.009***	0.009***	0.008	0.004	0.009*
	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)
Time^4	-0.000***	-0.000**	-0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	116,927	116,927	116,927	116,927	116,927	116,927

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.9 Results for technology originality, new entrants and incumbents

	Baseline (orig.)	Pooled (orig.)
Standards		
Standards # originality	0.729***	
	(0.123)	
Standards # orig. (smart grids)		0.538***
		(0.104)
Standards # orig. (solar)		-0.265
		(0.271)
Standards # orig. (wind)		-0.222
		(0.337)
Patent originality	-2.512***	0.691
	(0.405)	(1.064)
Duration	0.241***	0.266***
	(0.016)	(0.018)
Duration squared	-0.006***	-0.006***
	(0.001)	(0.001)
Patent claims	0.006***	0.006***
	(0.002)	(0.002)
Assignee: academic	-1.002***	-0.993***
	(0.097)	(0.096)
Assignee: company university	-0.144	-0.125
	(0.695)	(0.684)
Assignee : government	0.126	0.119
	(0.188)	(0.187)
Assignee: individual	0.203**	0.199**
	(0.080)	(0.082)
Assignee : other partnerships	-1.788***	-1.803***
	(0.421)	(0.429)
Assignee : unknown	0.414***	0.422***
	(0.106)	(0.106)
Technology: solar	-1.795***	1.190
	(0.190)	(1.065)
Technology : wind	0.119	2.180**
	(0.123)	(0.925)
Technology maturity	2.102***	1.763***
	(0.192)	(0.275)
Patents in cited year	0.000	0.000
	(0.000)	(0.000)
Patents in citing year	0.000	0.000
	(0.000)	(0.000)
Time	2.663***	2.466***
	(0.341)	(0.352)
Time^2	-0.402***	-0.359***
	(0.050)	(0.055)
Time^3	0.021***	0.018***
	(0.003)	(0.003)
Time^4	-0.000***	-0.000***
	(0.000)	(0.000)
Observations	116,927	116,927
Pseudo R-squared	0.0996	0.104

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.B Robustness analyses

Appendix 2.B.1 Including all inventors

Table 2.10 presents results for models that vary the sample of citing patents included in the citation counts. The main specification restricts the cited and citing patents to ones that have at least one inventor located in the United States. This excludes most inventions that were developed elsewhere by foreign inventors and were eventually filed in the United States as their secondary market. This allows to only count citations by patents that are comparable in their targeted primary market, since patents by inventors from the same market are more likely to cite each other. Furthermore, this allows to only include in the analysis citing patents that are directly affected by the standards included in the scope of the analysis, as those are restricted to standards relevant to the USA market. As expected, the coefficients for the standards variable are stronger in the main model that only includes citations by USA-based inventors, as this is the subsample of citing patents for which the sampled standards are most relevant.

Table 2.10 Effects of standards on citations by all inventors

	Baseline	Baseline (all inv.)	Pooled	Pooled (all inv.)
Standard	0.600***	0.326***		
	(0.095)	(0.071)		
Smart grids # standards			0.429***	0.193***
			(0.100)	(0.071)
Solar # standards			-0.445***	-0.209**
			(0.123)	(0.085)
Wind # Standards			-1.333***	-1.430***
			(0.172)	(0.113)
Duration	0.244***	0.265***	0.259***	0.267***
	(0.016)	(0.012)	(0.017)	(0.013)
Duration squared	-0.006***	-0.006***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent originality	0.187	0.366**	0.204	0.364**
	(0.260)	(0.165)	(0.261)	(0.164)
Patent claims	0.006***	0.010***	0.006***	0.010***
	(0.002)	(0.001)	(0.002)	(0.001)
Assignee: academic	-1.000***	-0.650***	-1.001***	-0.653***
	(0.097)	(0.089)	(0.097)	(0.089)
Assignee: company university	-0.142	-0.666	-0.143	-0.680
	(0.695)	(0.502)	(0.695)	(0.504)
Assignee : government	0.124	-0.254**	0.123	-0.257**
	(0.189)	(0.127)	(0.189)	(0.127)
Assignee: individual	0.211***	0.188***	0.202**	0.171***
	(0.080)	(0.064)	(0.080)	(0.065)
Assignee : other partnerships	-1.787***	-1.018***	-1.793***	-1.021***
	(0.422)	(0.284)	(0.421)	(0.285)
Assignee : unknown	0.417***	0.326***	0.420***	0.319***
	(0.106)	(0.084)	(0.107)	(0.085)
Technology: solar	-1.913***	-1.671***	2.408***	0.782***
	(0.176)	(0.115)	(0.429)	(0.298)
Technology : wind	0.093	0.395***	5.510***	5.382***
	(0.106)	(0.078)	(0.480)	(0.315)
Technology maturity	2.215***	1.989***	1.109***	0.985***
	(0.183)	(0.125)	(0.191)	(0.118)
Patents in cited year	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Patents in citing year	0.000	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Time	2.739***	1.753***	2.066***	1.059***
	(0.341)	(0.252)	(0.301)	(0.217)
Time^2	-0.417***	-0.293***	-0.277***	-0.152***
	(0.050)	(0.036)	(0.044)	(0.031)
Time^3	0.022***	0.015***	0.013***	0.006***
	(0.003)	(0.002)	(0.003)	(0.002)
Time^4	-0.000***	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	116,927	246,562	116,927	246,562
Pseudo R-squared	0.0991	0.104	0.102	0.106

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.B.2 Alternative counts of standards

Table 2.11 shows results for alternative measurements of the standards variable. The main specification uses the first release of standards developed by USA-based and international standard-setting organizations (SSOs). This assumes that the first release of a standard is the most relevant for informing follow-on invention. It also assumes that standards developed by international SSOs are broadly relevant across different country markets, including the United States. Alternative specifications show results when including revisions into these standards stocks, as well as when limiting the stocks to standards released by USA-based SSOs (i.e., excluding international standards), counting both the first releases only, as well revisions. The model that includes international standards in the scope of the analysis yields higher coefficients, which confirms the relevance of these standards in the United States market and validates the decision to include them in the analysis. While standards revisions were excluded in the main specification, they also appear relevant, since the models that includes them in the counts also yield higher estimates. It could be that the frequent updating of standards sends a signal to the market that these updates are highly relevant and current.

Table 2.11 Effects of different measures of the standards variable

	USA-Int First (Baseline)	USA-Int First + revisions	USA First	USA First + revisions
Standards	0.600***	1.036***	0.496***	0.590***
	(0.095)	(0.114)	(0.052)	(0.057)
Duration	0.244***	0.255***	0.259***	0.259***
	(0.016)	(0.016)	(0.016)	(0.016)
Duration squared	-0.006***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent originality	0.187	0.195	0.199	0.200
	(0.260)	(0.261)	(0.261)	(0.261)
Patent claims	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Assignee: academic	-1.000***	-1.001***	-1.001***	-1.001***
	(0.097)	(0.097)	(0.096)	(0.096)
Assignee: company university	-0.142	-0.140	-0.138	-0.139
	(0.695)	(0.694)	(0.693)	(0.694)
Assignee : government	0.124	0.123	0.121	0.122
	(0.189)	(0.189)	(0.189)	(0.189)
Assignee: individual	0.211***	0.208***	0.208***	0.206**
	(0.080)	(0.080)	(0.080)	(0.080)
Assignee : other partnerships	-1.787***	-1.789***	-1.789***	-1.791***
	(0.422)	(0.421)	(0.422)	(0.421)
Assignee : unknown	0.417***	0.420***	0.422***	0.421***
	(0.106)	(0.106)	(0.106)	(0.106)
Technology: solar	-1.913***	-1.270***	-1.718***	-1.562***
	(0.176)	(0.182)	(0.157)	(0.158)
Technology : wind	0.093	0.401***	0.781***	0.653***
	(0.106)	(0.115)	(0.144)	(0.124)
Technology maturity	2.215***	1.299***	2.050***	1.478***
	(0.183)	(0.203)	(0.168)	(0.178)
Patents in cited year	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Patents in citing year	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Time	2.739***	1.855***	2.446***	1.862***
	(0.341)	(0.337)	(0.322)	(0.327)
Time^2	-0.417***	-0.279***	-0.369***	-0.279***
	(0.050)	(0.050)	(0.047)	(0.048)
Time^3	0.022***	0.013***	0.019***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
Time^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	116,927	116,927	116,927	116,927
Pseudo R-squared	0.0991	0.100	0.101	0.101

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.B.3 Simple count of citations (semi-elasticity)

Table 2.12 shows results for the main specification, interpreted as an elasticity, alongside a model that uses the simple stock of standards, whose coefficient may be interpreted as a semi-elasticity. As expected, the coefficient is lower in the semi-elasticity model. This is due to the magnitude of this variable: the stock grows from 5 to 86 standards for smart grids, from 26 to 95 for solar, and from 11 to 37 for wind over the course of the sample period. Therefore, in all years and technologies covered in the analysis the addition of one standard represents a higher percentage than 1%, explaining why the coefficient is smaller when using the simple stocks than when using their log transformation.

Table 2.12 Effect of standards as an elasticity and semi-elasticity

	Baseline	Semi-elasticity
Standards	0.600***	0.014***
	(0.095)	(0.002)
Duration	0.244***	0.244***
	(0.016)	(0.016)
Duration squared	-0.006***	-0.006***
	(0.001)	(0.001)
Patent originality	0.187	0.188
	(0.260)	(0.261)
Patent claims	0.006***	0.006***
	(0.002)	(0.002)
Assignee: academic	-1.000***	-1.000***
	(0.097)	(0.097)
Assignee: company university	-0.142	-0.143
	(0.695)	(0.696)
Assignee : government	0.124	0.125
	(0.189)	(0.189)
Assignee: individual	0.211***	0.210***
	(0.080)	(0.080)
Assignee : other partnerships	-1.787***	-1.788***
	(0.422)	(0.422)
Assignee : unknown	0.417***	0.416***
	(0.106)	(0.106)
Technology: solar	-1.913***	-1.314***
	(0.176)	(0.199)
Technology : wind	0.093	0.108
	(0.106)	(0.096)
Technology maturity	2.215***	1.646***
	(0.183)	(0.202)
Patents in cited year	0.000	0.000
	(0.000)	(0.000)
Patents in citing year	0.000	0.000**
	(0.000)	(0.000)
Time	2.739***	2.499***
	(0.341)	(0.338)
Time^2	-0.417***	-0.357***
	(0.050)	(0.050)
Time^3	0.022***	0.017***
	(0.003)	(0.003)
Time^4	-0.000***	-0.000***
	(0.000)	(0.000)
Observations	116,927	116,927
Pseudo R-squared	0.0991	0.0994

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.B.4 Alternative lags

Table 2.13 and 2.14 presents model that use different lags of the standards variable, showing results for the first, second, third and fourth lags for both the baseline specification and for the pooled model. In the baseline model, the effect of standards grows overtime, informing the choice of the second lag as the preferred specification. This affords sufficient time for the standards variable to take effect, while also including more observations in the analysis than when using the third and fourth lags, as the latter yields results that are meaningfully comparable.

Table 2.13 Effects of standards using different lags, baseline model

	Baseline Lag 1	Baseline Lag 2	Baseline Lag 3	Baseline Lag 4
Standards	0.352***	0.600***	0.556***	0.823***
	(0.081)	(0.095)	(0.105)	-0.114
Duration	0.287***	0.244***	0.197***	0.184***
	(0.014)	(0.016)	(0.019)	(0.023)
Duration squared	-0.008***	-0.006***	-0.004***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Patent originality	0.220	0.187	0.147	0.090
	(0.258)	(0.260)	(0.267)	(0.280)
Patent claims	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Assignee: academic	-0.995***	-1.000***	-1.007***	-1.008***
	(0.096)	(0.097)	(0.101)	(0.105)
Assignee: company university	-0.215	-0.142	-0.055	0.075
	(0.684)	(0.695)	(0.707)	(0.709)
Assignee : government	0.115	0.124	0.132	0.103
	(0.187)	(0.189)	(0.193)	(0.202)
Assignee: individual	0.212***	0.211***	0.212**	0.192**
	(0.077)	(0.080)	(0.084)	(0.091)
Assignee : other partnerships	-1.676***	-1.787***	-2.143***	-2.671***
	(0.381)	(0.422)	(0.508)	(0.617)
Assignee : unknown	0.431***	0.417***	0.399***	0.381***
	(0.104)	(0.106)	(0.111)	(0.114)
Technology: solar	-1.919***	-1.913***	-2.178***	-1.965***
	(0.162)	(0.176)	(0.184)	(0.203)
Technology : wind	-0.092	0.093	-0.010	0.153
	(0.099)	(0.106)	(0.112)	(0.115)
Technology maturity	2.191***	2.215***	2.475***	2.231***
	(0.166)	(0.183)	(0.194)	(0.219)
Patents in cited year	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Patents in citing year	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Time	1.879***	2.739***	4.551***	5.712***
	(0.253)	(0.341)	(0.445)	(0.584)
Time^2	-0.308***	-0.417***	-0.651***	-0.779***
	(0.039)	(0.050)	(0.062)	(0.079)
Time^3	0.017***	0.022***	0.035***	0.041***
	(0.003)	(0.003)	(0.004)	(0.005)
Time^4	-0.000***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	137,608	116,927	98,059	81,136
Pseudo R-squared	0.104	0.0991	0.0976	0.101

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2.14 Effects of standards using different lags, pooled model

