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Summary

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Keywords: Clean-energy Technologies, Electricity Liberalisation, Climate Change, Patent Data

JEL Classification: L94, O31, Q42, Q55

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Can electricity liberalisation foster the development of radical clean-energy technologies? *

Matteo Romagnoli†

December 18, 2022

Abstract

The paper investigates the effect of electricity liberalisation on the variety of clean-energy patent' search space to asses whether a more competitive electricity market can foster the development of radical clean-energy technologies. This idea is tested using a cross-section of patents filed in the period 1990-2017, a set of patent-level indicators and an instrumental variable approach. Results show that electricity liberalisation pushes clean-energy patents to cite knowledge from technological fields other than their own. However, the reform does not significantly affect the overall breath of the knowledge base of these patents. Additional insights are drawn by looking at the correlation between electricity liberalisation and an indicator of novelty in patents' search space. The results are consistent with the claim that electricity liberalisation has a positive effect on the development of radical clean-energy technologies. At the same time, by describing how the reform changes clean-energy patents' search space, they define this effect more precisely.

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1 Introduction

The optimal regulatory framework for the electricity market is an hot topic of discussion among academics, policy makers and market agents. In the European Union the recent power price crisis, triggered by the Russian invasion of Ukraine in February 2022, has reignited the discussion on whether the current design of the electricity market is fit-for-purpose (ACER, 2022). [1] In 2021, the design of the electricity market has been a topic of discussion also in the U.S., when the Texas blackout sparked a debate on the role played by electricity liberalisation in the failure of the power system.

There are many dimensions according to which one can judge the performance of an electricity market; among others: security of supply, affordability, ability to attract investments, number and type of services offered, quantity and quality of innovation. By shedding light on the relationship between different regulatory frameworks and each of these dimensions, the academic literature has brought and can bring relevant contributions to the aforementioned debate. This is the aim of this paper, which studies the relationship between electricity regulation and innovation, focusing in particular on the effect of electricity liberalisation on the development of radical clean-energy technologies.

The importance of having a regulatory framework in the electricity sector able to foster the development of radical clean-energy innovations can not be overstated. Radical technologies are widely recognized to be fundamental in triggering technological and societal changes (Acemoglu et al 2020, Rizzo et al., 2018, Arthur 2007, Olsson 2000, Nelson and Winter 1982). As way of example, the European Union Innovation Fund, one of the world's largest funding programs aimed at supporting low-carbon innovations, explicitly focuses on "highly innovative technologies" and "breakthrough technologies" [2]. Breakthrough clean-energy innovations are a major tool at our disposal to decarbonise electricity supply, an objective of the utmost importance given the high contribution of electricity generation to global greenhouse gas emissions [3].

Part of the complexity in the development of highly innovative clean-energy technologies comes from the fact that the electricity sector is a large technical system, i.e. a system characterized by capital-intensive infrastructures, a variety of actors and many

[1] As an example, the last "Assessment of the EU wholesale Electricity Market Design" by ACER (Agency for the Cooperation of Energy Regulators") is focused on precisely this issue (ACER, 2022).

[2] See:https://www.euinnovationfund.eu/ and https://ec.europa.eu/commission/presscorner/detail/en/ip_22_4402

[3] https://ourworldindata.org/emissions-by-sector;https://www.iea.org/reports/global-energy-review-co2-emissions-in-2021-2

complex technical components all of which interact together (Markard and Truffer, 2006; Joerges, 1998; Hughes, 1987). Due to these features, large technical systems tend to suffer from inertia and path-dependence, with technological progress that is often characterized by incremental improvements (Hughes, 1987).

In this context, it has been hypothesised that electricity liberalisation, by increasing the variety of clean-energy technologies' search space, can act as a driver for the development of radical innovations in this field (Negro et al., 2012; Markard and Truffer, 2006). The search space of a patent can be defined as the totality of knowledge inputs on which the invention relies, i.e. the set of the sources used to developed the invention. A diverse search space is characterised by knowledge inputs coming from different technological fields and it is therefore evidence that the patent is building on different strand of knowledge. A well-established body of literature in innovation theory highlights how some characteristics of the search space of an invention, such as breadth and complexity, are linked with its radicalness, originality and novelty (Barbieri et al., 2020, Verhoeven et al 2016 Squicciarini et al., 2013 Shane, 2001, Trajtenberg et al.,1997).

In a nutshell, the main idea behind the effect of interest can be expressed as follows. In regulated markets, monopolists have low incentives to develop radical clean-energy technologies that are far from their knowledge base and can jeopardize their exiting assets. Conversely, they are more likely to deal with the problem of decarbonizing energy supply with incremental innovations that are more compatible with their existing asset base and therefore less costly for them to develop and adopt (Nesta et al., 2014; Negro et al., 2012). Such incremental improvements are generally the results of patents with a narrow search space, because they strongly rely on the knowledge already available in their technological fields (Squicciarini et al 2013; Shane 2001). The liberalisation of the electricity market, by allowing new players to enter into the market and by creating a more competitive environment, can favor a broader approach to R&D and a wider search space in the development of clean-energy technologies, thus leading to more radical clean-energy innovations (Negro et al., 2012; Markard and Truffer, 2006). Section 2 discusses this point more in depth.

This paper contributes to the literature on electricity liberalisation and innovation by being the first one to test this idea empirically, exploiting patent data and a well-established set of patent-level indicators (see Verhoeven et al., 2016; Squicciarini et al., 2013). This kind of indicators have been extensively used in the innovation literature (see for instance Barbieri et al., 2020; Verhoeven et al., 2016; Squicciarini et al., 2013; Harhoff e tal 2003; Hall at al., 2001; Shane, 2001; Trajtenberg et al., 1997) and allow me to study how the search space of clean-energy technologies changes as the electricity market becomes more competitive.

To uncover the casual effect of interest, I rely on an Instrumental Variable (IV) approach. The proposed strategy follows Nicolli and Vona (2019) and uses regulation in telecommunication as an instrument for regulation in electricity. The intuition behind this approach is that the reform of the telecommunication sector occurred before the one of the electricity market and was instrumental in giving momentum to the latter (Pollitt 2012, Joskow 2008). At the same time, this reform can be considered independent from the direct lobbying power of actors in the energy sector (Nicolli and Vona 2019) and from technological developments in energy-supply technologies. As robustness check, I also use regulation in air transport as instrument and provide the results in Appendix A.5.

Results from the empirical analysis are consistent with the claim that electricity liberalisation can foster radical clean-energy innovations. In particular, they show that the reform pushes clean-energy patents to cite more knowledge from outside technological fields, i.e. technological fields other than the ones they are allocated to; a pattern that has been found to lead to more radical inventions (Squicciarini et al., 2013; Shane, 2001). In addition, by describing in depth the effect of the reform on the search space of these patents, the results also point out the limits of this effect.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature and formalizes the research hypothesis. Section 3 describes the data used and Section 4 discusses the empirical strategy. Section 5 is dedicated to the IV strategy, Section 6 presents the results and Section 7 concludes.

2 Liberalisation and Innovation in the Electricity Sector

The electricity sector is one of the best examples of a large technical system (Hughes, 1987). Joerges (1998) defines large technical systems as complex systems of physical structure and machinery, integrated over space and time and supporting other technical systems. The strong interactions between the different components of a large technical system, as well as the interactions between the system itself and the other technical systems it supports, make innovation in these environments often characterised by incremental improvements rather than radical changes (Negro et al 2012, Markard and Truffer 2006, Hughes 1987).

That being said, there are many examples of radical innovations being developed in large-technical systems. Hughes (1987) identifies "reverse salients" as the main sources of these radical innovations [4]. Markard and Truffer (2006) focus instead on external factors that can act as triggers for this kind of inventions. Some example of these external factors include technological developments in related fields, government intervention or changes in the preferences of the customer base. In light of this discussion, Markard and Truffer (2006) look at the electricity sector and analyze a series of 44 interviews collected in more than 30 utilities [5], presenting case study evidence focused on fuel cell innovation strategy. They conclude that the liberalisation of the electricity sector can be one of these external driver which increases the variety of the search space of clean-energy technologies, thus fostering the development of more radical clean-energy innovations. A similar argument is presented by Negro et al. (2012). In this regard, the positive relationship between the variety of the search space of an invention and its radicalness has been widely documented and it is now a well-known phenomenon (Barbieri et al., Verhoeven et al., 2016, 2020, Squicciarini et al., 2013, Shane, 2001; Trajtenberg et al.,1997). Section 3.1 discusses this point more in depth.

A first channel through which electricity liberalisation can impact the search space of clean-energy patents is by allowing new entrants in the market. The importance of new

[4] Reverse salient are defined as "those components that lagged behind other components in an expanding system, thus threatening the possibility of expansion for the whole system" (Hughes, 1987 - Summary). As an example Hughes (1987) brings the early days of electricity supply "when the prevailing direct current (DC) technology was not able to transmit ever more growing energy flows efficiently over long distances" (Hughes, 1987 - Summary).