	Pooled Lag 1	Pooled Lag 2	Pooled Lag 3	Pooled Lag 4
Smart grids # standards	0.324***	0.429***	0.145	0.619***
	(0.097)	(0.100)	(0.105)	(0.148)
Solar # standards	-0.545***	-0.445***	-1.130***	-0.024
	(0.100)	(0.123)	(0.172)	(0.353)
Wind # Standards	-1.678***	-1.333***	-1.435***	-0.224
	(0.160)	(0.172)	(0.198)	(0.269)
Duration	0.306***	0.259***	0.213***	0.188***
	(0.015)	(0.017)	(0.020)	(0.024)
Duration squared	-0.009***	-0.006***	-0.004***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Patent originality	0.244	0.204	0.158	0.093
	(0.259)	(0.261)	(0.267)	(0.280)
Patent claims	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Assignee: academic	-0.996***	-1.001***	-1.008***	-1.008***
	(0.096)	(0.097)	(0.101)	(0.105)
Assignee: company university	-0.215	-0.143	-0.054	0.073
	(0.683)	(0.695)	(0.706)	(0.710)
Assignee : government	0.113	0.123	0.131	0.104
	(0.187)	(0.189)	(0.193)	(0.202)
Assignee: individual	0.202***	0.202**	0.202**	0.187**
	(0.077)	(0.080)	(0.085)	(0.091)
Assignee : other partnerships	-1.683***	-1.793***	-2.149***	-2.673***
	(0.380)	(0.421)	(0.507)	(0.616)
Assignee : unknown	0.431***	0.420***	0.409***	0.386***
	(0.104)	(0.107)	(0.111)	(0.114)
Technology: solar	2.464***	2.408***	3.439***	0.916
	(0.398)	(0.429)	(0.512)	(0.856)
Technology : wind	6.303***	5.510***	4.569***	2.570***
	(0.448)	(0.480)	(0.519)	(0.625)
Technology maturity	1.087***	1.109***	1.495***	1.665***
	(0.157)	(0.191)	(0.223)	(0.293)
Patents in cited year	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Patents in citing year	0.000***	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Time	1.313***	2.066***	4.013***	5.709***
	(0.214)	(0.301)	(0.431)	(0.653)
Time^2	-0.179***	-0.277***	-0.529***	-0.746***
	(0.033)	(0.044)	(0.060)	(0.089)
Time^3	0.008***	0.013***	0.027***	0.039***
	(0.002)	(0.003)	(0.004)	(0.005)
Time^4	-0.000*	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	137,608	116,927	98,059	81,136
Pseudo R-squared	0.108	0.102	0.0998	0.101

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.B.5 Modelling technology maturity using stocks

Table B5 shows results for an alternative specification of the technology maturity variable. The preferred specification uses the log transformation of the stock of patents, to account for changes in the maturation rate of each technology. Table 2.15 table shows that using the simple stocks of patents yields a stronger coefficient in the baseline model, but comparable results in the pooled model. This provides support for the decision to use the log transformation of this variable in the main specification, as it allows to normalize across technologies that have substantially different levels and growth rates over the course of the sample period.

Table 2.15 Modelling technology maturity

	Baseline (log stock)	Baseline (stock)	Pooled (log stock)	Pooled (stock)
Standards	0.600***	1.078***		
	(0.095)	(0.099)		
Smart grids # standards			0.429***	0.534***
			(0.100)	(0.141)
Solar # standards			-0.445***	-0.352***
			(0.123)	(0.121)
Wind # Standards			-1.333***	-1.661***
			(0.172)	(0.264)
Duration	0.244***	0.234***	0.259***	0.257***
	(0.016)	(0.016)	(0.017)	(0.017)
Duration squared	-0.006***	-0.005***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent originality	0.187	0.179	0.204	0.202
	(0.260)	(0.260)	(0.261)	(0.261)
Patent claims	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Assignee: academic	-1.000***	-1.000***	-1.001***	-1.001***
	(0.097)	(0.097)	(0.097)	(0.097)
Assignee: company university	-0.142	-0.137	-0.143	-0.142
	(0.695)	(0.695)	(0.695)	(0.695)
Assignee : government	0.124	0.124	0.123	0.124
	(0.189)	(0.188)	(0.189)	(0.189)
Assignee: individual	0.211***	0.211***	0.202**	0.199**
	(0.080)	(0.080)	(0.080)	(0.080)
Assignee : other partnerships	-1.787***	-1.784***	-1.793***	-1.793***
	(0.422)	(0.423)	(0.421)	(0.421)
Assignee : unknown	0.417***	0.433***	0.420***	0.429***
	(0.106)	(0.106)	(0.107)	(0.106)
Technology: solar	-1.913***	0.006	2.408***	3.572***
	(0.176)	(0.109)	(0.429)	(0.505)
Technology : wind	0.093	0.528***	5.510***	6.964***
	(0.106)	(0.122)	(0.480)	(0.476)
Technology maturity	2.215***	0.000**	1.109***	-0.000
	(0.183)	(0.000)	(0.191)	(0.000)
Patents in cited year	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Patents in citing year	0.000	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Time	2.739***	1.324***	2.066***	1.416***
	(0.341)	(0.286)	(0.301)	(0.294)
Time^2	-0.417***	-0.149***	-0.277***	-0.144***
	(0.050)	(0.039)	(0.044)	(0.040)
Time^3	0.022***	0.004	0.013***	0.004*
	(0.003)	(0.002)	(0.003)	(0.002)
Time^4	-0.000***	0.000	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	116,927	116,927	116,927	116,927
Pseudo R-squared	0.0991	0.0968	0.102	0.101

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.B.6 Alternative modelling of time trends

Table 2.16 shows results for a specification that models time trends using 3-year fixed effects instead of the polynomial approach used to model time non-parametrically in the main specification. I use 3-year fixed effects in this robustness check, as opposed to single year fixed effects, as the latter would be collinear with the other market trend variables included in the model. Results show that using the 3-year fixed effects yield comparable estimates in the baseline model, but stronger negative coefficients for the standards variable in solar and wind technologies in the pooled model.

Table 2.16 Alternative techniques for modelling years

Polynomials:	Baseline	Pooled	3-year fixed effects:	Baseline	Pooled
Standards	0.600***		Standards	0.544***	
	(0.095)			(0.090)	
Smart grids # standards		0.429***	Smart grids # standards		0.327***
		(0.100)			(0.101)
Solar # standards		-0.445***	Solar # standards		-0.832***
		(0.123)			(0.130)
Wind # Standards		-1.333***	Wind # Standards		-2.162***
		(0.172)			(0.152)
Duration	0.244***	0.259***	Duration	0.213***	0.250***
	(0.016)	(0.017)		(0.016)	(0.017)
Duration squared	-0.006***	-0.006***	Duration squared	-0.005***	-0.006***
	(0.001)	(0.001)		(0.001)	(0.001)
Patent originality	0.187	0.204	Patent originality	0.124	0.181
	(0.260)	(0.261)		(0.257)	(0.260)
Patent claims	0.006***	0.006***	Patent claims	0.006***	0.006***
	(0.002)	(0.002)		(0.002)	(0.002)
Assignee: academic	-1.000***	-1.001***	Assignee: academic	-1.001***	-1.002***
	(0.097)	(0.097)		(0.097)	(0.097)
Assignee: company university	-0.142	-0.143	Assignee: company university	-0.143	-0.146
	(0.695)	(0.695)		(0.697)	(0.697)
Assignee : government	0.124	0.123	Assignee : government	0.131	0.128
	(0.189)	(0.189)		(0.188)	(0.188)
Assignee: individual	0.211***	0.202**	Assignee: individual	0.227***	0.204**
	(0.080)	(0.080)		(0.079)	(0.080)
Assignee : other partnerships	-1.787***	-1.793***	Assignee : other partnerships	-1.778***	-1.791***
	(0.422)	(0.421)		(0.422)	(0.420)
Assignee : unknown	0.417***	0.420***	Assignee : unknown	0.451***	0.433***
	(0.106)	(0.107)		(0.106)	(0.106)
Technology: solar	-1.913***	2.408***	Technology: solar	0.435***	4.822***
	(0.176)	(0.429)		(0.124)	(0.446)
Technology : wind	0.093	5.510***	Technology : wind	0.037	7.714***
	(0.106)	(0.480)		(0.102)	(0.415)
Technology maturity	2.215***	1.109***	Technology maturity	-0.298**	-0.318***
	(0.183)	(0.191)		(0.126)	(0.113)
Patents in cited year	0.000	0.000	Patents in cited year	-0.000*	0.000
	(0.000)	(0.000)		(0.000)	(0.000)
Patents in citing year	0.000	0.000	Patents in citing year	0.000***	0.000***
	(0.000)	(0.000)		(0.000)	(0.000)
Time	2.739***	2.066***	2004-2006	-0.404***	-0.147
	(0.341)	(0.301)		(0.154)	(0.159)
Time^2	-0.417***	-0.277***	2007-2009	-0.008	0.649***
	(0.050)	(0.044)		(0.163)	(0.173)
Time^3	0.022***	0.013***	2010-2012	-0.247	0.673***
	(0.003)	(0.003)		(0.183)	(0.192)
Time^4	-0.000***	-0.000***	2013-2015	-0.979***	0.175
	(0.000)	(0.000)		(0.194)	(0.200)
			2016-2018	-1.406***	-0.102
				(0.201)	(0.208)
			2019	-1.896***	-0.505**
				(0.207)	(0.219)
Observations	116,927	116,927		116,927	116,927
Pseudo R-squared	0.0991	0.102		0.0938	0.101

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.B.7 Controlling for non-observable confounders

Table 2.17 shows results from the main specification alongside a model that controls for unobserved heterogeneity at the patent level using a random effects model. With the exception of the patent originality control variable, which is significant in the random effects model, the two models yield comparable results providing reassurance that the preferred specification does not omit important confounders.

Table 2.17 Controlling for unobserved heterogeneity with random effects

	Baseline	Baseline (RE)	Pooled	Pooled (RE)
Standard	0.600***	0.461***		
	(0.095)	(0.087)		
Smart grids # standards			0.429***	0.309***
			(0.100)	(0.088)
Solar # standards			-0.445***	-0.616***
			(0.123)	(0.115)
Wind # Standards			-1.333***	-1.881***
			(0.172)	(0.160)
Duration	0.244***	0.291***	0.259***	0.310***
	(0.016)	(0.016)	(0.017)	(0.016)
Duration squared	-0.006***	-0.006***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent originality	0.187	1.336***	0.204	1.357***
	(0.260)	(0.193)	(0.261)	(0.193)
Patent claims	0.006***	0.011***	0.006***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Assignee: academic	-1.000***	-0.940***	-1.001***	-0.940***
	(0.097)	(0.093)	(0.097)	(0.093)
Assignee: company university	-0.142	-0.698**	-0.143	-0.700**
	(0.695)	(0.306)	(0.695)	(0.308)
Assignee : government	0.124	0.154	0.123	0.154
	(0.189)	(0.175)	(0.189)	(0.175)
Assignee: individual	0.211***	0.451***	0.202**	0.449***
	(0.080)	(0.062)	(0.080)	(0.062)
Assignee : other partnerships	-1.787***	-1.354***	-1.793***	-1.372***
	(0.422)	(0.512)	(0.421)	(0.513)
Assignee : unknown	0.417***	0.919***	0.420***	0.898***
	(0.106)	(0.107)	(0.107)	(0.107)
Technology: solar	-1.913***	-1.983***	2.408***	2.665***
	(0.176)	(0.165)	(0.429)	(0.428)
Technology : wind	0.093	0.760***	5.510***	7.653***
	(0.106)	(0.099)	(0.480)	(0.446)
Technology maturity	2.215***	2.443***	1.109***	1.256***
	(0.183)	(0.165)	(0.191)	(0.171)
Patents in cited year	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Patents in citing year	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Time	2.739***	2.760***	2.066***	1.982***
	(0.341)	(0.318)	(0.301)	(0.286)
Time^2	-0.417***	-0.429***	-0.277***	-0.273***
	(0.050)	(0.046)	(0.044)	(0.042)
Time^3	0.022***	0.023***	0.013***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
Time^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	116,927	116,927	116,927	116,927
Pseudo R-squared	0.0991		0.102	
Number of id		18,868		18,868
Log-likelihood		-108339		-108019

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.C Data construction

Appendix 2.C.1 List of sampled standards

Smart Grids							
IEC 60870-6-503:1997	1997	IEC 61850-7-410:2007	2007	IEC 62351-8:2011	2011	IEC 62351-3:2014	2014
IEC 60870-6-802-1997	1997	IEC 62351-1	2007	IEC 62541-4:2011	2011	OASIS Energy Interoperation	2014
IEC 60870-6-702-1998	1998	IEC 62361-4:2007	2007	IEC 62541-6:2011	2011	IEEE 1815.1	2015
CEA-709.4-1999	1999	IEC 62351-6:2007	2007	IEEE 1701	2011	MultiSpeak V5.0	2015
MultiSpeak V1.1	2000	ANSI C12.1-2008	2008	IEEE C37.238-2011	2011	ANSI/ASHRAE/NEMA Standard 201	2016
IEC 61850-3:2002	2002	ANSI C12.19-2008	2008	NAESB REQ 20	2011	NAESB RMQ.26	2016
IEC 61850-4:2002	2002	ANSI C12.22-2008	2008	NISTIR 7761	2011	ANSI/NEMA SG-IPRM 1-2016	2016
IEC 61850-1:2003	2003	IEC 62351-2	2008	OASIS WS-Calendar	2011	IEC 62351-7:2017	2017
IEC 61850-2:2003	2003	IEC 62351-5:2009	2009	IEEE C37.118-2011	2011		
IEC 61850-5:2003	2003	Smart Energy Profile 2.0	2009	CEA-852.1-2010	2012		
IEC 61850-7-1	2003	ITU-T G.9960	2009	CEA-CEDIA-CEB29-2012	2012		
IEC 61850-7-2:2003	2003	Multispeak V4.x	2009	ISO/IEC 15067-3:2012	2012		
IEC 61850-7-3:2003	2003	NEMA SG-AMI 1-2009	2009	IEC 61850-90-5	2012		
IEC 61850-7-4:2003	2003	ANSI C12.20-2010	2010	IE 62541-7:2012	2012		
ANSI/IEEE 1547-2003	2003	ASHRAE 135-2010	2010	IEEE 1377-2012	2012		
MultiSpeak V2.2	2003	CEA-709.1-C-2010	2010	IEEE 1901.2-2013	2012		
CEA-709.3-1999(R2004)	2004	CEA-852-B-2010	2010	ITU-T G.9903	2012		
IEC 61850-6:2004	2004	IEC 62351-7:2010	2010	OASIS EMIX V1.0	2012		
IEC 61850-8-1:2004	2004	IEC 62541-1:2010	2010	OpenADR-2.0a	2012		
IEC 61850-9-2:2004	2004	IEC 62541-2:2010	2010	OpenADR2.0b	2012		
IEC 61850-10:2005	2005	IEC 62541-3:2010	2010	ANSI/CTA-2045	2013		
IEC 61850-10:2005	2005	IEEE 1815-2010	2010	IEEE 2030.5-2013	2013		
MultiSpeak V3.0	2005	IEEE 1901-2010	2010	NAESB REQ 19	2013		
ANSI C12.18-2006	2006	IEEE C37.239-2010	2010	NAESB REQ 21	2013		
NEMA ANSI C12.21:2006	2006	ITU-T G.9972 (06/10)	2010	NAESB REQ 22	2013		
CEA-709.2-A-2000 (R2006)	2006	NIST IR 7628	2010	NISTIR 7943	2013		

Solar							
ASTM E424-71	1971	IEC 60364-7-712 Ed. 1.0 b:2002	2002	IEC 62759-1:2015	2015	IEC TS 62788-7-2:2017	2017
ASTM-E1084-86	1986	ASTM E927-04a	2004	IEC TS 62910:2015	2015	IEC 61724-1:2017	2017
ASTM E772-87	1987	ASTM E1830-04	2004	IEC 62446-1:2016	2016	IEC 62979:2017	2017
IEC 60904-1:1987	1987	ASTM E1171-04	2004	IEC 62548:2016	2016	IEC TS 63049:2017	2017
IEC 60891:1987	1987	IEC 62124:2004	2004	IEC TS 62782:2016	2016	IEC TS 62916:2017	2017
IEC 60904-2:1989	1989	ASTM E973-05	2005	IEC 62788-1-2:2016	2016	IEC TS 60904-13:2018	2018
IEC 60904-3 Ed. 1.0 b:1989	1989	IEC 62093:2005	2005	IEC 62788-1-4:2016	2016	CSA/ANSI C450-2018	2018
ISO 9060:1990	1990	ASTM E2481-06	2006	IEC 62788-1-5:2016	2016	SCTE 246 2018	2018
ISO 9059:1990	1990	IEC TS 62257-7-1:2006	2006	IEC 61215-1:2016	2016	IEC TS 62738:2018	2018
IEC 60904-5:1993	1993	IEC 62116:2008	2008	IEC 61215-1-1:2016	2016	IEC TS 62915:2018	2018
ISO 9846:1993	1993	IEC TS 62257-9-6:2008	2008	IEC 61215-1-2:2016	2016	IEC 61853-3:2018	2018
ISO 9847:1992	1993	IEC 60904-4 Ed. 1.0 b:2009	2009	IEC 61215-1-3:2016	2016	IEC 61853-4:2018	2018
IEC 60904-7:1995	1995	ASTM E2685-09	2009	IEC 61215-1-4:2016	2016	IEC TS 60904-1-2:2019	2019
IEC 60904-8:1995	1995	IEC 62109-1:2010	2010	IEC 61215-2:2016	2016	IEC 62892:2019	2019
IEC 60904-9 Ed. 1.0 en:1995	1995	ASTM E2848-11	2011	IEC TS 62941:2016	2016	IEC TS 62994:2019	2019
IEC 61701:1995	1995	IEC 62109-2:2011	2011	IEC 61853-2:2016	2016	IEC TS 63019:2019	2019
IEC TS 61836:1997	1997	IEC 61853-1:2011	2011	IEC 61215-1-4:2016	2016	IEC 63202-1:2019	2019
IEC 60904-10:1998	1998	IEC/TS 62727 Ed. 1.0 en:2012	2012	IEC TS 61724-2:2016	2016		
ASTM E1040-98	1998	NECA 412-2012	2012	IEC TS 61724-3:2016	2016		
ISO 9488:1999	1999	ASTM E2908-12	2012	IEC 60904-1-1:2017	2017		
ASTM E1362-99	1999	ASTM E2766-13	2013	IEC 60904-8-1:2017	2017		
ASTM E1143-99	1999	IEC TS 62548:2013	2013	NSF/ANSI 457-2017	2017		
ASTM E2047-99	1999	IEC 62716:2013	2013	IEC PAS 62257-10:2017	2017		
ASTM E1125-99	1999	IEC 62817:2014	2014	IEC TS 62446-3:2017	2017		
ASTM E1462-00	2000	IEC 62790:2014	2014	IEC 62788-1-6:2017	2017		
ASTM E1021-95(2001)	2001	IEC 62894:2014	2014	IEC TS 62788-2:2017	2017		

Wind			
PTC 42 - 1988	1988	IEC 61400-23:2014	2014
IEC 61400-1:1994	1994	IEEE C37.30.2-2015	2015
IEC 61400-2:1996	1996	IEC 61400-27-1:2015	2015
AGMA 921-A97	1997	IEEE2400-2016	2016
IEC 61400-11:1998	1998	IEEE/IEC 60076-16-2018	2018
IEC 61400-12-0:1998	1998	IEC 61400-3-1:2019	2019
IEC 60050-415 Ed. 1.0 b:1999	1999	IEC TS 61400-3-2:2019	2019
ISO 12494:2017	2001	IEC 61400-21-1:2019	2019
IEC TS 61400-13:2001	2001	IEC TR 61400-21-3:2019	2019
IEC WT 01 Ed. 1.0 en:2001	2001	IEC TS 61400-25-71:2019	2019
IEC TS 61400-23:2001	2001	IEC 61400-26-1:2019	2019
IEC TR 61400-24:2002	2002		
IEC 61400-12-1:2005	2005		
IEC TS 61400-14:2005	2005		
IEC 61400-25-1:2006	2006		
IEC 61400-25-2:2006	2006		
IEC 61400-25-3:2006	2006		
IEC 61400-25-5:2006	2006		
IEC 61400-25-4:2008	2008		
IEC 61400-3:2009	2009		
IEC 61400-24:2010	2010		
IEC 61400-25-6:2010	2010		
IEC 60076-16 Ed. 1.0 b:2011	2011		
IEC TS 61400-26-1:2011	2011		
IEC 61400-4:2012	2012		
IEC 61400-12-2:2013	2013		

Appendix 2.C.2 Sampling strategy for standards

- Smart grids:
    - List extracted from the Smart Electric Power Alliances' Catalogue of Standards: https://sepapower.org/knowledge/catalog-of-standards/ (excluding standards related to electric vehicles).
- Solar Photovoltaic and Wind.
    - Keyword searches were conducted in the webstore search engines and on the websites of the following standardization organizations:
        - American National Standards Institute, International Electrotechnical Commission, CSA America, National Electrical Manufacturers Association, American Society of Mechanical Engineers, American Society for Testing and Materials, Institute of Electrical and Electronics Engineers.
        - Keywords used in the searches: wind energy, wind turbines, offshore wind, eolian, solar photovoltaic, solar PV, solar energy, solar power, solar panel.

- Excluded standards:
    - Standards pertaining to solar thermal collectors and solar concentrators.
    - Standards aimed at establishing best practices for technicians installing and maintaining solar panels and wind turbines, or for the design of mounting equipment.
        - For example: UL 2703 "Mounting systems, mounting devices, clamping-retention devices, and ground lugs".
    - Standards pertaining more generally to power conversion, power storage, and other general aspects of distributed energy systems, unless directly relevant to smart grids.
        - For example: "IEC 62257-7-4 "Recommendations for renewable energy and hybrid systems for rural electrification – Part 7-4: Generators – Integration of solar with other forms of power generation within hybrid power systems", "IEC 60269-6 Low-voltage fuses – Part 6: Supplementary requirements for fuse-links for the protection of solar photovoltaic energy systems", "IEC 61427-1:2013: Secondary cells and batteries for renewable energy storage – General requirements and methods of test – Part 1: Photovoltaic off-grid application".

Appendix 2.C.3 Technology classes for sampling patents

Technology	Cooperative Patent Classification
Smart grids	Y02B 70/30 Y02B 70/3225 Y02B 70/34 Y02B 90/20 Y02E 40/70 Y04S 10/00 (and all its subclasses) Y04S 20/00 and all its subclasses) Y04S 40/00 (and all its subclasses) Y04S 50/00 (and all its subclasses)
Solar	Y02E 10/50 (and all its subclasses)
Wind	Y02E 10/70 (and all its subclasses)

Appendix 2.C.4 Measuring patent originality

The patent originality measure summarizes the diversity of knowledge upon which an invention builds. It captures the breadth and balance in the representation of patent classes cited by patent I, using information on the patent classes of the patent's backward citations.

I use IPC codes at the 7-digit levels and follow the measurement approach proposed in Squicciarini et al. (2013, p.49), who define the originality of patent i as:

$$Originality_i = 1 - \sum_{j}^{n_i} s_{ij}^2$$

Where s_{ij} is the ratio of citations made by patent i to patent class j out of the total number of patent classes that appear in patent j's backward citations:

$$s_{ij} = \frac{\sum_j^{n_p} c}{\sum_p^{n} t}$$

Where c is the number of times patent class j is listed across all of the cited patents p that are cited by patent i. The denominator t represents the total number of times any patent class is cited across all of the cited patents p, counting the same patent class every time it is listed in the cited patents.

Chapter 3 Knowledge trajectories and transfers in smart grids technology: an analysis of the patent citation network

Myriam Gregoire-Zawilski

Abstract

This paper explores the importance of knowledge transfers for advancing technology development in highly interdisciplinary sectors of technology, using smart grids technology as a case. I use patent citation data to identify inventions that are highly influential within the citation network. Using this subsample of influential patents, I garner qualitative insights about the field's main knowledge trajectory. For example, influential patents appear to play an important role in transferring expertise across different sectors of smart grid technology. Findings from this exploratory analysis can help identify where important knowledge flows have occurred, with a view to informing future research on the causal effects of technology standards on knowledge transfers.

3.1 Introduction

Beyond affecting patenting intensity and the quality of follow-on inventions, another way in which standards may shape innovation is by facilitating knowledge transfers. This may be particularly beneficial when innovation requires interdisciplinary knowledge. By consolidating a dominant design, standards might help establish compatibility requirements for the industry, as well as shared priorities about the sequence in which different technical problems should be tackled. Overall, standards can make knowledge more widely accessible and reduce technological uncertainty. Together, these might help inventors learn from the experiences of others in the field, especially when innovating in different components of a technology requires shared knowledge. For example, standards might help inventors in downstream components integrate lessons from inventions located upstream in the product design hierarchy. Standards might be, in fact, one of few channels for encouraging knowledge transfers when technologies are distributed/decentralized. I use smart grids as a case of a technology whose development and deployment occurs in a highly decentralized fashion. In other complex technologies that are more centralized, like wind turbines, inventors might achieve this goal through other means, such as learning-by-interacting with other value-chain actors (Tang and Popp, 2016; Malhotra et al, 2019).

To study the effects of standards on knowledge flows, I must first identify meaningful categories of smart grids inventions across which important knowledge transfers occur. In this paper, I begin exploring this question using a mixed-method approach to map important knowledge trajectories in the field. This mix of quantitative and qualitative methods allows me to understand broad trends in smart grid patenting, while also gaining in-depth qualitative insights into the content of important patents and how the core focus of smart grid innovation has evolved over time. Knowing which components of smart grid technology were developed over time, for example, provides an indication of where important knowledge might have flowed across the smart grid design architecture. Knowing who the important innovators are in the field, what the influential inventions are, as well trends in patent citations, can also provide valuable insights for defining groups of patents to include in an analysis of the effects of standards on knowledge transfers.

The remainder of this paper is structured as follows: in the next section, I review the theoretical literature on technological trajectories to garner insights into patterns of technical change in green energy technologies, how smart grids differ, and related implications for knowledge transfers within the field. In section 3.3, I then present how I use data on the network of patent citations to identify influential patents and trace the field's core knowledge trajectory. In section 3.4, I present results from my descriptive analysis, and in section 3.5, I discuss the theoretical and policy relevance of these results.

3.2 Literature review

3.2.1 Technology lifecycles and understanding factors shaping technological trajectories

Across many different sectors of innovation, studies have found that technology evolves through a series of generalizable stages. The early stages are characterized by competition between different design concepts before consensus is reached on a dominant design (Murmann and Frenken, 2006). After the establishment of a dominant design, technological trajectories converge onto more cumulative and incremental paths (Dosi, 1982). They might undergo extended periods of incremental knowledge accumulation, occasionally disrupted by new technological breakthroughs

Even when new technological paradigms emerge, knowledge trajectories tend to remain cumulative. For example, in the fuel cells sector, innovation in the 1950-60s established foundational principles for the design of fuel cells. At the time, the dominant designs were Alkaline FC (AFC) and Molte Carbonate (MCFC). Even as R&D moved to producing new cell designs in later years, foundational knowledge from these earlier designs transferred into these new applications (Verspagen, 2007).

Research also shows that the engineering characteristics of technologies play an important part in ordering technological trajectories. Different components of a technology serve different functions, that might have ramifications for developing other components. These can inform the sequence in which the industry tackles different technical problems. Components that support core functions of a technology are developed first. Resolving technical challenges in these areas then propels innovation in components that serve more peripheral functions (Murmann and Frenken, 2006). For example, a core component of wind turbines is the rotor. The industry focused on solving engineering challenges related to the aerodynamics of rotor blades and on developing blade materials and coatings before shifting its attention to refining power train technology (Huenteler, 2016a, 2016b).

The extent to which these processes unfold in a sequential manner varies across different technologies, influenced by a complex interplay of technological, market, and other social factors. With time, technological pathways become entrenched, making deviations from core trajectories more unlikely (Malerba et al., 2007). However, external demand and technological shocks can alter these paths, and create opportunities for novel paths to emerge and new players to enter (Malhotra et al., 2021). Understanding these dynamics is crucial for anticipating future technological developments.

3.2.2 Technological trajectories in green energy innovation

Studies using patent citation networks to map technological trajectories show that green energy technologies experience markedly different paths. For example, solar photovoltaic (PV) technology underwent an incremental trajectory, exhibiting a persistent focus on PV cell, a core component of photovoltaic modules, initially through product inventions, and later, process inventions. This path can be attributed to the scalability of solar PV technology and policy-driven demand for affordable solar panels. As more companies began manufacturing solar panels, the innovation trajectory shifted towards process innovation achieved through learning-by-doing. Wind turbine technology, in contrast, experienced more balanced R&D activity (of its core/influential patents) across different components, unfolding in a sequential manner downstream the design hierarchy. This suggests that in complex technologies, getting consensus on a dominant design is paramount for coordinating technology development in different components and moving innovation along the product architecture (Huenteler 2016a, 2016b).