[5] The utilities are from Germany, the Netherlands and Switzerland

entrants for the development of radical innovations is largely acknowledged in the literature (e.g. Acemouglu et al., 2022; Akcigit and Kerr, 2018; Klepper 1996; Winter, 1984). The model presented by Klepper (1996) in particular predicts that, when competition is low, the diversity of R&D will be compromised. A narrow approach to R&D is likely to be particularly detrimental for clean-energy technologies because their development requires a variety of knowledge inputs and competences that are far from the traditional knowledge base of incumbents (Barbieri et al., 2020; De Marchi, 2012). An increase in competition can instead be expected to have the opposite effect. New entrants have a comparative advantage in the adoption of radical technologies and consequently they can foster their development (Acemouglu et al., 2022; Akcigit and Kerr, 2018). More generally, a key determinant of radical innovations at the firm level appears to be how "open to disruption" the firm is, and new entrants often have more to gain by disrupting the status-quo (Acemouglu et al., 2022). This can be expected to lead to a wider approach to R&D and a wider search space, especially in the case of the electricity sector, where new entrants are not tied to the traditional large-scale plants and technologies generally used by incumbents (Nesta et al., 2014; Nicolli and Vona, 2016). The literature on the relationship between innovation and product cannibalisation is also relevant to this point as radical clean-energy technologies are often competence-destroying for incumbents in the electricity market (Nesta et al., 2014). When cannibalisation is an issue, competitive pressure has been shown to be essential in order to push incumbents to innovate (Conner 1988, Reinganum, 1983), which suggests that more competition in the electricity market can also have a positive impact on the search space of clean-energy patents developed by electric utilities.

The entry of new players is not the only channel through which liberalisation can foster the development of more radical clean-energy technologies. Dolphin and Pollitt (2020) use patent data from the UK and show that, after the reform of the electricity market, innovation activity shifted from regulated monopolist to electric equipment manufacturer. The latter are less tied to traditional generation technologies and have different incentives with respect to the former, thus they can be expected to rely on a wider search space.

Finally, privatisation can change the innovation environment within the incumbents and make them more likely to rely on a wider knowledge base. This is in line with the evidence suggesting that investor-owned electric utilities are more responsive to renewable policies than state-owned utilities (Nicolini and Tavoni 2017, Delmas and Montes-Sancho al 2011, Carley 2009).

Existing empirical studies on the relationship between electricity liberalisation and innovation have mainly looked at the effect of the reform on the "quantity" of innovations developed (e.g. number of patents) or the amount of inputs used in the research process (e.g. investment in R&D). A useful way to categorize this literature is by distinguish between studies focused on clean-energy technologies and studies that look at all kinds of innovations developed in the electricity sector.

Among the latter, a first body of literature finds a decrease in R&D expenditures and overall patent activity after the electricity market has been liberalised, e.g., Sanyal and Gosh (2013), Sterlacchini (2012), Jamasb and Pollitt (2008) and Dooley (1998). [6] A recent paper by Marino et al (2019) highlights the presence of an inverted-U relationship between electricity liberalisation and the number of patents developed in the electricity sector. Wang and Mogi (2017) find instead an increase in patenting from Japanese electric utilities after liberalisation coupled however with a decrease in R&D expenditures.

The literature focused on the relationship between liberalisation and clean-energy technologies shows instead a positive effect of market structure reforms on patenting. The heterogeneous effect of electricity liberalisation on clean-energy technologies and traditional technologies is now a well established fact in the literature (see for instance Li et al 2020). Nicolli and Vona (2016) find that lowering entry barriers has a positive effect on patents in renewable energy technologies and this effect is stronger for those technology that are characterised by the potential entry of small and independent power producers. Nesta et al (2014) show that liberalisation in the electricity sector led to an higher number of patents in clean-energy technologies and, when paired with environmental policies, it also increased the number of clean-energy triadic-patent families. A similar result is highlighted by Jamasb and Pollitt (2011) in the context of the UK electricity reform. Finally, Jacobsson and Bergek (2004) provide anecdotal evidence of the role played by new entrants in the evolution of the German wind energy sector.

Based on this discussion, the research hypothesis of the paper is that electricity liberalisation widens the search space of clean-energy patents, thus being a driver for the development of radical clean-energy technologies. Section 3.1 discusses the patent indicators used to measure the breadth and complexity of a patent's search space and

[6] Among these, the paper by Sanyal and Gosh (2013) is the only one that also measures the effect of liberalisation on patent quality using patent-level indicators. Focusing on the US they find a negative effect of the 1992 Energy Policy Act on the average number of forward citations and the generality of patents filed by electric equipment manufacturer.

how these characteristics relate to the radicalness, originality and novelty of an invention. The same section also discusses more in depth how these indicators are built and their interpretation.

3 Data and Descriptive Statistics

Using the database PATSTAT, I gathered data on clean-energy patent applications filed at the European Patent Office (EPO) between 1990 and 2017. I follow a common approach in the literature and identify clean-energy technologies through the code "Y02E" of the Cooperative Patent Classification (see for instance Calel and Dechelepretre 2016, Dechezleprêtre et al 2017). The resulting cross-section of patents was merged with the OECD Patent Quality Indicators database (February 2022) (Squicciarini et al., 2013), which contains information on a variety of patent quality indicators computed at the application level. Finally, information on the patent indicators developed by Verhoeven et al. (2016) were made available by the authors and added to the dataset. Section 3.1 discusses in detail each indicator used in the analysis.

To avoid double counting of the same invention, only one application was selected from each patent family. [7] A well-known issue with this approach is that patent applications belonging to the same family often display different values of the same indicator. Following Barbieri et al. (2020) and Verhoeven et al. (2016) I select within each family only the application with the highest value of the indicator of interest. Section A.5 of the Appendix shows that the results are robust also to selecting the application with the lowest value of the indicator of interest.

Figure 1 plots the number of clean-energy patents in the sample by year and Y02E 6-digits sub-class. As one would expect, the classes Y02E/10 (Energy generation through renewable energy sources) and Y02E/60 (Enabling technologies; Technologies with a potential or indirect contribution to GHG emissions mitigation) are by far the ones with more patent families filed in the period of interest. [8]

Each patent is assigned to a country based on the address of the inventor(s). Using the country of the inventor(s) rather than the one of the applicant connects the document with the environment in which it was developed and allows to make a direct link with the

[7] A patent family is defined by the EPO as "a collection of patent applications covering the same or similar technical content", see https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/patent-families.html

[8] In this regard, note that the class Y02E/60 contains all patents regarding energy storage.

notion of territory (Baudry and Dumont, 2006). Table 1 breaks down the patent families in the sample by inventor's country and shows that more than 60% of the families in the sample come from Germany and Japan combined, two well-known leaders in the development of clean-energy technologies. [9]. When assigning a patent to the country of origin of the inventor(s), shared applications with inventors in different countries pose a problem. Since they are a relatively rare occurrence in the dataset, the analysis that follows is focused only on patents that I was able to unambiguously assigned to a single country. In Section A.6 of the Appendix I also consider patents with inventors in different countries and show that doing so does not change the results of the analysis.

The name of the applicant(s) for each patent application has been retrieved using the OECD HAN database (February 2022). [10] Table 2 breaks down the total number of applicants (3688) according to how many patent families they have filed in the period of interest and Table 3 provides the list of the top ten applicants in the sample in terms of patent families filed. Having information on the applicant allows me to build the cumulative stock of clean-energy patent families at the applicant level. In order to do this I apply the perpetual inventory method using a depreciation rate of 15%. [11] This value for the depreciation rate is commonly used in the literature; see for instance Kafouros et al (2021), Hussinger and Pacher (2019), Hall (2005).

Finally, the resulting dataset was enriched with a variety of country level control variables. Among these we have the PMR index for the electricity sector (henceforth PMR_{elec}) i.e., the main independent variable of interest of this study. The OECD PMR database (2018) contains an array of time-varying sector-specific indicators computed to measure the level of liberalisation in different sectors of the economy (Vitale et al., OECD, 2020). The use of the PMR_{elec} index is very common in the literature studying electricity liberalisation, see for instance Marino et al., 2019, Nicolli and Vona 2019, Nicolli and Vona 2016, Nesta et al, 2014. In its last iteration, the indicator covers the period 1975-2018 and ranges from 6 to 0, with higher levels signalling a more regulated

[9] Patents from the United States and South Korea are not included in the sample because, at the time of writing, the index of the OECD Product Market Regulation database (Vitale et al., OECD, 2020) measuring liberalisation in the electricity sector is not computed for these countries.

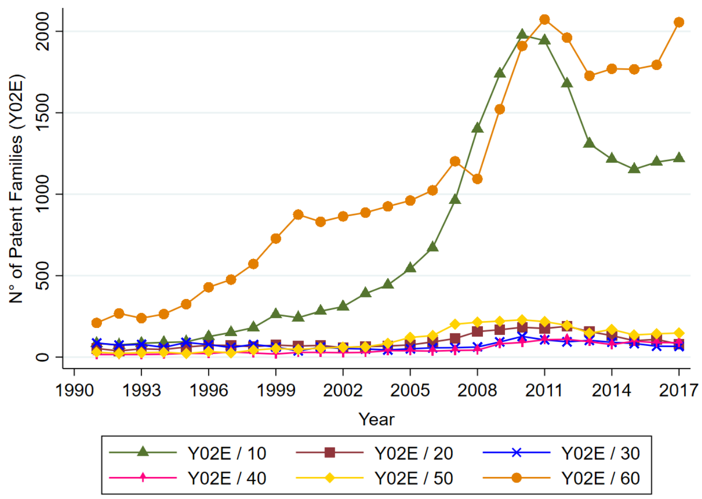
[10] For applications with more than one applicant we focus on the applicant that filed the highest number of patent families in the period of interest. Note that more than 92% of the applications in our sample are linked to only one applicant and more than 99% are linked to at most two applicants.

[11] According to the perpetual inventory method the patent family stock for firm i at time t (K_{it}) can be computed as $K_{it} = P_{it} + (1\text{-}\delta)K_{i,t1}$, where P_{it} is the number of patent families developed by firm i in year t and δ is the depreciation rate.

electricity market. Figure A.1 in the Appendix plots the evolution of the PMR_{elec} index by country in the period of interest.

Descriptive statistics for the variables discussed in this section, together with other variables used in the subsequent analysis are presented in Table 4.

Figure 1: Number of patent families by year and 6-digits Y02E code



Notes: Each patent application is allocated to all the Y02E 6-digits technological fields listed in the document.

Table 1: Patent Families by Country

Country	N°of Patent Families	Share
Australia	525	0.94
Austria	721	1.30
Belgium	510	0.92
Canada	1117	2.01
Denmark	2435	4.38
Finland	588	1.06
France	4798	8.62
Germany	13916	25.01
Ireland	115	0.21
Italy	1616	2.90
Japan	21364	38.40
Netherlands	1312	2.36
Norway	357	0.64
Poland	95	0.17
Spain	1103	1.98
Sweden	1095	1.96
Switzerland	1143	2.05
United Kingdom	2832	5.09
Total	55642	100.00

Notes: The table breaks down the overall number of patent families in the sample according to the inventor(s)' country.

Table 2: Breakdown of applicants by number of clean-energy patent families filed.

N° Patent Families	N°of Applicants	Total Number of Families Filed
1	6,059	6,059
between 2-5	2604	7,181
between 6-10	477	3,592
between 11-15	178	2,289
between 16-20	90	1,592
between 21-25	62	1,413
between 26-30	45	1,252
between 31-35	38	1,271
between 36-40	23	879
between 41-45	11	468
between 46-50	17	820
between 51-55	11	579
between 56-60	11	633
between 61-65	10	633
between 66-70	13	880
between 71-75	5	367
between 76-100	27	2,351
between 101-200	33	4,841
between 201-300	13	3,285
between 301-500	8	2,932
between 501-1000	7	4,659
> 1000	5	7,666
Total	3688	55,642

Notes: The table breaks down the number of applicants in the sample according to the number of clean-energy patent families filed between 1990 and 2017. Column 3 reports the overall number of patent families filed by applicants in each category.

Table 3: Top 10 Applicants for n° of Y02E patent families filed (1990-2017)

Name	Country	N° of Patent Families
1) Siemens AG	Germany	2022
2) Matsushita Elect	Japan	1996
3) CEA	France	1271
4) Toyota Jidosha	Japan	1252
5) Nissan Motor	Japan	1125
6) Vestas Wind Systems	Denmark	805
7) Mitsubishi Heavy Ind	Japan	774
8) Toshiba	Japan	767
9) Robert Bosch GMBH	Germany	688
10) Sony Copr	Japan	594

Notes: The table shows the name, country and number of patent families filed by the top 10 applicants in the sample for number of of Y02E patent families filed between 1990 and 2017.

Table 4: Descriptive Statistics

Variable	Variable Description	Observations	Mean	Std. Deviation	Min	Max	Source
Radicalness	Radicalness Index (Squicciarini 2013, Shane 2001)	55,642	0.32	0.25	0	1	OECD Patent Quality database (Feb. 2022)
Originality	Originality Index (Squicciarini 2013, Trajtenberg et al.,1997)	55,634	0.69	0.21	0	0.98	OECD Patent Quality database
PMR_{elec}	Regulation in the Electricity Sector	55,642	1.36	0.96	0.14	6.28	OECD PMR database (2018)
EPS_{tech}	Stringency of policies supporting green technologies	55,642	3.16	1.31	0.5	6	OECD EPS database (2022)
GDP_{pc}	GDP per capita PPP (constant 2017 international $)	55,642	43,300.38	6,350.86	23,064.95	7,7749.2	World Bank
Oil price (imports)	Crude oil import prices ($/barrel)	55,642	67.28	32.70	11.8	117.78	OECD Data
Patent Scope	N° of IPC 4-digit codes to which a patent is assigned	55,642	2.01	1.23	1	15	OECD Patent Quality database
Bwd Citations	N° of citations to older patents	55,642	6.95	8.04	0	485	OECD Patent Quality database
N° of Applicants	N° of applicants listed in the patent	55,642	1.08	0.34	1	13	OECD Han database (Feb. 2022)
Patent family stock	Cumulative count of applicant's Y02E families	55,642	80.49	139.27	1	785.44	Author's calculations
Novelty Technological Origins	Verhoeven et al. (2016) NTO indicator	45,574	0.29	0.45	0	1	Verhoeven et al. (2016)

3.1 Examining the search space of clean-energy technologies

To measure the effect of liberalisation on the search space of clean-energy patents I rely on two well-established indicators computed in the OECD Patent Quality Indicators database (February 2022) (Squicciarini et al., 2013). These are the Radicalness Index (a là Shane 2001) and the Originality Index (a là Trajtenberg et al.,1997). In addition, to further investigate the main results obtained using these two indexes, I exploit the Novelty in Technological Origins (NTO) indicator developed by Verhoeven et al,. (2016).

Note that the research question of the paper naturally leads to the use of indicators that rely on ex-ante characteristics of an invention to define its radicalness and novelty. This ex-ante approach defines radical innovations in terms of the characteristics of the underlying knowledge recombination process and therefore it is directly concerned with the search space of the invention (Verhoeven et al,. (2016). For a detailed discussion on the ex-ante and ex-post approaches to define radicalness see Barbieri et al. (2020) and Verhoeven et al,. (2016).

The remainder of this section discusses the three indicators that will be used as dependent variables in the study.

3.1.1 Radicalness Index

The radicalness index measures the radicalness of a patent looking at how how much it differs with respect to the patents it cites (Shane 2001). The intuition behind this indicator is that "when a patent cites previous patents in classes other than the ones it is in, that pattern suggests that the invention builds upon different technical paradigms from the one in which it is applied" (Shane, 2001, p. 210. See also Barbieri et al., 2020, Verhoeven et al,. 2016, Squicciarini et al. 2013, Rosenkopf and Nerkar 2001).

Following the definition of Shane (2001), the index for a focal patent p, with J representing the set of patents cited by patent p and j = 1,2,3...J, is defined by Squicciarini et al. (2013) as:

$$Radicalness_p = \Sigma_j^{n_p} CT_j/n_p; \quad IPC_{pj} \neq IPC_p \tag{1}$$

Where CT_j is the count of IPC-4 digit codes (IPC_{pj}) of patent j that are not allocated to the focal patent p, weighted by the times each IPC-4 digit code appears at the most disaggregated level available in the backward citations of patent j. The denominator, n_p, is the count of the overall IPC classes in the backward citations of patents belonging to the set J, counted at the most disaggregated level available. The indicator is therefore normalised so that its value ranges from zero to one.

High levels of this index signify that the patent takes knowledge from outside technological fields and applies it to its own technological fields.

Based on the research hypothesis, electricity liberalisation is expected to widen the search space of clean-energy patents. Part of this process could entail also the exploration of outside technological fields, thus we expect the reform to have a positive effect on the radicalness index.

3.1.2 Originality Index

The originality index measures how much the backward citations of a patent are spread across different technological fields (Trajtenberg et al.,1997). The intuition behind this indicator is that knowledge recombination processes relying on a diversified set of knowledge sources are supposed to lead to more original outcomes (Barbieri et al., 2020, Dechezleprêtre et al., 2017; Verhoeven et al,. 2016, Squicciarini et al. 2013, Trajtenberg et al.,1997).

Building on Hall at al. (2001), Squicciarini et al. (2013) compute the originality indicator as follows:

$$Originality_p = 1 - \Sigma_j^{n_p} s_{pj}^2 \tag{2}$$

Where s_{pj} is the percentage of citations made by patent p to patent class j out of the n_p IPC 8-digit patent codes contained in the patents cited by patent p. Note that the indicator is built starting from an Hirschman-Herfindahl Index that measures the extent to which the backward citations of the patent are concentrated among different technological fields (i.e., $\Sigma_j^{n_p} s_{pj}^2$). This being the case, the indicator ranges from zero to one and higher values of the indicator signal patents with backward citations spread across many different fields.

Based on the research hypothesis, we expect liberalisation to increase the variety of knowledge inputs that go into clean-energy technologies. This could push these technologies to cite a wider array of technological fields, which would positively impact the originality index.

3.1.3 Novelty in Technological Origins

The NTO indicator was developed by Verhoeven et al. (2016) in order to identify novel patterns of citations in patents, i.e., pattern of citations that have never occurred before. The emergence of such patterns suggests that the underlying technology uses a new or different approach than than those used by its predecessors (Rizzo et al. 2018, Verhoeven et al. 2016, Arthur 2007).

With respect to the radicalness index, Verhoeven et al. (2016) argue that "citing from 'outside' fields of knowledge is not a sufficient condition to actually apply a novel approach since a large number of previous patents might have already sourced knowledge from these 'outside' fields before" (Verhoeven et al., 2016 - pag 714). The same logic can be applied to the originality index; having backward citations spread across many technological fields does not imply novelty in the search space because other patents might have relied on a similar knowledge recombination process before.

To more accurately identify novelty in the search space of a patent, Verhoeven et al. (2016) develop the "Novelty in Technology Origins" indicator. [12] This indicator identifies a patent "as having Novelty in Technological Origins (NTO) if it makes a combination between its own IPC code and an IPC code from its referenced patents that has not occurred in the years previous to the application year of the patent" (Verhoeven et al., 2016 - pag 711) [13]. The NTO indicator takes value one if the patent is classified as having novelty in technological origins and zero otherwise. An updated version of the data used in Verhoeven et al. (2016), computed using PATSTAT (2018), was made available by the authors. This being the case, to avoid possible truncation effects, the sample when using this variable is restricted to the period 1990-2014.