Complex technologies may, also, never move into the process innovation stage, as observed in wind (Huenteler 2016b).

Furthermore, to forecast technological change and inform policy decisions, we need a better understanding of the circumstances under which technological change occurs along cumulative paths and of when those get disrupted. For example, in the lithium-ion batteries sector, booming demand for electric vehicles radically shifted the focus of inventive activity. This new use environment valued different features, such as portability and low weight. Opportunities and market demand were significant enough to prompt innovation back into core design components, radically steering technology onto a different path (Malhotra et al., 2021).

In sum, technological trajectories are shaped both by design considerations (technology-push) and markets (demand-pull), and the combination of both vary across different technologies (Malhotra et al., 2021; Murmann and Franken, 2006). One lesson from the lithium-ion battery case is that the direction of these trajectories is not immutable, even though technological paradigms tend to become entrenched over time, raising possible concerns about incumbent advantages and barriers to entry (Malerba et al., 2007). Shifts in circumstances can open windows of opportunity for new actors to enter this innovation space, as Malhotra and colleagues observed in the batteries case (Malhotra et al., 2021). Policy-induced shifts in demand therefore have the potential to compel significant change in the core design of technologies and redirect trajectories in directions that can help fulfill social goals. These transitions also represent opportunities for public policies to support the entry of new R&D actors whose knowledge is valuable in the pursuit of these goals. In grid technologies, these include new actors with specialized knowledge of information technologies, for example, to support the digitalization transition. Better understanding movement along technical trajectories in response to external changes is therefore highly relevant to understanding how industries integrate novel general-purpose technologies, such as digital technologies, and more recently, artificial intelligence.

3.2.3 Relevance for theory and policy

One area of opportunity for advancing theory lies in exploring how technological characteristics generate different types of knowledge trajectories. As illustrated by various examples of green energy technologies, these trajectories might be incremental, evolving from product to process innovation, they may be closely structured along the design hierarchy, or comprise a hybrid of both. They might also respond differently to changes in external demand and advances in general-purpose technology. Understanding these trajectories can help better identify these opportunities across different technologies and inform policy to guide technical change towards the achievement of social goals.

Smart grid technology constitutes a compelling case for advancing theoretical understanding of these issues as it presents a distinctive set of characteristics. Like wind, its product architecture is intricate, composed of many components linked in a complex web of interfaces requiring interoperability. Unlike wind, a highly vertically integrated industry, R&D and technology adoption in smart grids occur in a decentralized fashion. Markets for these technologies are more fragmented, which may affect how the focus of inventive activity travels across different components over time, and how these paths transform with changing external contexts. Through an exploratory analysis of smart grid technological trajectories, this paper advances understanding of these issues. I find that the sequence through which different components of smart grid technology were developed was more strongly influence by market demand, initially in already established end-user consumer markets, and then evolved through a series of concerns emerging over time, such as grid stability and performance, and later, decarbonization and renewables integration. The emergence of a dominant design, formalized in technology standards developed in the late 2000s and early 2010s, appears to coincide with a period of intense innovation in the communication and information layers, which are core components of smart grid technology. After this period, the industry began developing a suite of applications to tackle emerging issues such as EV integration, microgrids and storage, but also continued R&D activities in pre-existing areas, indicating that new standards might have made previous knowledge antiquated, but also prompted innovation in new areas. Together these show that while a technology's design architecture can have a structuring effect, in decentralized technologies, changes in external factors also have a strong influence, perhaps stronger than in vertically integrated sectors.

This has important implications for designing policies that leverage an adequate mix of technology-push and demand-pull instruments that are tailored to each technology's particular knowledge trajectory. For example, consumer subsidies might not only accelerate technology adoption in technologies characterized by incremental trajectories, as seen in the PV case, but can also create markets that demand different service characteristics from technologies, helping steer innovation in entirely new directions (Malhotra et al., 2021). In other technologies, like wind, demand-side approaches might not be sufficient, because technology is too complex. Technology-push instruments might be advised (Malhotra et al., 2021) to help support R&D across the different components of the design hierarchy. In complex technologies characterized by fragmented R&D and markets, policy interventions that support coordination may be particularly advised to consolidate a dominant design and propel innovation downstream the design hierarchy.

Moreover, mapping technological trajectories can help identify where important knowledge flows occur. In complex and interdisciplinary technologies like smart grids, knowledge flows across different components play a pivotal role in diffusing a new technological paradigm across the industry and ensuring interoperability among different components.

For instance, in wind energy, deployment subsidies proved most effective when combined with policies supporting knowledge transfers between different actors of the value-chain (Tang and Popp, 2016; Tang, 2018). This underscores the importance of knowledge flows, both from outside the field as well from within the field, for technological advancement. The latter may be particularly important in complex interdisciplinary distributed technologies, like smart grids. Technology standards might have significantly contributed to shaping knowledge trajectories through facilitating knowledge transfers across the different domains of smart grid technology, helping to translate core technology for various grid applications. This paper therefore also serves as a preliminary exploration of important knowledge flows within the field. To achieve this, I use a mixed-methods methodology to trace the field's core technological trajectory, described in the next section.

3.3 Methods

To gain insights into how smart grids technology has evolved over time, I leverage main path analysis from the innovation studies literature (Hummon and Dereian, 1989; Verspagen, 2007; Fontana et al., 2009). In recent years, this method has notably been used in studies of green innovation (Huenteler et al., 2016a, 2016b; Malhotra et al., 2019; Malhotra et al., 2021). It leverages data on patent citations to identify important knowledge paths within a sector of technology, and the influential patents located along these paths.

Patent citations are widely used in innovation studies as a proxy for knowledge flows. They provide a paper trail that allows researchers to track the knowledge antecedents and descendants of patented inventions (Jaffe and Trajtenberg, 2002). Patent applicants have a duty to disclose, trough citations, when their invention uses knowledge that is already protected within the United States market. Because of the legal ramifications for intellectual property protection, in my analysis I only include citations between patents that were granted in the United States.

3.3.1 Mixed-methods research design

I use network connectivity methods as a bridge between large-N quantitative inquiry and small-N in-depth qualitative analysis of smart grid technological pathways (Huenteler et al., 2016a, 2016b). I start with the full sample of 14,498 patents that were granted in the United States between 1980 and 2021 and use the connectivity algorithm to identify a subset of 154 patents that are highly influential within the smart grid citation network. Following Huenteler and colleagues, I identify influential patents as those that make up 80% of the network's weight (Huenteler et al., 2016a, 2016b; Malhotra et al., 2021). I then manually code the abstracts of these patents along different service characteristics and components of the smart grid's design architecture (Huenteler et al., 2016a; 2016b; Malhotra et al., 2021). These categories are informed by desk research. This mixed method approach allows me to garner descriptive insights about knowledge flows and technological trajectories in smart grids at a high-level and at a highly granular scale.

3.3.2 Connectivity algorithm

The assumption is that patents that are central in the patent citation network are a representative depiction of how the field's foundational knowledge has evolved over time. To implement the connectivity algorithm, I first obtain data on patent citations in the form of matrix C_{ij}, where *i* represents the cited patent and *j* represents the citing patent. C refers to the citation that connects the two vertices. This citation network is directed: knowledge can only flow from patent *i* to patent *j* (Verspagen, 2007, Fontana et al., 2009). Following extant literature, I then compute a search path node pair (SPNP) indicator for each of the edges in the network (Verspagen, 2007, Fontana et al., 2009). The SPNP measure captures whether the edge lies along important knowledge pathways. The SPNP is the product of n_i and m_j, where n_i is the sum of all distinct patents on the backward path to cited patent *i* (including *i* in the count), and m_j is the sum of all distinct patents of the forward path from citing patent *j* (including *j* in the count). The SPNP value therefore depends on the importance of knowledge trajectories both upstream and downstream from an edge. It provides information on the position of an edge within the overall network. To have a high SPNP value, patents *i* and *j* need to build on the field's core knowledge, but also provide a knowledge foundation upon which important patents subsequently build. A drawback of this approach is that the algorithm weights patents in the center of knowledge trajectories more heavily (Verspagen, 2007)[46]. For example, a pioneering patent that uncovered novel research directions that later became highly important in the industry, but that itself does not cite previous patents in the field has, by construction, a low SPNP value. Similarly, patents

[46] I only include smart grids patents within this network. Therefore, when patents build extensively on knowledge external to the field, these knowledge antecedents are not counted as part of their SPNP value. While this might under-weight patents that were pioneers in bringing new knowledge into the field, I find that the patents that the connectivity algorithm identifies as important are nevertheless more interdisciplinary than the average (for example, these patents have higher originality on average, a measure captures the diversity in CPC classes represented in the patent's backward citations across all fields of technology, not just smart grids). Even when excluding their linkages to knowledge antecedents outside of the smart grids sector, these patents have high SPNP values. This indicates that thes4e influential patents build both on substantial knowledge from inside as well as outside the field.

that build on the industry's core state-of-the art knowledge but receive few citations also have low SPNP values. To the extent that I am interested in capturing patents that are part of well-established knowledge trajectories, those are patents that build on solid foundations and have also informed substantial follow-on R&D activity, this interpretation of the SPNP is adequate in the context of my study.

Furthermore, I use the SPNP indicator instead of other metrics conventionally used in network analysis, such as eigenvector centrality, because it was developed specifically for applications using patent citations data (Hummon and Dereian, 1989). Like eigenvector centrality, the SPNP indicator takes into consideration the importance of a node's neighbors. Patents that are connected to other important patents generally have a high SPNP value, because their neighbors also have several knowledge antecedents and descendants. However, the SPNP allows to subsequently trace all the paths in the network, from each source (a patent that does not cite but it cited) to each sink (a patent that cites but is not cited) to find which of these paths has the highest sum of SPNP (Verspagen, 2007). Therefore, I favor this method over other traditional network analysis approaches because it is particularly suited to examining knowledge trajectories.

3.3.3 Sampling decisions

I compute these SPNP values for a network of patents granted in the United States between 1980 and 2021. I exclude patents prior to 1980 from the analysis because I assume these are outdated. I construct the citation network for this entire period. In this context, patents that are identified as influential are situated along trajectories that have remained relevant until today. Some studies using connectivity analysis construct separate networks for each year in their sample period, comprising all patent citations leading up to year *t* (Huenteler et al., 2016a; 2016b). Those allow to compare how the network has evolved over time, particularly to identify patents that once were influential but are not anymore, as well as when the core knowledge trajectory stabilized. The former allows to identify previous research directions that turned out to be dead ends. The latter lends insights into a technology's process of maturation and consolidation around a dominant design (Huenteler et al., 2016b).

Furthermore, I include self-citations in the network. Important innovators most likely pursue research directions cumulatively, building on their past experiences, as well as on the knowledge of others. Ideas might need to gain traction internally before they are picked up by other inventors. Including these as part of knowledge trajectories is therefore important. While self-citation bias is a possible concern, the risk of excluding important information from the analysis is greater. Additionally, following extant literature, I only include citations within a 5-year window from the cited patent's application date (Huenteler et al., 2016a, 2016b; Malhotra et al., 2021). This avoids over-weighting older patents that had more time to accrue citations and that might continue to get cited for legal reasons even after the technology has become obsolete. Because I am interested in knowledge flows across different components of the smart grid, I check that excluding citations beyond 5 years does not bias my data. For example, it could be that citations across different smart grid subsystems have longer lags than citations within the same subsystems. Using patent classes to proxy for subsystems, I find that the distribution of citation lags is similar within and across subclasses, providing reassurance that using a 5-year citation window is appropriate.

3.3.4 Identifying influential patents

To convert the SPNP value from the edge-level to the patent-level, I follow Huenteler and colleagues (2016a) and assign the SPNP value of the edge to both its nodes *i* and *j*. I then take the sum of the SPNP values over the entire sample of patents and identify influential patents as those constituting 80% of the network's total weight. Having obtained a sub-sample of influential patents, I manually code these inventions along different smart grid components and service characteristics. This mixed-methods approach enables me to generate descriptive statistics at a large scale for the entire sample, and to compare the characteristics of influential patents with the rest. Additionally, it allows for a detailed examination of the content of these patents to gain insights into the evolution of the field's core knowledge path.

Overall, these methods facilitate my descriptive analysis of the evolution of the focus of smart grid patenting and contribute to the broader goal of identifying components of smart grid technology across which important knowledge flows have occurred. These could then be leveraged to analyze how public policies, such as technical standards and regulations, affect knowledge flows within smart grid technology.

3.4 Descriptive results

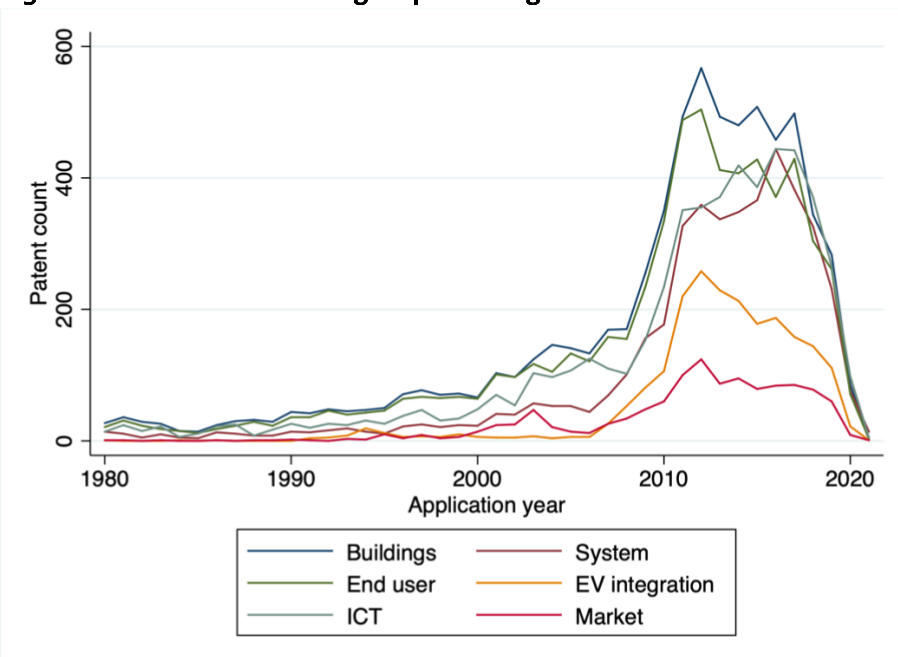
I begin with a descriptive analysis of overarching trends in smart grid patenting over the period 1980-2020. I investigate how patenting intensity has evolved and document which domains of smart grid technology have attracted the lion's share of R&D activity. I then examine the characteristics of influential patents and firms, to garner insights about what it takes to produce impactful innovation in this field, and associated policy implications. In the latter part of my analysis, I document knowledge trajectories within the field. First, I examine where knowledge flows have predominantly occurred. Next, I present descriptive statistics about the evolution of the citation networks' connectivity, offering insights into patterns of technological convergence within the field. Finally, using the subsample of highly influential patents that I obtained through the connectivity analysis and coded manually to capture detailed information about their targeted users and service characteristics, I demonstrate how the substantive focus of smart grid R&D has shifted overtime.