[12] The paper by Verhoeven et al. (2016) also introduces other indicators which are not discussed here because they are less relevant for this analysis.

[13] The IPC codes used to build the indicator are 6-digits IPC codes

The expected effect of electricity liberalisation on the NTO indicator is harder to describe than in the case of the radicalness and the originality indexes. If electricity liberalisation has an impact on the search space of clean-energy patents, it seems natural to expect that these patents will end up borrowing knowledge from, or expand into, the same technological fields. This is a direct consequence of the fact that only a limited number of technological fields will contain knowledge that is useful for the development of clean-energy technologies. That being said, the correlation between electricity liberalisation and the NTO indicator might take the form of an an inverted-U. When the market is first opened, we expect an increase in the number of novel connections made by clean-energy patents that are exploring outside fields not cited before. Further reforms of the electricity market might not trigger additional novel connections because the most interesting technological fields have already been explored. Section 5.2 presents evidence of this pattern and discusses how it relates with the main results of the paper and how it can help us interpreting them.

4 Methodology and Identification Strategy

To investigate the effect of electricity liberalisation on the indicators of interest I rely on the specification presented in equation (3). Note that, since the unit of analysis is the single patent application, the resulting dataset is a cross-section of patents; see Barbieri et al., (2020) and Rizzo et al., (2018) for similar applications.

$$PatInd_i = \beta_1 LagPMR_{elec,i} + \beta_2 Lag\mathbf{X}_i + \beta_3 \mathbf{A}_i + App_i + Tech_i + Country_i + Year_i + \varepsilon_i \quad (3)$$

$PatInd_i$ represents one of the patent indicators discussed in the previous section computed for patent i. The variable PMR_{elec} and the control variables in matrix $\mathbf{X}$ are lagged one year to account for the lag in the effect of policy variables.

The main coefficient of interest is β_1, which quantifies the effect of a change in the degree of electricity liberalisation on $PatInd_i$.

The matrix $\mathbf{X}$ contains country-level control variables that might affect the development of clean-energy patents. First, I use the sub-index of the OECD Environmental Policy Stringency database (2022) that measures the use of policies aimed at supporting clean-energy innovations (Kruse et al., 2022). I also control for GDP per capita [14] and

[14]Source: World Development Indicators - World Bank. Retrived through Our Wolrd in Data 22 June 2022

the price of crude oil imports computed at the country level [15]. The inclusion of crude oil prices in the model is important in light of the effect that oil price shocks had on low-carbon patenting in the early 1980s (on this see for instance Calel and Dechezleprêtre., 2016).

A is a matrix of applicant and application level control variables. To proxy the resources and knowledge available at the applicant level I include in the regression the stock of clean-energy patent families computed for each applicant. The latter is built using the perpetual inventory method with a discount rate of 15% as discussed in the previous section. The relationship between the stock of clean-energy patent families and the indicator of interest is unlikely to be a linear one. On the one hand, new entrants are expected to develop more radical inventions and this would suggest a negative effect of the applicant's patent family stock on the radicalness and originality indexes. On the other hand, this negative effect might be weaker (or become positive) for applicants filing a lot of patents, because these actors will likely have access to more resources and can build on a larger body of knowledge. This being the case I also include in the specification the squared value of the applicant's patent family stock.

Following previous literature, application-level control variables are chosen based on how the patent indicators are built. First, since all the indicators we have discussed rely on information about prior knowledge, I control for the number of backward citations (Barieri et al., 2020, Hall et al., 2001) [16]. Furthermore, when the dependent variable is the radicalness index, I also control for the number of IPC full-digit codes the invention is allocated to, i.e. the scope of the patent (Barieri et al., (2020), Sapsalis et al., 2006). Results from previous literature suggests that the number of backward citations is positively correlated with our dependent variables, while the scope of the patent is negatively correlated with the radicalness index (see for instance, Barieri et al., 2020). Finally, I control for the number of applicants listed in the patent as more than one applicant working on the same invention could translate into more resources available for its development and a wider knowledge base.

The specification is then augmented with applicant (App_i), technology class ($Tech_i$), country ($Country_i$) and year ($Year_i$) fixed effects [17] The inclusion of applicant fixed

[15] Source: OECD (2022), Crude oil import prices (indicator). doi: 10.1787/9ee0e3ab-en (Accessed on 22 June 2022)

[16] To deal with outliers in backward citations I follow Squicciarini et al (2013) and wisorize this variable over its 98% distribution

[17] In the OECD Patent Quality database information on the technological fields of the patent is based

effects in the model allows to control for time-invariant heterogeneity across applicants. However, at the same time it prevents the inclusion in the regression of the 6,059 patents from applicants that have filed only one patent family in the period of interest (Correia, 2015); see Table 2. This being the case, I will present the results both with and without applicants fixed effects in the model.

As the "treatment variable" (i.e., PMR_{elec}) is at the country level, I cluster the standard errors at this level (Abadie et al., 2017). Doing so generates few clusters (18) that are heterogeneous in size; see Table 1. In this context, wild cluster bootstrapping has been proved to perform much better than inference based on clustered standard errors relying on large-sample theory (Roodman et al 2019, Cameron and Miller, 2015). This being the case, for all specifications I report p-values and confidence intervals obtained implementing a wild cluster bootstrap using the STATA command 'boottest' (Roodman et al., 2019).

To estimate the model I rely on linear regression analysis [18]. The radicalness and originality indexes can take any value between zero and one, thus a natural choice could have been to rely on a fractional model. Using a linear model allows me to easily include applicant fixed effects and, more importantly, to rely on wild-bootstrap based inference; which has been shown to be more reliable with respect to the alternative "score bootstrap" used for extremum estimators such as maximum likelihood (Roodman et al., 2019). Similar choices are not uncommon in the literature, see for instance Porter and Serra (2019). As robustness check, Section A.3 of the Appendix presents the results using a fractional probit model with inference based on score bootstrap. The same logic explains why I decided to use a Linear Probability Model when focusing on the NTO indicator as dependent variable of the model.

4.1 Instrumental Variable strategy

The proposed estimation strategy could suffer from endogeneity coming from different sources.

First, while the PMR_{elec} index is commonly used in the literature (e.g. Marino et al., 2019; Nicolli and Vona, 2019; Nicolli and Vona, 2016; Nesta et al., 2014), it is at

on the WIPO taxonomy (Schmoch, 2008). For patents allocated to more than one technology field they keep only the one with the majority of IPC codes. Finally, in case a patent has the same number of IPC codes for different technology fields it is randomly allocated to a technology fields.

[18] The model is estimated in STATA using the command reghdfe by Correia (2016)

best an imperfect proxy for the effective market power of incumbents (Nicolli and Vona, 2019).

Second, the development in the 1990s of more scalable technologies for energy generation (e.g., gas-fired plants and RETs) was a key factor that made the liberalisation of the electricity sector possible in the first place, so one might worry about possible reverse causality (Batlle and Ocaña,. 2013).

Finally, countries that have the potential to develop more radical clean-energy innovations might also be the ones that reform first (or more) the electricity market. This could happen if "green lobbies" have the ability to affect both the development of radical clean-energy technologies and the regulation of the electricity sector (Nicolli and Vona 2019).

To deal with these issues, and uncover the causal effect of interest, I follow Nicolli and Vona (2019) and use an instrumental variable strategy where regulation in telecommunication is used as an instrument for regulation in electricity. Regulation in the telecommunication sector is measured using the PMR index for this particular industry. A robustness check using regulation in air transport as IV is provided in Section A.5 of the Appendix [19].

Both the reforms of telecommunication and air transport took place before the liberalisation of the electricity sector and played an instrumental role in giving momentum to the latter (Nicolli and Vona, 2019; Pollitt, 2012; Joskow, 2008). At the same time, these reforms can be considered independent from the lobbying power of actors in the energy sector and from technological developments in energy-supply technologies. On this assumptions rest the validity of the proposed strategy.

Wild bootstrap inference requires some caution when it comes to IV estimation. First, following Roodman et al. (2019) and Davidson and MacKinnon (2010) I rely on equal-tail p-values as opposed to symmetric p-values in order to assess the statistical significance of these estimates.[20]. Second, the tests for weak instruments relying on first-stage regressions also requires additional attention when clustered standard errors relying on large-sample theory are applied in sub-optimal contexts. Young (2022) uses a sample of 1309 instrumental variables regressions in 30 published papers and shows that

[19]In the case of Air Transport, when using clustered standard errors based on asymptotic theory the instrument appears to be strong enough, but the p-value of the first-stage regression obtained using wild bootstrap would lead us to conclude the opposite. This being the case, it is possible that these suffer from weak-instruments issues

[20]Results are however very similar using symmetric p-value

these tests reject the null 100% of the times at the 0.01 level using clustered standard errors based on large-sample theory, but only 80% of the times once bootstrap techniques are applied. This being the case, when testing the strength of the instrument I will also report the p-value from the first-stage regression obtained using wild bootstrap techniques. Third, the choice between studentized wild bootstrapping (bootstrapt-t) and unstudentized wild bootstrapping (bootstrap-c) is not straightforward in IV settings. Studentized wild bootstrapping is generally considered the best choice according to asymptotic theory (Hall, 1992) but results from Young (2022) and Wang (2021) provide evidence that in IV applications unstudentized wild bootstrapping (bootstrap-c) might perform better. In light of this, I will provide inference on the main coefficient of interest using also unstudentized wild bootstrapping.

5 Results

5.1 The effect of electricity liberalisation on the search space of clean-energy technologies

Table 5 shows the results from the naïve OLS estimation of the model discussed in Section 4. Note that the wild cluster bootstrap does not assume normality and therefore it does not calculate standard errors (Roodman et al 2019). This being the case I follow Porter and Serra (2019) and report the obtained p-values and 95% confidence intervals in the result tables.

The coefficient associated with PMR_{elec} is always statistically significant and of the expected sign. When the dependent variable is the radicalness index (columns 1 and 2) the estimated effect is significant at the 99% threshold, while for the originality index (columns 3 and 4) the threshold of significance is 95%. The magnitude of the estimated coefficient is much stronger in the case of the radicalness index than for the originality index. To see this, we can compare the estimated effect of a one-unit change in PMR_{elec} with the average value that these indexes take in the sample. The average value of the radicalness index among patent families in the sample is 0.32 (see Table 4). The estimated effect in columns 1 and 2 is therefore roughly 6% of the mean of the variable. The average value that the originality index takes in the sample is 0.69 (see Table 4). Thus, in this case, the effect of PMR_{elec} ranges between 0.6% and 1.1% of the mean of the variable. In other words, the estimated effect of electricity liberalisation on the originality index, even if statistically different from zero, is close to zero in magnitude.

Looking at the other control variables, we see that they are generally of the expected sign. [21] Country level control variables other than the PMR_{elec} are generally not significant, on the other hand applicants and application level controls display a strong correlation with both dependent variables. As expected, the coefficient associated with the scope of the patent is negative and highly significant and the one associated with backward citations is always positive and significant at least at the 95% threshold. Contrary to expectations, the number of applicants listed in the document is not an important factor in the analysis. Finally, there is evidence in favor of the hypothesised inverted-U relationship between the patent family stock and the radicalness and originality indexes.

Table 6 reports the result when implementing the IV strategy discussed in Section 4.1. The test for weak instrument based on the first-stage regression with clustered standard errors that rely on large-sample theory always returns an F statistic well above the usual cut-off level of 10 (Stock et al., 2002). Following Young (2022), I further test the strength of the instrument looking at the p-value obtained from the first-stage regression when testing the coefficient of the instrument using wild clustered bootstrapping. This p-value is always significantly lower that 0.01. As shown in Appendix A.4, this is not true for the robustness check done using air transport as IV, which however appears to be strong enough when the test is based on clustered standard errors that rely on large-sample theory.

Results from column 1 to 3 of Table 6 are in line with what we see in Table 5. In column 4 the p-value associated with the estimated coefficient for PMR_{elec} is substantially higher and the effect is no longer statistically significant. Looking at the magnitude of the estimated coefficients, 2SLS estimates always fall into the OLS 95% confidence interval, thus providing evidence in favor of OLS estimates. In light of this, the loss of significance in column 4 could be explained by the combination of the lower statistical power associated with 2SLS estimates and an estimated effect of PMR_{elec} on the originality index that is close to zero in magnitude.

Following Young (2022) and Wang (2021), I further test the significance of the PMR_{elec} coefficient relying on unstudentized wild bootstrapping (bootstrap-c). The p-value obtained applying this procedure confirms the significant effect of electricity liberalisation on the radicalness index and casts additional doubts on the relationship between electricity liberalisation and the originality index, with the coefficient of PMR_{elec}

[21] The only two exceptions are the estimated coefficients for the price of oil imports in column 4 and for the *Number of applicants* in column 1. Note however that in both cases these coefficients are far from being significant

in column 3 that is no longer significant at the 95% level.

Summing up, the estimated effect of electricity liberalisation on the radicalness index is always statistically significant and meaningful in magnitude. On the other hand, the effect of electricity liberalisation on the originality index is weak at best and not robust. This pattern is confirmed in the robustness checks presented in the Appendix (see Sections A.3, A.4, A.5 and A.6). When considered together, these results suggest that electricity liberalisation pushes clean-energy patents to cite knowledge from technological fields other than their own, but the bulk of clean-energy patents' search space remains concentrated around the same number of technological fields.

Overall, the results presented in this section are evidence that electricity liberalisation affects the search space of clean-energy patents and can be a driver for the development of radical clean-energy technologies, as sometimes hypothesised in the literature (Negro et al., 2012, Markard and Truffer, 2006). At the same time, the analysis also helps to define the boundaries of this effect by describing what features of clean-energy patents' search space are affected by higher levels of competition in the electricity market.

The next section will exploit the NTO indicator in order to further investigate the obtained results.

5.2 Electricity liberalisation and Novelty in Technological Origins: further insights on the main results

Table 7 and 8 provide evidence for the inverted-U correlation between the NTO indicator and electricity liberalisation hypothesised in Section 3.1.3. The results in column 1 of Table 7 are obtained using a linear probability model and inference based on clustered wild bootstrapping. The estimated model is the same presented in Section 4, without the inclusion of applicant fixed effects and with the addition of the squared value of the PMR_{elec} index. Columns 2 and 3 estimate the same model using as dependent variables the radicalness and originality indexes. In Table 8, I present the marginal effects of these estimates. The remainder of this section will discuss the three main takeaways that can be drawn from this analysis, focusing on how these results can inform our interpretation of the results presented in the previous section.

First, the expected inverted-U correlation between the PMR_{elec} index and the NTO indicator is borne out by the data. The liberalisation of an heavily regulated electricity market is correlated with an higher likelihood that clean-energy technologies will make novel connections in their search space. As the electricity market becomes more competitive, this correlation first becomes not significant then changes sign. As discussed in Section 3.1.3, this pattern is expected because there are only a limited number of technological fields that have significant synergies with clean-energy technologies. When these fields have been explored, further liberalising the electricity market is unlikely to trigger a significant number of novel connections.

Second, column 2 displays the opposite trend, with higher level of PMR_{elec} that are correlated with a stronger effect of liberalisation on the radicalness index. Looking together at the results from column 1 and 2 of Table 8 we see that, as the electricity market becomes more competitive, the propensity of clean-energy technologies to cite new technological fields and their propensity to cite outside technological fields start moving in opposite directions. This suggests that, at first, the exploration of new technological fields can be a driver of the increase in outside knowledge cited by clean-energy patents. However, after a certain point, this is no longer the case; electricity liberalisation still drives clean-energy technologies to cite outside technological fields, but these are the same fields already explored when the market was first opened to competition.

Finally, column 3 confirms that the effect on the originality index is weak and characterised by a low level of significance. However, if we look only at the magnitude of the estimated marginal effect, it is interesting to note that it decreases monotonically as the market becomes more liberalised, following the same trend as the NTO indicator.

Table 5: OLS estimates of Equation (3)

	(1)	(2)	(3)	(4)
	Rad	Rad	Ori	Ori
Lag PMR_{elec}	-0.0190	-0.0197	-0.0042	-0.0079
	(0.0002)	(0.0000)	(0.0303)	(0.0502)
	[-0.0237, -0.0157]	[-0.0268, -0.0145]	[-0.0098, -0.0010]	[-0.0126, 0.0000]
Lag EPS_{tech}	0.0022	0.0015	0.0042	0.0025
	(0.4151)	(0.6101)	(0.1650)	(0.3446)
	[-0.0054, 0.0069]	[-0.0072, 0.0064]	[-0.0025, 0.0100]	[-0.0049, 0.0079]
Lag GDP_{pc}	0.0628	0.1353	0.324	0.3769
	(0.6006)	(0.1219)	(0.1183)	(0.0306)
	[-0.3360, 0.3514]	[-0.0506, 0.3325]	[-0.0613, 0.5497]	[0.0405, 0.7544]
Lag Oil price (imports)	0.1442	0.0993	0.0054	-0.0227
	(0.1981)	(0.5052)	(0.9587)	(0.8238)
	[-0.0770, 0.3785]	[-0.1266, 0.4299]	[-0.2808, 0.2190]	[-0.3772, 0.2396]
Patent Scope	-0.0263	-0.0192		
	(0.0014)	(0.0002)		
	[-0.0445, -0.0140]	[-0.0311, -0.0080]		
Bwd Citations	0.0031	0.0038	0.0101	0.0111
	(0.0008)	(0.0011)	(0.0340)	(0.0025)
	[0.0014, 0.0062]	[0.0020, 0.0065]	[0.0068, 0.0156]	[0.0087, 0.0147]
Number Applicants	-0.0008	0.0018	0.0066	0.0080
	(0.8266)	(0.6482)	(0.1764)	(0.1963)
	[-0.0258, 0.0124]	[-0.0129, 0.0129]	[-0.0085, 0.0167]	[-0.0050, 0.0115]
Family Stock	-0.0142	-0.0286	-0.0128	-0.0333
	(0.0605)	(0.0150)	(0.0028)	(0.0808)
	[-0.0330, 0.0473]	[-0.0357, -0.0093]	[-0.0321, -0.0044]	[-0.0504, 0.0028]
Family $Stock^2$	0.0021	0.0041	0.0028	0.0049
	(0.0547)	(0.0095)	(0.0025)	(0.0866)
	[-0.0002, 0.0039]	[0.0016, 0.0057]	[0.0006, 0.0061]	[-0.0011, 0.0084]
Applicant FE	Yes	No	Yes	No
Technology FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	49,583	55,642	49,542	55,600