3.4.1 General trends in smart grid patenting

Figure 3.1 shows low levels of patenting activity in the 1980s and 1990s, followed by a sharp increase in the 2000s, peaking around 2011, and declining thereafter. The dip at the end of the sample period is attributable not only to this declining trend, but also to truncation bias. This occurs because many applications filed after 2018 were likely pending by the time the version of the PATSTAT database I use (2022) was released.

A notable trend throughout the sample period is the predominance of inventions related to buildings and other end-user applications, and the lesser focus on inventions that support distribution, transmission, and renewables integration ("systems" inventions). This is concerning given the severity of grid management bottlenecks, especially in the face of the increased frequency in severe weather events causing grid disturbances and the urgency to integrate distributed energy generation at a larger scale. Systems-related innovations is one of the domains of smart grid technology where innovation is urgently needed to confront these challenges. A possible explanation for these trends is that market demand has been greater and more predictable in end-consumer applications, such as home energy management automation systems and other inventions supporting demand response and load shedding on the end-consumer's premises. Utilities, on the other hand, are infamous for being risk-averse to adopting new technologies, particularly in markets that are highly regulated (Brown et al., 2018).

Figure 3.1 **Trends in smart grid patenting**



Note: The counts represent applications that were eventually granted in the United States, sorted by filing year. These counts do not adjust for overlap in technology classes; patents classified under multiple categories contribute to the counts of each respective technology domain they fall under.

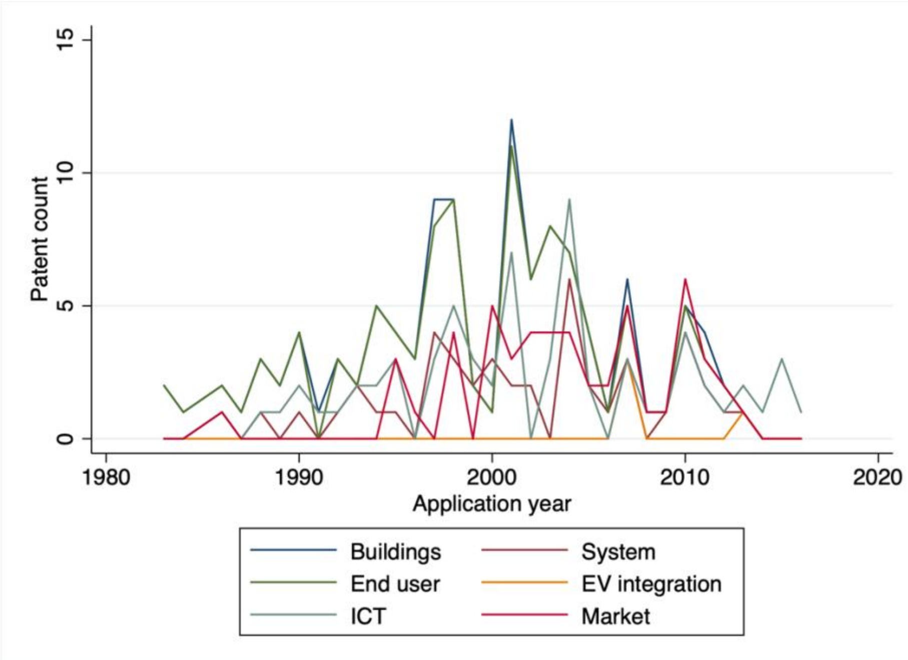
Counts of patents related to information and communication technologies ("ICT") closely track trends in buildings and end-user innovation, partly because there is overlap between technology classes. Smart grid technology is primarily about digitalizing electricity management at various locations of the electricity system. Therefore, ICT patents generally co-occur with other domains of smart grid technology. For example, an invention like the Google Nest thermostat falls under the ICT and end-user categories.

Finally, inventions related to the integration of electric vehicles on the grid - for example to serve as flexible storage solutions - and innovations in electricity marketing - such as energy trading or billing software used by aggregators or net metering participants – have lower patenting levels. This could be because these areas of technology are still in their infancy and have lower market demand compared to other categories.

The descriptive results above only inform us on general trends in the intensity and focus of R&D activity overtime across different smart grid technology domains. Patents are notable for varying in quality, which cannot be fully captured through simple counts. Therefore, Figure 3.1 offers an incomplete representation of where important inventive activity has occurred. For instance, while we observe the highest patent counts in buildings technology, this may be due to intense market competition in this sector, without necessarily indicating commercial success for all patented inventions. Furthermore, patent counts do not inform us on knowledge flows and on whether some areas of technology are more foundational to the field than others, and what has been the direction and sequence of knowledge transfers across these different domains.

To begin unpacking these questions, I first illustrate trends in patenting activity across these same categories of smart grid technology, but in the subsample of influential patents. Those are patents making up 80% of the citation network weight. These patents are located along the field's core knowledge trajectories. They can be interpreted as inventions contributing important knowledge to the field. Strikingly, when restricting patent counts to this subsample, in Figure 3.2 we observe a more balanced representation of the different smart grid technology domains. These suggests that important inventions contribute knowledge that is broadly relevant to the field.

Figure 3.2 **Trends in smart grid patenting, influential patents**



Note: The counts represent applications that were eventually granted in the United States, sorted by filing year for the subsample of influential patents that make up 80% of the citation network weight. These counts do not adjust for overlap in technology classes; patents classified under multiple categories contribute to the counts of each respective technology domain they fall under.

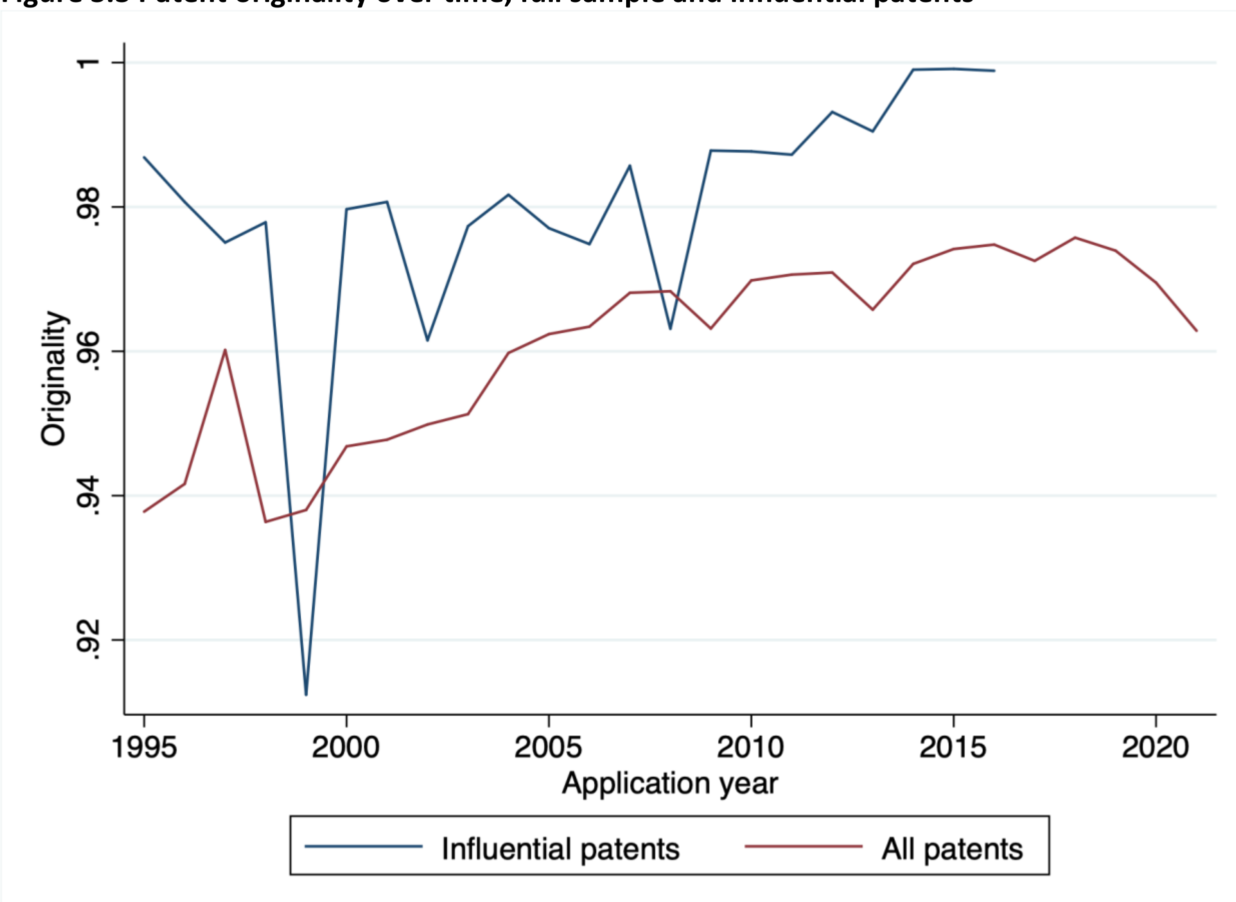
Examining this more closely, Table 3.1 shows that influential patents are more interdisciplinary than smart grid inventions of peripheral importance. Most core patents are classified under two or more different smart grid domains, as shown in the far-right column, whereas almost half of smart grid inventions fall under only one category.

Table 3.1. Interdisciplinarity of inventions

Number of smart grids domains	Percentage of inventions	
	All patents	Influential patents
1	47.22	16.88
2	35.82	38.31
3	11.31	25.97
4	4.79	14.29
5	0.81	4.55
6	0.06	0

Relatedly, influential patents also draw on more diverse combinations of knowledge. Figure 3.3 shows the median originality score of patents in the full sample and in the subsample of influential patents over time. Originality scores capture the diversity in the technology classes of a patent's backward citations. In other words, it measures whether patents build on diverse combinations of knowledge, including knowledge external to the field. Overall, patent originality is high in smart grids, due to the inherent interdisciplinary nature of these technologies, and it also rises overtime as digitalization calls for increasingly complex technology. Still, influential inventions are distinctly more original than the rest, providing further evidence that to produce impactful innovation, inventors must have the capacity to draw on broad and diverse knowledge, as well as bring external knowledge into the field. To garner further insights about the expertise and skills needed to produce influential invention in this field, and related policy implications, I next present descriptive statistics on the field's most important and most influential innovators.

Figure 3.3 Patent originality over time, full sample and influential patents



Note: Counts represent the median originality score of granted patents filed in each year since 1995. Originality scores were computed at the 7-digit level, following the method proposed by Squicciarini and colleagues (2013).

3.4.2 Firm-level descriptive statistics: important and influential smart grids inventors

Table 3.2 lists the 30 largest smart grid innovators, sorted in descending order by their count of patents. These counts include the totality of granted patents filed by these firms between the years 1980-2020. Together, these firms hold close to 35% of all granted smart grids patents in the United States. This level of concentration is not unusual. For example, Verspagen (2007) observes similar shares in fuel cell technology[47]. What is different, however, is that these large innovations hold a smaller share of influential patents, around 23%. In fact, two-thirds of the firms on this list never produced an influential patent. The few that are highly successful in producing important inventions are firms whose core activities are in the electricity sector, such as such as General Electric, Asea Brown Boveri and Siemens (except for AT&T). A few electronics companies – Toshiba, Intel, and Hitachi – also produced influential inventions, to a lesser degree. These results suggest that the firms that contribute important knowledge to the field are the ones possessing core knowledge in the electricity sector, but also have the capability to bring in expertise from other sectors, such as digital technologies.

The information presented in Table 3.3 complements these findings. This table shows the list of 30 largest influential firms, sorted in descending order by the number of influential patents they produced during the period 1980-2020. While this list includes some of the large innovators, like General Electric, Asea Brown Boveri, Itron and Toshiba, it includes several smaller specialized firms, such as Square D, a manufacturer of electrical equipment (whose parent company is Schneider Electric); Consert a start-up eventually acquired by Toshiba who develops intelligent energy distribution systems; and GridPoint, another company specialized in grid management technologies. The list even includes individuals listed as sole applicants on patents (i.e., no company co-applicants). Together, these 30 companies/individuals hold about 58% of all influential smart grid patents, a higher concentration than in the general sample. However, they hold a much smaller share of total patents - only about 14%.

[47] Verspagen finds that the 28 most prolific firms in the fuel cells sector are responsible for 52% of patents in the field's citation network. The descriptive statistics I present in Tables 3.2 and 3.3 are not directly comparable, as I also included patents that are isolates in the count (never cite and are never cited) and might therefore underestimate large firms' share of patents when only considering patents that are connected to other patents through citations.