Notes: OLS regressions. I report wild bootstrap cluster p-values in parentheses and wild bootstrap cluster 95% confidence intervals in square brackets, generated using boottest command in Stata (Roodman et al., 2019) for standard errors clustered at the country level (18 clusters)

Table 6: 2SLS estimates of Equation (3)

	(1)	(2)	(3)	(4)
	Rad	Rad	Ori	Ori
Lag PMR_{elec}	-0.0221	-0.0169	-0.0043	-0.0054
	(0.0012)	(0.0050)	(0.0370)	(0.2498)
	[-0.0359, -0.0146]	[-0.0237, -0.0090]	[-0.0211, -0.0002]	[-0.01529, 0.0089]
Lag EPS_{tech}	0.0027	0.0012	0.0042	0.0022
	(0.3762)	(0.6883)	(0.1186)	(0.4206)
	[-0.0058, 0.0083]	[-0.0067, 0.0063]	[-0.0017, 0.0090]	[-0.0062, 0.0079]
Lag GDP_{pc}	0.0303	0.1572	0.3300	0.3970
	(0.7789)	(0.1606)	(0.1904)	(0.0372)
	[-0.3787, 0.3365]	[-0.0945, 0.4251]	[-0.1517, 0.5489]	[0.0323, 0.8186]
Lag Oil price (imports)	0.1563	0.0856	0.0056	-0.0353
	(0.1656)	(0.6083)	(0.9729)	(0.7061)
	[-0.0646, 0.3974]	[-0.1374, 0.4344]	[-0.2808, 0.2243]	[-0.3859, 0.2111]
Patent Scope	-0.0262	-0.0192		
	(0.0010)	(0.0000)		
	[-0.0443, -0.0140]	[-0.0311, -0.0080]		
Bwd Citations	0.0031	0.0038	0.0101	0.0111
	(0.0006)	(0.0010)	(0.0324)	(0.0016)
	[0.0014, 0.0062]	[0.0020, 0.0064]	[0.0068, 0.016]	[0.0086, 0.0147]
Number Applicants	-0.0008	0.0019	0.0066	0.0080
	(0.8289)	(0.6457)	(0.1776)	(0.1924)
	[-0.0260, 0.0123]	[-0.01275, 0.01290]	[-0.0090, 0.0168]	[-0.0047, 0.0115]
Family Stock	-0.0142	-0.0287	-0.0128	-0.0333
	(0.0656)	(0.0136)	(0.0100)	(0.0786)
	[-0.0324, 0.0477]	[-0.0358, -0.0092]	[-0.0322, -0.0026]	[-0.0503, 0.0025]
Family Stock^2	0.0021	0.0041	0.0028	0.0050
	(0.0576)	(0.0094)	(0.0040)	(0.0866)
	[-0.0003, 0.0040]	[0.0016, 0.0057]	[0.0005, 0.0060]	[-0.0009, 0.0088]
Applicant FE	Yes	No	Yes	No
Other FEs	Yes	Yes	Yes	Yes
P-value Bootstrap-c PMR_{elec}	0.0000	0.0010	0.0620	0.2400
F-stat first stage	57.05	75.22	57.08	75.27
First Stage Bootstrap	0.0026	0.0015	0.0026	0.0015
Observations	49,583	55,642	49,542	55,600

Notes: 2SLS regressions. Regulation in the telecommunication sector is used as instrument for regulation in the electricity sector. I report wild bootstrap cluster p-values in parentheses and wild bootstrap cluster 95% confidence intervals in square brackets, generated using boottest command in Stata (Roodman et al., 2019) for standard errors clustered at the country level (18 clusters). The significance of the coefficient associated with PMR_{elec} is tested also relying on unstudentized wild bootstrapping (P-value Bootstrap-c PMR_{elec})

Table 7: OLS estimates of Equation (3) with the addition of Lag PMR^2_{elec}

	(1)	(2)	(3)
	NTO	Rad	Ori
Lag PMR_{elec}	0.03618	-0.0258	-0.0026
	(0.0082)	(0.0040)	(0.7677)
	[0.0145, 0.0092]	[-0.0421, -0.0145]	[-0.0258, 0.0212]
Lag PMR^2_{elec}	-0.0072	0.0011	-0.0009
	(0.0002)	(0.0994)	(0.4638)
	[-0.0165, -0.0035]	[-0.0005, 0.0033]	[-0.0044, 0.0027]
Controls	Yes	Yes	Yes
Applicant FE	No	No	No
Technology FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	45,574	55,642	55,600

Notes: OLS regressions of model 3 with the addition of Lag PMR^2_{elec}. I report wild bootstrap cluster p-values in parentheses and wild bootstrap cluster 95% confidence intervals in square brackets, generated using boottest command in Stata (Roodman et al., 2019) for standard errors clustered at the country level (18 clusters).

Table 8: Marginal Effects of models estimated in Table 7

	(1)	(2)	(3)
	NTO	Rad	Ori
Lag $\text{PMR}_{elec} = 0$	0.0362	-0.0258	-0.0026
	(0.0082)	(0.0040)	(0.7677)
	[0.0145, 0.0917]	[-0.0421, -0.0145]	[-0.0258, 0.0212]
Lag $\text{PMR}_{elec} = 1$	0.0219	-0.0236	-0.0045
	(0.0072)	(0.0016)	(0.4825)
	[0.0069, 0.065]	[-0.0360, -0.0147]	[-0.0203, 0.0119]
Lag $\text{PMR}_{elec} = 2$	0.0076	-0.0214	-0.0064
	(0.1082)	(0.0004)	(0.1822)
	[-0.0019, 0.0285]	[-0.0302, -0.0142]	[-0.0152, 0.0051]
Lag $\text{PMR}_{elec} = 3$	-0.0067	-0.0192	-0.0083
	(0.2892)	(0.0000)	(0.0181)
	[-0.0167, 0.0130]	[-0.0262, -0.0139]	[-0.0120, -0.0030]
Lag $\text{PMR}_{elec} = 4$	-0.0210	-0.0170	-0.0102
	(0.0352)	(0.0004)	(0.0323)
	[-0.0523, -0.0018]	[-0.0228, -0.0123]	[-0.0147, -0.0030]
Lag $\text{PMR}_{elec} = 5$	-0.0353	-0.0148	-0.0122
	(0.0044)	(0.0026)	(0.0703)
	[-0.0880, -0.0150]	[-0.0215, -0.0090]	[-0.0205, 0.0037]
Lag $\text{PMR}_{elec} = 6$	-0.0496	-0.0126	-0.0141
	(0.0019)	(0.0196)	(0.1521)
	[-0.1193, -0.0238]	[-0.0216, -0.0038]	[-0.0283, 0.0096]
Controls	Yes	Yes	Yes
Applicant FE	No	No	No
Other FEs	Yes	Yes	Yes
Observations	45,574	55,642	55,600

Notes: The table reports marginal effect of PMR_{elec} for the models presented in Table 7. I report wild bootstrap cluster p-values in parentheses and wild bootstrap cluster 95% confidence intervals in square brackets, generated using boottest command in Stata (Roodman et al., 2019) for standard errors clustered at the country level (18 clusters)

6 Discussion and conclusions

The literature on the relationship between electricity liberalisation and innovation has sometimes hypothesised that a more competitive electricity market can affect the search space of clean-energy patents and therefore be a driver for the development of radical clean-energy technologies (Negro et al., 2012, Makard and Truffer, 2006). This paper contributes to this literature by being the first one to test this idea empirically using patent data and patent-level indicators (see, e.g., Verhoeven et al,. 2016, Squicciarini et al 2013).

The results suggest that electricity liberalisation pushes clean-energy patents to explore "outside" technological fields, i.e. to borrow knowledge from technological fields other than their own. This pattern is correlated with the radicalness of an invention, as it signals that the patent relies on different paradigms with respect to the one to which it is applied (Barbieri et al 2020, Squicciarini et al 2013, Shane 2001). At the same time, electricity liberalisation does not significantly change the breath of clean-energy patents' search space; a characteristic that is correlated with the originality and complexity of the invention (Barbieri et al., 2020, Dechezleprêtre et al., 2017; Verhoeven et al,. 2016, Squicciarini et al. 2013, Trajtenberg et al.,1997).

More insights on the relationship of interest can be drawn by looking at the correlation between electricity liberalisation and an indicator of novelty in the search space of patents (Verhoeven et al,. 2016). The liberalisation of an heavily regulated electricity market is positively correlated with the likelihood that clean-energy patents will explore new technological fields, i.e. technological fields never cited before by patents in the same domain. As the electricity market becomes more competitive, this is no longer the case. This patter is expected, due to the finite number of technological fields from which clean-energy technologies can borrow useful knowledge. Once these fields have been explored, further liberalising the electricity market is unlikely to trigger a substantial numbers of new explorations. On the contrary, the positive effect of electricity liberalisation on clean-energy patents' propensity to cite knowledge from outside (but not necessarily new) technological fields remains strong and statistically significant as the market becomes more competitive. This suggest that, when the market is first opened to competition, the exploration of new technological fields can be a driver of clean-energy patents' increased reliance on outside knowledge. On the other hand, additional reforms of an already liberalised electricity market increase the propensity of clean-energy technologies to cite outside technological fields, but these fields are the same already explored when the market was first opened to competition.

The results are therefore consistent with the claim that electricity liberalisation is a driver for radical clean-energy technologies. At the same time, by describing precisely how a more competitive electricity market affects the search space of clean-energy technologies, they also point out the limits of this effect.