Table 3.2. Largest smart grids patent applicants

Company name	Patent count (all)	Share of all (%)	Patent count (influential)	Share of influential (%)
General Electric	491	3.39	6	3.90
IBM	341	2.35	0	0
Siemens	288	1.99	4	2.60
Asea Brown Boveri	286	1.97	7	4.55
Toyota	252	1.74	0	0
Panasonic	234	1.61	1	0.65
Intel	201	1.39	0	0
Toshiba	186	1.28	2	1.30
Samsung	184	1.27	0	0
Mitsubishi	182	1.26	0	0
NEC	172	1.19	0	0
Itron	165	1.14	2	1.30
Sony	161	1.11	0	0
Hitachi	161	1.11	1	0.65
AT&T	156	1.08	9	5.84
Panasonic	149	1.03	0	0
Schneider	137	0.94	0	0
Google	132	0.91	0	0
Schweitizer	119	0.82	0	0
LG	113	0.78	0	0
Causam	107	0.74	3	1.95
Broadcom	104	0.72	0	0
Cisco	104	0.72	0	0
Ford	97	0.67	0	0
Honda	96	0.66	0	0
Eaton	96	0.66	0	0
Honeywell	88	0.61	0	0
Qualcomm	88	0.61	0	0
Landys + Gyr	84	0.58	0	0
Fujitsu	82	0.57	0	0
Total:	5,056	34.9	35	22.74

The prominence of smaller, specialized firms in the production of influential patents suggests that the need to modernize and digitalize the industry has created opportunities for new firms to enter what is otherwise a highly regulated and concentrated market. The significance of these firms in driving impactful innovation has important implications for policy, particularly for understanding how different policy initiatives, such as technical standards, R&D incentives, incubators, etc. support the entry of new actors to help respond to the needs of digital (and other like) transitions, in industries that require highly complex technology and interdisciplinary knowledge.

Table 3.3. Most influential smart grids applicants

Company name	Patent count (all)	Share of all (%)	Patent count (influential)	Share of Influential (%)
Power measurement	42	0.29	10	6.49
AT&T	156	1.08	9	5.84
Asea Brown Boveri	286	1.97	7	4.55
General Electric	491	3.39	6	3.90
Square D	47	0.32	5	3.25
Consert	10	0.07	4	2.60
Siemens	288	1.99	4	2.60
Cannon	5	0.03	3	1.95
Causam	107	0.74	3	1.95
Hunt technology	12	0.08	3	1.95
Battelle Memorial Institute	44	0.3	3	1.95
Yingo electronics	9	0.06	3	1.95
Statsignal systems	9	0.06	3	1.95
First Pacific Networks	3	0.02	2	1.30
Stonewater control systems	2	0.01	2	1.30
Consellation energy group	2	0.01	2	1.30
Itron	165	1.14	2	1.30
Tecom	2	0.01	2	1.30
Elster	42	0.29	2	1.30
Viridity	10	0.07	2	1.30
Toshiba	186	1.28	2	1.30
Smartsynch	8	0.06	2	1.30
James D. Romanowiz	2	0.01	2	1.30
Enernoc	44	0.3	2	1.30
Gridpoint	22	0.15	2	1.30
Robert J. Brown	2	0.01	2	1.30
Total:	1,996	13.74	89	57.83

3.4.3 Mapping knowledge flows within smart grids technology

Mapping where important knowledge flows occur across the different domains of smart grid technology can also provide useful insights for policy. For example, it can highlight areas where knowledge transfers are lacking and where policies encouraging research collaborations or cross-sectoral learning in other ways may be helpful. To advance understanding of knowledge transfers across different domains of smart grids, Tables 3.4, 3.5, and 3.6 depict cross-citations. To ensure comparability across the three tables, I show the share of citations in each cell rather than the absolute count of citations.

Table 3.4 begins by showing knowledge flows for the full sample. As expected, within-domain citations (shown in grey) are more frequent than cross-domain citations. We nevertheless observe non-negligible knowledge flows across the following domains: buildings and systems (gen, trans, distr); end-user and systems; buildings and ICT; end-user and ICT. In the full network, these knowledge flows occur to a comparable extent in both directions. However, a clear direction emerges for market patents. Market applications are cited as frequently in buildings and end-user patents than in other market patents, but the reverse is not true. Few market patents cite buildings and end-user inventions. This could be a sign that the market domain is further upstream in the design hierarchy: important design decisions need to be made in market technologies, such as billing software, before end user devices, such as smart thermostats, can work to their full potential for achieving tasks like controlling electricity consumption in response to real-time price changes. Results from extant literature suggest that the direction of citations can inform us on the design hierarchy. For example, in the wind turbines sector, Huenteler and colleagues (2016b) find there are twice as many citations from patents in lower levels of the design hierarchy to patents in higher levels, such as power train patents citing rotor patents, than in the reverse direction. In the case of wind, this indicates that knowledge is flowing from the upper levels to the lower levels in a way that is congruent with the authors' assessment of the wind turbine design hierarchy.

Table 3.5 shows more clearly the direction of these knowledge flows for smart grids. This table only contains citations across influential patents, making it more directly comparable to the cross-citations table found in Huenteler and colleagues (2016b). It shows that knowledge travels more often from systems patents to end-user and buildings patents, and from ICT to end-user and buildings patents. For example, there is three times as much buildings patents citing systems patents than systems patents citing buildings patents. That knowledge flows down more often from systems and ICT inventions to other domains of smart grid technology suggests that these two domains are located upstream in the design hierarchy.

Finally, Table 3.6 explores whether citation patterns are different between core and peripheral INVENTIONS. It shows citations from non-influential patents (peripheral) to influential patents (core). While within-domain citations remain important, their incidence is lower. This suggests that influential patents play an important role in supporting cross-domain learning. When peripheral patents build on knowledge external to their technology domain, they appear more likely to cite influential patents.

Table 3.4. Knowledge flows within full network

		Cited						
		Buildings	Gen, trans, distr	End user	EV integr.	ICT	Market	Total citing (j)
Citing	Buildings	14.92	2.90	0.47	0.61	3.38	2.62	24.90
	Gen, trans, distr	2.65	8.84	2.68	0.84	1.59	1.58	18.18
	End user	0.28	2.83	13.42	0.57	3.52	2.60	23.22
	EV integr.	0.87	1.27	0.80	5.30	0.44	0.85	9.53
	ICT	2.80	1.72	2.85	0.56	8.44	1.62	17.99
	Market	0.90	0.76	0.91	0.34	0.78	2.50	6.19
	Total cited (i)	22.42	18.32	21.13	8.22	18.15	11.77	100.00

Table 3.5 Knowledge flows within influential patents

		Cited (influential)						
		Buildings	Gen, trans, distr	End user	EV integr.	ICT	Market	Total citing (j)
Citing (influential)	Buildings	16.67	4.61	0.37	0.29	5.63	3.36	30.92
	Gen, trans, distr	1.46	3.00	1.54	0.22	0.80	0.73	7.75
	End user	0.00	4.53	15.94	0.29	5.63	3.22	29.61
	EV integr.	0.22	0.00	0.29	0.00	0.15	0.00	0.66
	ICT	2.70	1.97	2.70	0.29	5.12	2.19	14.99
	Market	2.05	2.56	2.12	0.22	2.85	6.29	16.08
	Total cited (i)	23.10	16.67	22.95	1.32	20.18	15.79	100.00

Table 3.6 Knowledge flows from influential to non-influential patents

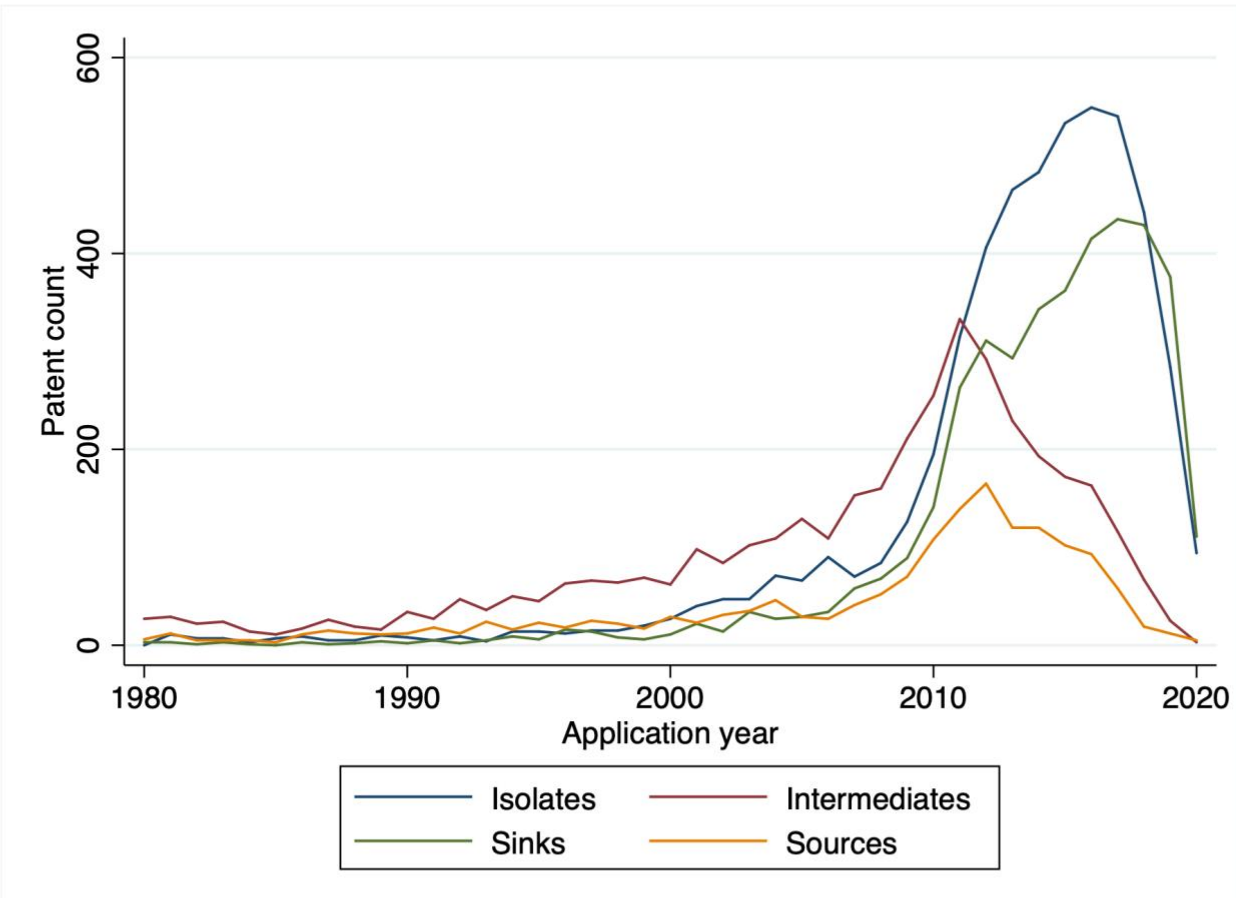
		Cited (Influential)						
		Buildings	Gen, trans, distr	End user	EV integr.	ICT	Market	Total citing (j)
Citing (non-influential)	Buildings	10.23	3.13	0.45	1.15	4.22	6.42	25.61
	Gen, trans, distr	2.47	4.61	2.43	0.85	1.17	2.20	13.73
	End user	0.30	2.99	9.72	1.15	4.41	6.44	25.01
	EV integr.	1.13	0.21	1.04	0.85	0.13	0.47	3.84
	ICT	3.03	1.88	2.92	0.77	9.36	3.92	21.88
	Market	1.62	0.55	1.58	0.53	0.85	4.80	9.94
	Total cited (i)	18.78	13.37	18.14	5.31	20.15	24.24	100.00

3.4.4 Evolution of the smart grids patent network

The connectivity analysis does not only inform us on which are the influential patents in a citation network, but also on patterns of technological convergence over time. Figure 3.4 graphs the composition of different types of patents within the citation network. Isolates are patents that are never cited and never cite. They are, in fact, located outside of the citation network. Intermediates are patents that cite and receive citations. Sources are patents that do not cite but are cited. Sinks are patents that cite but are never cited (Verspagen, 2007; Fontana et al., 2009).

Figure 3.4 shows that a substantial share of the growth in smart grid patenting is driven by isolates. While the number of isolates is lower than other types in the early years, they grow to become the most important category in 2010s. This is much higher than what the literature has found in other sectors of technology such as fuel cells and ethernet (Verspagen, 2007; Fontana et al., 2009). It might occur because these patents draw solely on knowledge external to the field, since patent citations to non-smart grids patents are not included in the network[48]. The high presence of isolates might therefore be a distinctive feature of highly interdisciplinary technologies.

Figure 3.4 Evolution of smart grid citation network



We nevertheless observe signs that the industry is converging onto common paths, as the number of sinks eventually surpasses the number of sources, as seen in other technologies (Verspagen, 2007; Fontana et al., 2009). The share of patents that constitute a start point in

[48] Also, patent citation data is highly skewed as most patents are never cited. However, here we might expect that even patents that never receive citations nevertheless cite prior art and would be included in the network as a sink rather than an isolate.

knowledge trajectories shrinks overtime, implying that citing patents (intermediates and sinks) converge onto a narrower knowledge base. To further explore how the focus of knowledge trajectories has evolved over time, the next section presents results on the content of influential patents. These data were obtained through coding their abstracts manually.

3.4.5 Evolution of core knowledge trajectories

I use network analysis to identify important patents that are representative of the field's core knowledge trajectories. After identifying a subset of 154 influential inventions from the initial 14,498 smart grids patents, I analyze their content at a level of detail not supported by quantitative approaches on large-N datasets. The qualitative analysis provides insights into how the focus of inventive activity in the core trajectory has travelled across different components of the smart grid architecture, and how this has evolved with demand for different smart grid applications over time.

I first coded patents along the type of user targeted by the invention, shown in Table 3.5. These reveal interesting trends over time. Inventions in the early years primarily target end-consumers. They concern home energy management, such HVAC automation and remote control of home appliances. The number of inventions targeted at utility users then begins to grow in the 1990s. Most inventions in this period target the interface between utilities and their customers. These include advanced metering infrastructure and inventions that enable utilities to remotely control and curtail power delivered to their customers. For these reasons, many patents from the 1990s-2000s period are coded under both user types. The focus on residential and utility target users then declines in the late 2000s, moving to customer-generators (residential renewable energy producers). While the number of patents targeting customer-generators remains low relative to other categories, this nevertheless shows a clear sequencing of targeted users throughout the different periods: from residential customers, to utilities, to customer-generators.

Importantly, it suggests that the focus of inventive activity is primarily driven by market demand rather than a more intentional ordering of inventive activities downstream the smart grid design hierarchy, especially in the early years. End-user customers readily existed in the early years of the sample, which is not the case for many other grid actors that are emerging with the decarbonization transition. After the deregulation of electricity markets in the 1990s, when performance-based grid management gained prominence, we observe a sway of patents focusing on helping utilities manage flexibility on the demand-side. Then, as the deployment of DERs advanced, new types of grid users gained in importance. Those include customer-generators, and to a lesser extent, electric vehicle users, micro-grids, electricity aggregators, etc. In the later years of the sample, we observe that companies began developing products for these new technology users as well.

Figures 3.6. and 3.7. further show the evolution of the grid functions performed by inventions on the main technological path, and their related service characteristics. Following extant literature, I define the latter as characteristics of a technology - such as reliability and cost - that are valued by particular users, or for particular uses (Malhotra et al., 2021; Saviotti and Melcalfe, 1984). For example, in the batteries sector, size and weight became important service characteristics when the demand for batteries for electric vehicles boomed, steering R&D resources away from stationary applications, such as grid-scale batteries, where other service characteristics are valued, like cycle life, energy density and scalability (Popp et al., 2024). Malhotra and colleagues (2021) even find that this shift in demand, caused by the emergence of the new EV use environment, prompted innovation back into the product architecture to adapt the dominant design of lithium-ion batteries to service characteristics valued in the EV market. Therefore, while a technology's design architecture might inform the sequence in which different technical problems are tackled (Murmann and Frenken, 2006), especially after a dominant design has taken root, this process is also moderated by other factors that include shifts in the demanded uses for a technology, and associated characteristics. An important question for the literature to address is when can we expect technological trajectories to follow the Murmann-Frenken model and when are those trajectories more haphazard? The smart grids case, as I describe below, offers valuable insights because it features aspects of both: some sequencing along the design hierarchy, as well as feedback from the emergence of new grid users demanding different service characteristics.

Figure 3.6 shows that in the early years of the sample, most patents focused on developing products for building energy management, whose principal service characteristics is the improvement of energy conservation on the demand-side of the grid. The focus later gradually moved from developing devices for end-users - for example to aid them save on their electricity bill - to developing technologies that service the overall grid network. This started with a focus on advanced metering infrastructure, which serves both end-users, to aid with managing their electricity consumption, and utilities, to improve knowledge of their customers' electricity consumption habits. From a focus on developing devices that collect energy consumption data, the sector then moved to developing applications for utilizing these data. In the late 1990s and early 2000s many influential patents developed control systems and devices to enable utilities to collect and aggregate data about electricity consumption and remotely curtail electricity provision to customers. These inventions served the purpose of facilitating peak load shedding and supporting grid management. They revolved around service characteristics valued by utilities, as the primary users of these technologies, such as grid stability.

In the early 2000s, innovation intensified in mainstay areas of smart grid technology such as data communication and data security. These patents spanned issues such as data storage, data exchange, data management, and data aggregation. Several of these patents developed wireless communication technologies for the grid. These inventions often targeted utilities or were non-specific about users, suggesting that they have broad application: in generation, transmission, distribution and behind the meter. It appears that the service characteristics valued by users during this period concerned reliability, speed and coverage of data transmission, as well as security in the face of growing concerns about the grid's vulnerability to cyberattacks and consumer data protection.

Once technology for collecting, managing, and sharing data became available, inventors turned their attention to utilizing these data to optimize grid operations. In parallel with innovations in data communication and data security, we also observe influential patents in the areas of forecasting and modelling during the 2000s.

Finally, starting in the late 2000s, grid technologies that support the decarbonization transition gained in importance, likely driven by growing demand from new grid users participating in distributed electricity markets. In this period, we begin to observe influential patents in novel areas such as microgrids, electric vehicle charging, storage integration, while innovation in DER integration also grows. Important service characteristics of these applications include grid sustainability and flexibility.

These descriptive data indicate that core knowledge development in smart grids underwent the following sequence. In the early years, inventive activity focused on areas where a consumer market readily existed, then shifting to concerns of grid stability and demand management likely propelled by pressure on utilities' performance following deregulation of the electricity sector. During the digital revolution the industry began to harness these new technologies to improve grid management. It first developed data communication and security inventions, followed by innovation in a sway of new applications related to distributed generation. At the same time, intensive inventive activity continued in pre-existing areas such as building energy management, load shedding and electricity marketing.

Figure 3.5 Patent counts by user type

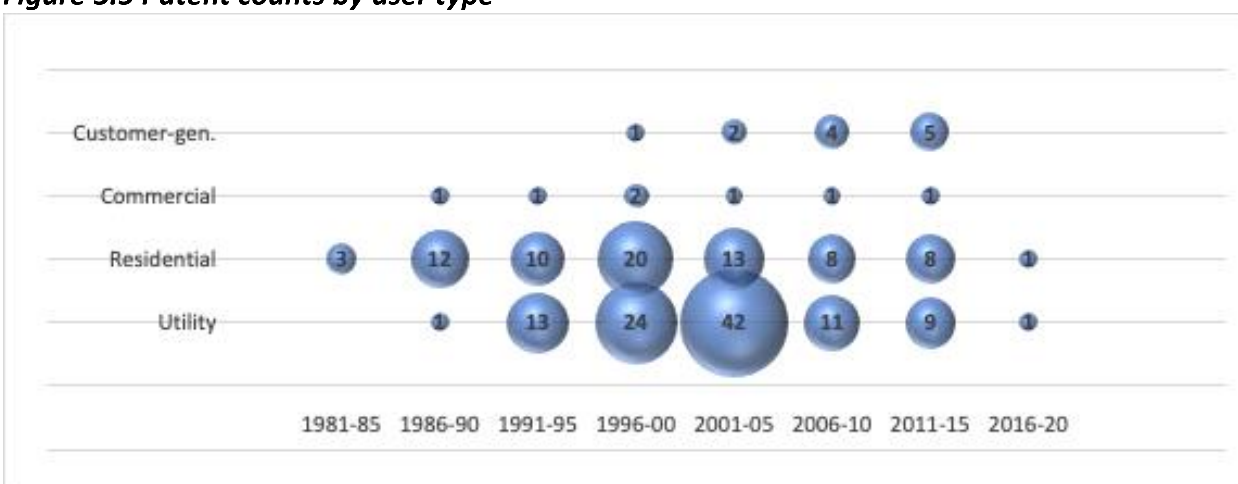


Figure 3.6 Patent counts by grid function

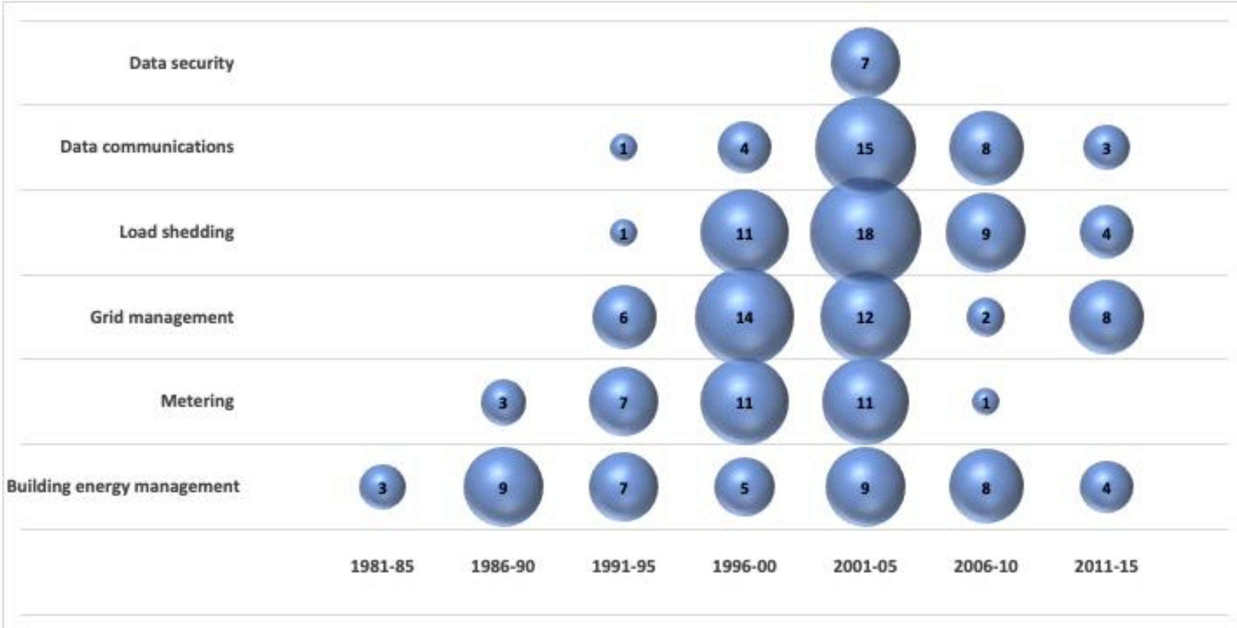
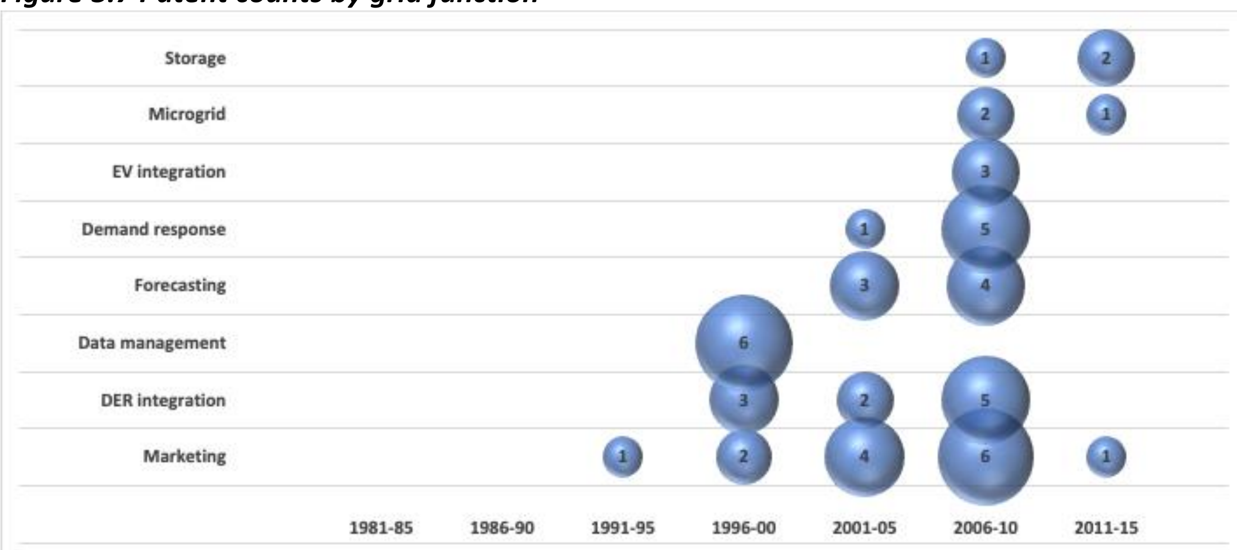
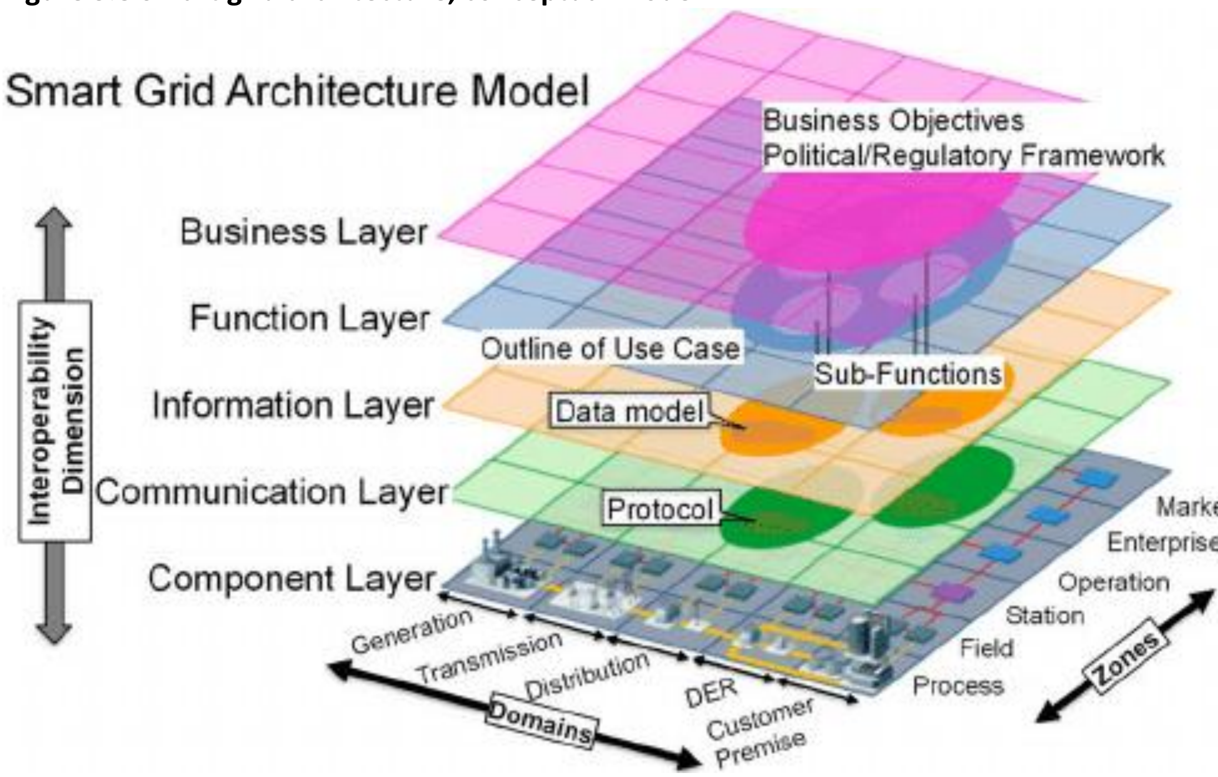


Figure 3.7 Patent counts by grid function



A possible interpretation is that the advent of a new general-purpose technology combined with changes in the regulatory/market environment for grid technologies opened opportunities to deploy these new digital technologies across the grid. The industry responded by developing inventions adapting these for use on the grid, consolidating a new dominant design for the industry. It started with developing data communication and information technologies, which became foundational knowledge for follow-on innovation. A common conceptual model of the smart grid used by industry presented in Figure 3.8 shows that these communication and information layers of the smart grid design architecture are central. In the early years, innovation started in the lower component layer. Then innovation in core communication and information layers appears to have triggered a new wave of innovation back down into the component layer, both in new use areas related to distributed generation demanded by new actors of the decarbonization transition, as well as in pre-existing areas where incumbent technology likely became obsolete.