The main contribution of the paper is to describe in detail the effect of electricity liberalisation on the search space of clean-energy technologies. This allows a more precise definition of how, and to what extent, electricity liberalisation can be a driver for the development of radical clean-energy technologies. From a policy making standpoint, understanding the relationship between electricity regulation and the quality of clean-energy innovations is particularly important in the current situation. To deal with the recent power price crisis, various changes to the design of electricity markets in Europe are under discussion and some of the proposed ideas would likely affect the level of competition in the market if implemented (ACER 2022). In this regard, these results warns about the possible negative effects of changes in the electricity market design that weaken competition on the quality of clean energy technologies.

The analysis has some limitations, which could be addressed by further research. First, the United States, which are a major developer of clean-energy technologies, could not be included in the sample. In part, this is because the 2020 iteration of the PMR_{elec} index does not include the U.S. at the time of writing (Vitale et al., OECD, 2020). More importantly however, a similar analysis for the U.S. would need to be carried out at the state level rather than the federal one and thus would require an indicator of regulation in electricity computed for each state. The use of an indicator computed at the federal level would hide the heterogeneous regulatory environments to which inventors in the different states are exposed. This heterogeneity is significant because the U.S. has never enacted a mandatory federal restructuring law, leaving to the states the most important decisions (Joskow, 2008). A similar analysis for the U.S., carried out at the state level, is therefore left for future research.

Second, the analysis takes only an ex-ante approach to the definition of radicalness (Verhoeven et al. 2016). This is the natural consequence of the research question of the paper, which is concerned with the effect of electricity liberalisation on the search space of clean-energy technologies. In future research, the analysis could be expanded by taking also an ex-post approach to the definition of radical technologies (see for instance Barbieri et al 2020, Acemoglue et al 2020).

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A Appendix

A.1 Y02E technologies

Y02E / 10: Energy generation through renewable energy sources:

• Geothermal energy

• Hydro energy

• Energy from the sea, e.g. using wave energy or salinity gradient

• Solar thermal energy, e.g. solar towers

• Photovoltaic [PV] energy

• Thermal-PV hybrids

• Wind energy

Y02E / 20: Combustion technologies with mitigation potential:

• Heat utilisation in combustion or incineration of waste

• Combined heat and power generation [CHP]

• Combined cycle power plant [CCPP], or combined cycle gas turbine [CCGT]

• Technologies for a more efficient combustion or heat usage

• Direct CO2 mitigation

• Indirect CO2mitigation, i.e. by acting on non CO2directly related matters of the process, e.g. pre-heating or heat recovery

Y02E / 30: Energy generation of nuclear origin:

• Nuclear fusion reactors

• Nuclear fission reactors

Y02E / 40: Technologies for an efficient electrical power generation,transmission or distribution:

• Flexible AC transmission systems [FACTS]

• Active power filtering [APF]

• Reactive power compensation

• Arrangements for reducing harmonics

• Arrangements for eliminating or reducing asymmetry in polyphase networks

• Superconducting electric elements or equipment; Power systems integrating superconducting elements or equipment

• Smart grids as climate change mitigation technology in the energy generation sector

Y02E / 50: Technologies for the production of fuel of non-fossil origin:

• Biofuels, e.g. bio-diesel

• Fuel from waste, e.g. synthetic alcohol or diesel

Y02E / 60: Enabling technologies; Technologies with a potential or indirect contribution to GHG emissions mitigation

• Energy storage using batteries

• Energy storage using capacitors

• Thermal energy storage

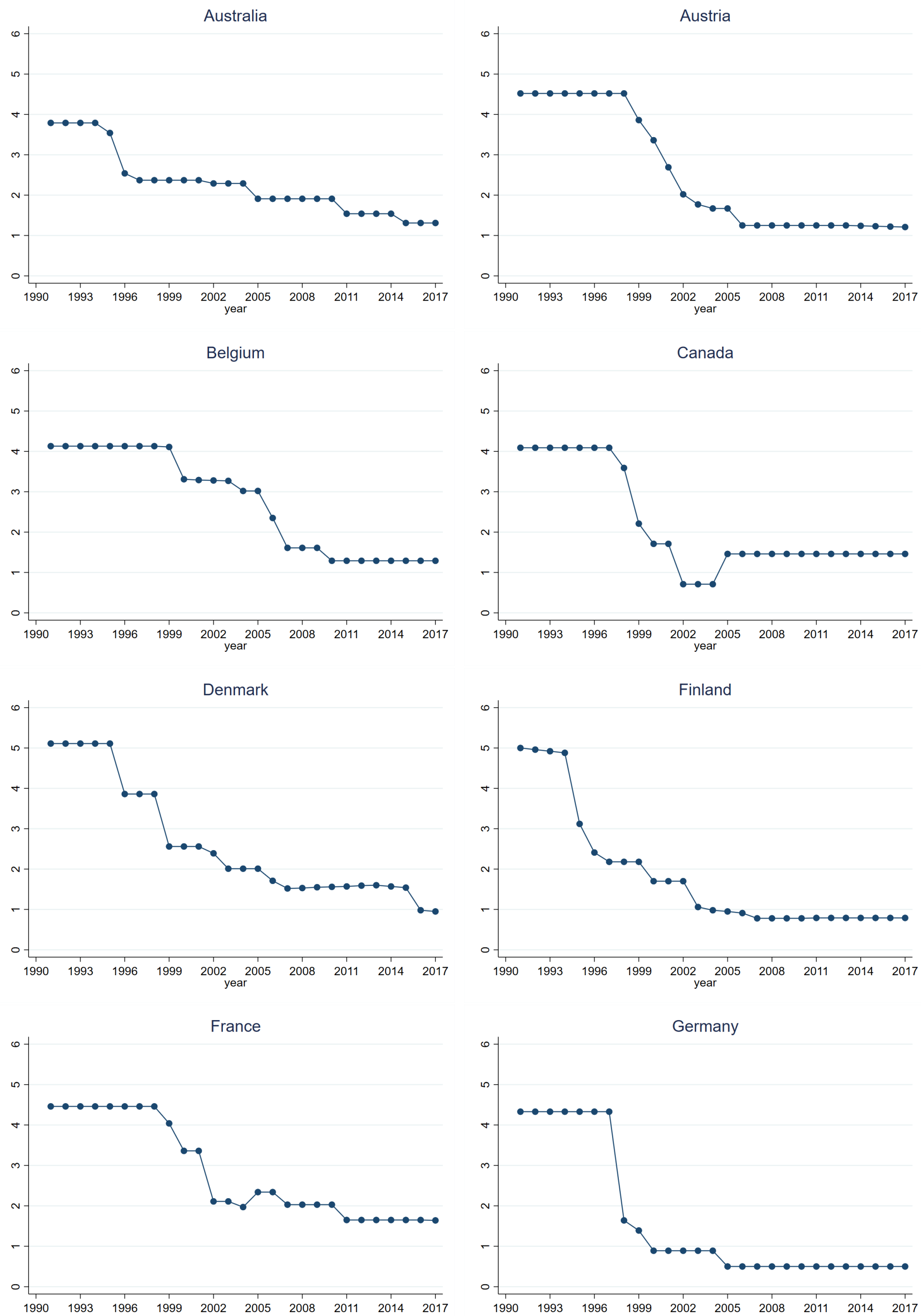
• Mechanical energy storage, e.g. flywheels or pressurised fluids

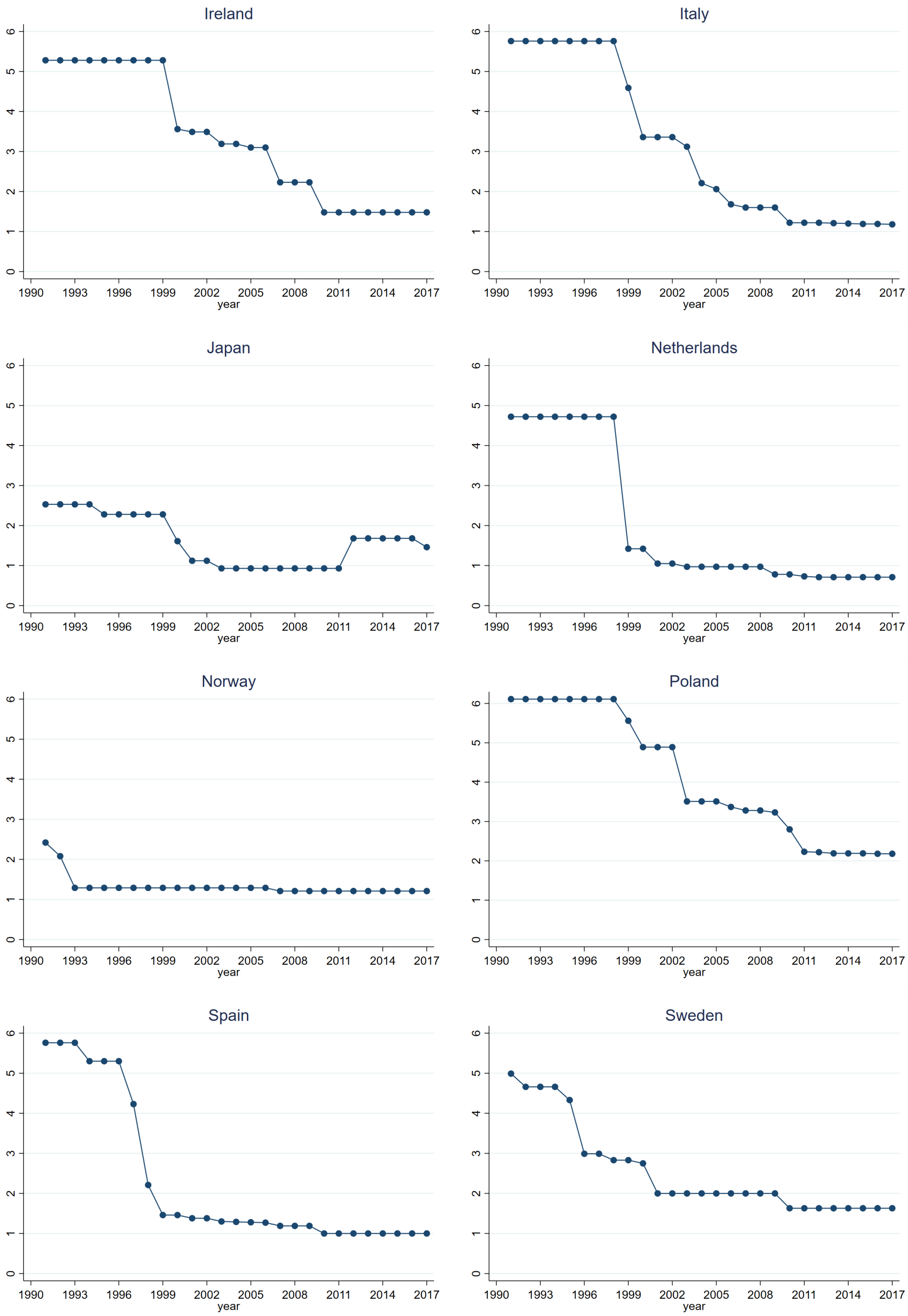
• Hydrogen technology

• Smart grids in the energy sector

Y02E / 70 :Other energy conversion or management systems reducing GHG emission

A.2 PMR_{elec} index by Country and year




Ireland
Italy
Japan
Netherlands
Norway
Poland
Spain
Sweden
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1990
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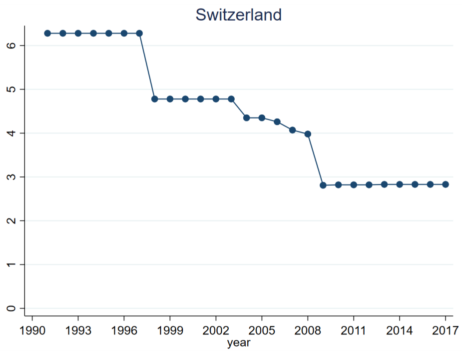

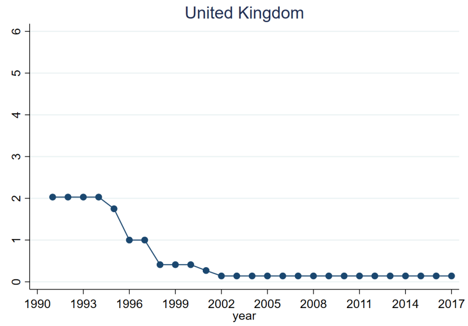

A.3 Fractional Probit Model

	(1)	(2)
	Radicalness	Originality
Lag PMR$_{elec}$	-0.0187	-0.0086
	(0.0002)	(0.0372)
Controls	Yes	Yes
Applicant FE	No	No
Technology FE	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
Yes		
Observations	55,642	55,600

Notes: Fractional probit regressions. The table reports marginal effects as opposed to regression coefficients. Score bootstrap cluster p-values in parentheses are generated using boottest command in Stata (Roodman et al., 2019) for standard errors clustered at the country level (18 clusters). The estimated model is the model presented in Section 4, without the inclusion of applicant fixed effects., i.e. the same model estimated in column 2 and 4 of Table 5.

A.4 2SLS using regulation in Air Transport as instrument

	(1)	(2)	(3)	(4)
	Rad	Rad	Ori	Ori
Lag PMR_{elec}	-0.0299	-0.0263	-0.0076	-0.0153
	(0.0216)	(0.0224)	(0.0956)	(0.0736)
	[-0.0614, -0.0098]	[-0.0549, -0.0131]	[-0.0408, 0.0037]	[-0.0510, 0.0041]
Controls	Yes	Yes	Yes	Yes
Applicant FE	Yes	No	Yes	No
Other FEs	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
P-value Bootstrap-c PMR_{elec}	0.0076	0.0008	0.0672	0.0134
F-stat first stage	33.01	35.62	33.03	35.67
First Stage Bootstrap p-value	0.0425	0.0176	0.0426	0.0175
Observations	49,583	55,642	49,542	55,600

Notes: 2SLS regressions. I report wild bootstrap cluster p-values in parentheses and wild bootstrap cluster 95% confidence intervals in square brackets, generated using boottest command in Stata (Roodman et al., 2019) for standard errors clustered at the country level (18 clusters). The estimated model is the same model presented in Section 4. The significance of the coefficient associated with PMR_{elec} is tested also relying on unstudentized wild bootstrapping (P-value Bootstrap-c PMR_{elec}). Note that when using clustered standard errors based on asymptotic theory the instrument appears to be strong enough, but the p-value of the first-stage regression obtained using wild bootstrap would lead us to conclude the opposite. This being the case, these estimates could suffer from weak-instruments issues.

A.5 Patent Family correction based on the lowest level of the indicator of interest

	(1)	(2)	(3)	(4)
Panel A: OLS estimates	Rad	Rad	Ori	Ori
Lag PMR$_{elec}$	-0.0190	-0.0192	-0.0029	-0.0068
	(0.0001)	(0.0000)	(0.0610)	(0.0568)
	[-0.0240, -0.0157]	[-0.0263, -0.0141]	[-0.0083, 0.0003]	[-0.0115, 0.0004]
Controls	Yes	Yes	Yes	Yes
Applicant FE	Yes	No	Yes	No
Technology FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	49,583	55,642	49,578	55,636
Panel B: 2SLS estimates (telecom)	Rad	Rad	Ori	Ori
Lag PMR$_{elec}$	-0.0191	-0.0147	-0.0012	-0.0038
	(0.0016)	(0.0114)	(0.6669)	(0.3810)
	[-0.0326, -0.0099]	[-0.0205, -0.0066]	[-0.0153, 0.0029]	[-0.0139, 0.0104]
Controls	Yes	Yes	Yes	Yes
Applicant FE	Yes	No	Yes	No
Other FEs	Yes	Yes	Yes	Yes
P-value Bootstrap-c PMR_{elec}	0.0002	0.0032	0.6679	0.3764
F-stat first stage	54.04	69.15	52.80	69.43
First Stage Bootstrap p-value	0.0023	0.0016	0.0023	0.0016
Observations	49,583	55,642	49,578	55,636

Notes: OLS regressions (Panel A) and 2SLS regression (Panel B). The table presents the results obtained selecting from each family only the patent associated to the lowest value of the indicator of interest. In Panel B regulation in telecommunication is used as instrument for regulation in the electricity sector. I report wild bootstrap cluster p-values in parentheses and wild bootstrap cluster 95% confidence intervals in square brackets, generated using boottest command (Roodman et al., 2019) for standard errors clustered at the country level (18 clusters). In Panel B, the significance of the coefficient associated with PMR_{elec} is tested also relying on unstudentized wild bootstrapping (P-value Bootstrap-c PMR_{elec})

A.6 Including patents with inventors in different countries

	(1)	(2)	(3)	(4)
Panel A: OLS regression	Rad	Rad	Ori	Ori
Lag PMR$_{elec}$	-0.0188	-0.0195	-0.0039	-0.0079
	(0.0009)	(0.0000)	(0.0443)	(0.0495)
	[-0.0245, -0.0140]	[-0.0255, -0.0148]	[-0.0100, -0.0003]	[-0.0128, -0.0001]
Controls	Yes	Yes	Yes	Yes
Applicant FE	Yes	No	Yes	No
Technology FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	51,216	57,368	50,741	56,875
Panel B: 2SLS regression	Rad	Rad	Ori	Ori
Lag PMR$_{elec}$	-0.0182	-0.0133	-0.0028	-0.0040
	(0.0049)	(0.0381)	(0.2480)	(0.4915)
	[-0.0309, -0.0070]	[-0.0203, -0.0012]	[-0.0145, 0.0029]	[-0.0158, 0.0130]
Controls	Yes	Yes	Yes	Yes
Applicant FE	Yes	No	Yes	No
Other FEs	Yes	Yes	Yes	Yes
P-value Bootstrap-c PMR_{elec}	0.0098	0.0292	0.2798	0.4606
F-stat first stage	55.95	70.87	54.97	69.31
First Stage Bootstrap p-value	0.0022	0.0016	0.0023	0.0016
Observations	51,216	57,368	50,741	56,875

Notes: OLS regressions (Panel A) and 2SLS regression (Panel B). The table presents the results when shared applications with inventors in different countries are included in the analysis. To include these applications I allocate them to the country where the market is less regulated among inventors' countries. The rationale behind this decision is that, given the research hypothesis of the paper, it is interesting to see if the highest level of liberalisation to which the invention is exposed has an effect on the search space of the patent. The estimated model is the same presented in Section 4. In Panel B regulation in telecommunication is used as instrument for regulation in the electricity sector. I report wild bootstrap cluster p-values in parentheses and wild bootstrap cluster 95% confidence intervals in square brackets, generated using boottest command (Roodman et al., 2019) for standard errors clustered at the country level (18 clusters). In Panel B, the significance of the coefficient associated with PMR_{elec} is tested also relying on unstudentized wild bootstrapping (P-value Bootstrap-c PMR_{elec})

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