Figure 3.8 Smart grid architecture, conceptual model



Source: Smart Grid Architecture Model (SGAM) framework developed by European standardization agencies CEN and CENELEC[49].

3.4.6 Summary of descriptive findings

- The greater focus of inventive activity has been in areas of technology where the customer base for specific products is readily available, such as buildings and end-user devices. R&D intensity has been lower in technologies that either do not have clearly

[49] https://www.cencenelec.eu/media/CEN-CENELEC/AreasOfWork/CEN-CENELEC_Topics/Smart%20Grids%20and%20Meters/Smart%20Grids/reference_architecture_smartgrids.pdf

defined customers or smaller markets, produce network externalities or other non-excludable benefits to the grid, such as systems, market, and EV integration technologies. Low demand from utilities averse to adopting new technology, especially in regulated contexts, might also explain lower patenting levels in these areas.

- Influential patents are more interdisciplinary and build on more original combinations of knowledge.
- Companies that produce a lot of inventions do not necessarily produce influential inventions. Companies that produce influential inventions appear to either be large electricity sector incumbent with greater capacity to integrate knowledge external to the field, or young companies specialized in grid technologies.
- Knowledge flows are higher within domains than across domains of smart grid technology. Cross-domain knowledge flows are higher between influential patents. Influential patents also seem important for transferring interdisciplinary knowledge to non-influential patents. Knowledge appears to flow from systems and ICT patents to buildings and end-user patent. The direction of these flows suggests that systems and ICT inventions are located higher in the design hierarchy.
- The citation network converges gradually onto a common knowledge base over time, but smart grids feature a distinctly high number of isolates. This may be because there is a high share of smart grids patents that draw solely on knowledge external to the field.
- Early innovation initially focused on home energy management and metering. Following deregulation in the 1990s and increased scrutiny of grid performance, core knowledge trajectories shifted toward grid and demand management. During the 2000s, innovation in the communication and information layer of the smart grid architecture, alongside the establishment of a dominant design through standardization, appears to have prompted R&D back into components. This period saw new grid technologies emerge in the areas of storage, micro-grids, and electric vehicle integration. It also saw continued innovation in areas that had already received substantial attention in earlier periods, such as grid management, load shedding, and building/home energy management, possibly to adjust

to the new information/communication paradigm. A combination of design architecture and market forces seems to have shaped knowledge trajectories.

In the next section, I discuss the relevance of these results for advancing theory and informing policy.

3.5 Discussion and conclusion

The main objective of this paper was to gain a detailed qualitative understanding of the content of knowledge trajectories and influential smart grids patents, with a view to informing the future research on the effects of standards on knowledge transfers in smart grids technology. Nonetheless, this descriptive analysis in-and-of itself reveals novel insights for theory and policy.

A first insight contributing to advancing theory is that the conceptual representations used to describe technological trajectories in other green energy technologies, such as wind (innovation traveling downstream components in the design hierarchy) and solar (incremental innovation from product to process innovation focused in one core component) are inadequate to describe the innovation trajectory of smart grids. In contrast with these other technologies, smart grid is a distributed technology, not a self-contained product sold to a single end-consumer. Instead, it encompasses a panoply of devices that connect to shared infrastructure. The different devices bought by individual consumers connect to the grid to achieve the common purpose of improving grid flexibility, grid stability, and facilitate renewables and EV integration, among other things. A 'smart' electrical grid, therefore, resembles a club good more than a private good. This characteristic seems to have shaped the knowledge trajectory of this sector, as it evolved from a core focus on end-user technologies for a readily available consumer base in the early stages, to novel applications for emerging types of consumers in recent years. The middle years focused on developing applications for utility users and integrating digital technologies, which appear to have provided foundational knowledge for later innovation in both ongoing and new areas. As a complex and distributed technology, smart grids appear to have followed a path loosely guided by the design hierarchy. Especially in the period that coincides with the development of many interoperability standards for data communications and security, we observe innovation travelling down from these core IT components to more peripheral applications, such as storage and renewables integration. However, compared to other complex technologies that are more centralized, like wind, technical change in smart grids appears to have been more strongly shaped by external factors such as changes in demand for novel applications - many of which have also been policy-driven - and changes in available general-purpose technology.

These observations offer important insights for policy. For instance, as noted by Malhotra et al. (2021), knowledge trajectories are incremental, but they are not set in stone. The authors' examination of the lithium-ion battery technology reveals that strong demand in new areas can steer innovation trajectories away from their core path. The authors speculate that this provides evidence that demand-pull policy instruments might not only help with supporting innovation in mature technologies, as extant literature shows (Johnstone et al., 2010), but can also be leveraged to encourage innovation in emerging areas, where technology-push instruments have traditionally been viewed as more effective (Malhotra et al., 2021). My analysis of the smart grid adds suggestive evidence that knowledge trajectories can be redirected by demand in new user environments.

Beyond reflecting on which balance of technology-push and demand-pull policy interventions can encourage green innovation in needed areas, my analysis of the smart grid case provides insights for interdisciplinary technologies, and other sectors undergoing digitalization, more generally. Innovating in these sectors requires expertise in several areas and bringing external knowledge into the field. As different innovation actors adapt to a new technological paradigm, lessons learned in one area of smart grid might be relevant to innovate in another. In complex technologies where core components affect the design of subsequent components, transferring knowledge from these core components might help accelerate technology development in areas further downstream, and facilitate compatibility between components. Therefore, interventions that facilitate knowledge transfers across various domains of smart grid technology are crucial for addressing the system's diverse technological needs. This may help ensure that challenges are tackled not only sequentially but also effectively, utilizing the best available knowledge. Standards are one possible tool that can facilitate knowledge transfers, through making the industry’s state-of-the-art knowledge more widely accessible. Future research should investigate this further through formally modelling the causal effects of standards on knowledge transfers between different domains of smart grid technology.

Conclusion: implications for policy and future research

In this dissertation, I examine the role of alternative green innovation policies, technology standards more specifically, in accelerating the development of technologies urgently needed to build a carbon-neutral economy by 2050. I focus on coordination challenges because they have received less attention than other market failures often discussed in the green innovation literature, like environmental externalities and knowledge spillovers. Compounding this dual externality problems, coordination challenges are poised to become increasingly prominent in emerging green technologies. My dissertation draws attention to these challenges and, using the case of smart grids as an example of a complex and interdisciplinary technology, presents findings of broader relevance to many emerging green technologies sharing similar features, including bioplastics, hydrogen, bioengineering, and carbon capture and storage.

While existing literature on standards primarily examines their legal and governance aspects, my dissertation contributes to emerging research about the impacts of standards on knowledge production. I unpack various dimensions of the relationship between standards and follow-on innovation, starting with their effect on R&D intensity. I find that standards cause a decline in patenting, particularly amongst large incumbent firms. However, I uncover that this occurs because standards focus innovation onto high-quality knowledge trajectories. They help integrate interdisciplinary knowledge into the field and encourage its utilization. Standard may therefore help establish and disseminate a new technological paradigm across an industry, for example, following breakthroughs in general purpose technology. This is relevant to many industries undergoing digital transitions, and increasingly, the automation revolution. Through formalizing a technology's design architecture, standards can also help structure how different technical problems are tackled sequentially. An important part of this implies diffusing new knowledge across the different components of a technology to ensure its use in the development of various applications that are compatible with one another. The last chapter begins to explore how standards support knowledge transfers across different domains of smart grid technology.

Future research should expand on these insights to explore how various green industrial policy instruments, including standards but also other tools like green procurement and public-private research collaborations, can support emerging clean technologies and shape the sustainability landscape leading up to 2050.

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136. Zhang, F., and K. S. Gallagher. “Innovation and Technology Transfer Through Global Value Chains: Evidence from China’s PV Industry.” *Energy Policy* 94 (2016): 191–203.

VITA

MYRIAM GREGOIRE-ZAWILSKI
426 Eggers Hall · Syracuse NY 13244
mgregoir@syr.edu

EDUCATION

PhD Public Administration, Syracuse University *2024*
Fields: Environmental and Energy Policy, Policy Process
Committee: Professors David Popp (Advisor), Saba Siddiki, and Peter Wilcoxen
Dissertation: "Technology policy for meeting net-zero carbon goals by 2050: Accelerating innovation in complementary technologies to decarbonize the electrical grid"

M.Sc. Political Science, Université de Montréal *2015*
Field: International Politics
Advisor: Professor Philippe Faucher
Thesis: "Building Brazil's comparative advantage? Coordination within the soybean value-chain in Mato Grosso and Paraná"

B.A. International Relations, The University of British Columbia *2011*

PUBLICATIONS

Gregoire-Zawilski, Myriam and David Popp (2024) Do Technology Standards Induce Innovation in Environmental Technologies When Coordination is Important? *Research Policy*, 53(1): 104888. https://doi.org/10.1016/j.respol.2023.104888

Popp, David, Francesco Vona, **Myriam Gregoire-Zawilski**, Giovanni Marin (2024) The Next Wave of Energy Innovation: Which Technologies? Which Skills? *Review of Environmental Economics and Policy* 18(1). https://doi-org/10.1086/728292

Ambrose, Graham, **Myriam Gregoire-Zawilski**, Saba Siddiki and Nick Oesterling. (2024) Understanding policy evolution using the institutional grammar: a case of net metering policies in the United States. *Policy Design and Practice.* https://doi-org/10.1080/25741292.2024.2342093

Gregoire-Zawilski, Myriam and Saba Siddiki (2023) Evaluating diffusion in policy designs: A study of net metering policies in the United States. *Review of Policy Research.* https://doi.org/10.1111/ropr.12572

Popp David and **Myriam Grégoire-Zawilski** (2023) Powering the next wave of green energy innovation. *PLOS Climate 2(1)*: e0000119. https://doi.org/10.1371/journal.pclm.0000119.

WORKING PAPERS

Gregoire-Zawilski, Myriam and David Popp (2023) *Do Technology Standards Induce Innovation in Environmental Technologies When Coordination is Important?* National Bureau of Economic Research Working Paper No. 30872.

Popp, David, Francesco Vona, **Myriam Gregoire-Zawilski**, Giovanni Marin (2024) *The Next Wave of Energy Innovation: Which Technologies? Which Skills?* National Bureau of Economic Research, Working Paper No. 30343 and CESifo Working Paper, No. 9878

PRESENTATIONS

Annual Conference of the Canadian Economics Association, online, May 2024	*2024*
Conference on Policy Process Research, Syracuse University, May 15th-17th	*2024*
University of Ottawa, Graduate School of Public and International Affairs.	*2024*
University of Wisconsin-Madison, Lafollette School of Public Affairs.	*2024*
Michigan Technological University, Department of Social Sciences.	*2023*
University of Georgia, Department of Public Administration and Policy.	*2023*
Fall Research Conference, Association for Public Policy Analysis and Management Atlanta, November 9th -11th.	*2023*
Annual PhD and Early Career Researcher Workshop, Canadian Resource and Environmental Economics Association, Winnipeg, June 5th-6th	*2023*
Annual Conference, Canadian Economics Association, Winnipeg, June 1st-3rd	*2023*
International Conference on Public Policy Design, Miami, February 24th-25th	*2023*
Conference on Policy Process Research, Denver, January 12th -14th	*2023*
Fall Research Conference, Association for Public Policy Analysis and Management, Washington, D.C., November 17th -19th	*2022*
Economics of Innovation in the Energy Sector Conference, National Bureau of Economic Research, Washington, D.C. September 30th	*2022*
Economics of Innovation in the Energy Sector Conference, National Bureau of Economic Research. Cambridge, Massachusetts. March 17th -18th	*2022*
Atlanta Academy on Science and Innovation Policy, Atlanta, Georgia. March 21st -25th	*2022*

AWARDS, DISTINCTIONS, RESEARCH GRANTS

Social Sciences and Humanities Research Council doctoral fellowship	*2023*
Canadian Resource and Environmental Economics Association travel grant	*2023*
National Bureau of Economic Research (Sloan Foundation grant #G-2019-12323)	*2022*
Birkhead-Burkhead summer research award	*2022*
Fellow, Atlanta Academy on Science and Innovation Policy	*2021*
Larry D. Schroeder Award for Excellence in PhD Research	*2021*

Birkhead-Burkhead Summer Research Award *2021*
Spencer D. Parratt Summer Research Award *2020*

TEACHING

Maxwell School of Citizenship and Public Affairs, Syracuse University

Instructor
Public Policy Process (PAI 760, master's, online) *2023*

Teaching Assistant
Introduction to Statistics (PAI 721, master's) *2021*
Economics for Public Decisions (PAI 723, master's) *2020*

Université de Montréal

Teaching Assistant
Political economy (POL 1025, undergraduate) *2013*
Politics and Globalization of Markets (POL 3602, undergraduate) *2012, 2013*
Introduction to International Studies (INT 1000, undergraduate) *2012*
Introduction to International Politics (POL 1954, undergraduate) *2012*
Introduction to International Relations (POL 1600, undergraduate) *2012*
International Political Economy (POL 2606, undergraduate) *2011*

EMPLOYMENT HISTORY

Syracuse University (Syracuse, United States) *2019-2024*
Graduate Associate, Center for Policy Research

International Development Research Centre (Ottawa, Canada) *2016-2019*
Program Management Officer, Technology and Innovation Program Area
Coordinator, Advisory Committee on Research Ethics

Organisation for Economic Co-operation and Development (Paris, France) *2015-2016*
Programme Assistant, Development Centre

Université de Montréal (Montreal, Canada) *2011-2014*
Teaching Assistant, Political Science Department
Research Assistant, Centre for East-Asian Studies
Summer School Coordinator, Montreal Centre for International Studies

CBC/Radio-Canada (Vancouver, Canada) *2008-2011*
Television and Radio Reporter

PROFESSIONAL SERVICE

Referee service: *Policy Studies Journal, Industry and Innovation*

LANGUAGES

French (native), English (bilingual proficiency), Portuguese (intermediate), German (beginner)