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Product Market Competition, Regulation and Innovation: the Impact of Electricity Market Liberalization on Innovation in the Power Generation Sector

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Abstract

This thesis investigates the relationship between product market competition, regulation and innovation. A challenge associated with studying this relationship is the reverse causality between competition and innovation. I therefore use the exogenous variation in the competitive conditions in the national power generation markets resulting from EU-wide deregulation of the European electricity markets. I furthermore argue that the regulatory change in this highly concentrated sector is a better approximation of the market structure and the competitive conditions in the sector than standard competition measures. The thesis tests the theory of an inverted-U relationship between competition and innovation introduced by Aghion et al. [2005]. This theory proposes that firms consider the difference in their *pre-* and *post-* innovation rents when investing in R&D. A strong inverted U-shape pattern is found between product market regulation and innovative output of European power generation firms, as measured by their patents. This pattern is robust to adjustment of patent value by their forward citations.

Keywords: Innovation, Product Market Competition, Electricity, Deregulation, Liberalization, Endogenous Growth Theory, Inverted-U Relationship, Patents

JEL: L43, L51, O31, O33, O38, O47

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1 Introduction

Innovation is a crucial determinant of technological progress and economic growth. In order to facilitate successful innovation, a properly functioning market environment is required as much of innovation takes place within profit-maximizing firms. When markets do not naturally provide the conditions required to foster innovative activity, the right market structure and level of competition should be ensured by appropriate regulation. In this thesis, I investigate the relationship between product market competition, regulation and innovation in the European Electricity Generation Sector. For several reasons, this relation is of crucial interest for economic policy: First, a market economy typically is characterized by underinvestment in research and development due to the inherent uncertainty of the research process, imperfectly appropriable returns from innovation and increasing returns in use [Arrow, 1962]. Even when inventors succeed in extracting economic value from their innovation due to intellectual property rights, there will be underutilization of valuable inventions compared to the socially desirable allocation [ibid.]. Second, a vast range of theoretical and empirical literature connects successful innovation to higher economic growth. In endogenous growth theory, technological change induced by innovation is the essential determinant of growth [Romer, 1990]. Third, regulation and the level of product market competition are important determinants of innovation within an industry, yet theoretical and empirical studies provide contradicting views regarding the specific relationship between innovation and the level of competition. Fourth, understanding innovation drivers in the electricity sector is particularly important. The European Union is transitioning the European energy system towards more sustainable energy sources, which will lead to increased consumption of electricity [European Parliament, 2016]. It is therefore important to ensure existence of cost-efficient and clean energy technologies, and innovation is pivotal to achieving this.

The classical, "Schumpeterian" view, represented by the majority of existing theories, argues for a negative linear relationship between innovation and competition, i.e. that higher product market competition leads to lower levels of innovation. The reason is that post-innovation rents a firm gains from innovating decrease in the number of firms in the market. Hence, innovation would be maximized in a monopoly setting. Nonetheless, notable exceptions exist in spite of this argument. Most prominently, Arrow [1962] suggests that monopolies have lower incentives to innovate when there is no threat of entry. In addition, empirical research, for instance Nickell [1996] and Blundell et al. [1999], mostly finds innovation is increasing with competition when estimating a linear relationship.

Aghion et al. [2005] aim to explain these seemingly contradicting results by developing a theory of an inverted-U shape relationship between competition and innovation, where innovation levels depend on the *difference* between post-innovation and pre-innovation rents, rather than on post-innovation rents alone. Thus, if increased competition reduces a firm's pre-innovation rents by a larger amount than it reduces its post-innovation rents, competition can increase profits from innovating and encourage innovation in order to "escape competition". In particular, when firms in a sector operate at a similar technological level. However, if firms are heterogeneous with respect to their level of technology, competition mainly affects the post-innovation rents of the laggard firms and thus the "Schumpeterian" effect of competition decreasing the level of innovation dominates.[1]

In studying the relationship between competition and innovation, an important challenge is the presence of reverse causality. While market structure is likely to affect innovation, firm innovation patterns may likewise affect the market structure in the industry. As noted by Gilbert [2006], a firm introducing an invention to the market that significantly decreases cost of production affects the market structure differently depending on whether it is positioned as a market leader (in which case it barely competes with the other firms anymore due to its superior technology) or as a laggard, in which case the firm might catch up with the rest of the firms in the market, leading to more intense competition.

The liberalization of electricity markets in the European Union is particularly well fit for the purpose of this study for the following reasons: (i) Regulation across the EU has been harmonized to facilitate the integration of the national markets,[2] (ii) Electricity market reforms exhibit variation across time and countries as the newer member states that joined the union in 2004 (or later) liberalized their energy markets later than the initial member states, (iii) market reforms were exogenous to the national markets, as they were driven by aspirations for further integration of the European Single Market as well as ambitions to improve efficiency, but with little links to innovation performance in the sector [Jamasb and Pollitt, 2005], (iv) Electricity is a homogeneous good, hence any innovation in the sector is likely to be efficiency-inducing rather than aimed at differentiation from competitors. Electricity thus complies with theoretical models of endogenous growth considered in this paper, where innovation is modeled as efficiency-improving.

While Aghion et al. [2005] study whether the inverted-U relationship holds across industries within a single country, this thesis makes an important contribution by assessing whether the relationship also holds for a single industry across a number of countries. To my knowledge, there has been no comprehensive evaluation of the impact of EU electricity market deregulation on innovation to date. In my thesis, I utilize the exogenous changes in product market competition through the EU Electricity Market liberalization and integration policies that took place in the 1990s and 2000s. The policy package included extensive deregulation of the EU electricity generation sector. Using an OECD index of regulatory stringency in the electricity market to measure the degree of openness to competition of the different markets and patent data from the European Patent Office PATSTAT database to measure innovation, I find a strong inverted-U shape relationship between product market regulation and innovation. I test the robustness of this result by weighting patents by their forward citations which further reaffirms this relationship.

[1]These effects will be referred to as "Escape-Competition" effect respectively "Schumpeterian Competition" effect throughout the remainder of this thesis.

[2]My dataset includes the EU-28 as well as Norway, which was an early liberalizer of its electricity markets and complies to EU electricity market rules.

2 Research Question

Based on the theoretical framework laid out in Aghion et al. [2005], I aim to answer the following research question:

Is there an inverted-U shape relationship between competition and innovation in the European electricity generation sector?

In other words, I aim to study whether companies consider product market structure when making an investment in research and development. More specifically, do they consider the difference between their expected pre-innovation and post-innovation rents? In this case, innovation rates should increase when firms can expect post-innovation rents to increase more than pre-innovation rents, tempting them to "escape competition". At the same time, innovation rates should decrease when firms can expect the post-innovation rents to decrease more than pre-innovation rents, leading to dominant "Schumpeterian" effects as firms switch focus to the maximization of more immediate returns.

3 Regulatory Framework

The EU electricity market liberalization is the largest cross-jurisdiction deregulation reform conducted in the electricity sector worldwide [Jamasb and Pollitt, 2005] and ultimately aimed at introducing competition in the electricity sector, increasing connectedness within the EU's internal electricity market as well as improving efficiency of the firms in the sector [European Parliament, 2016].

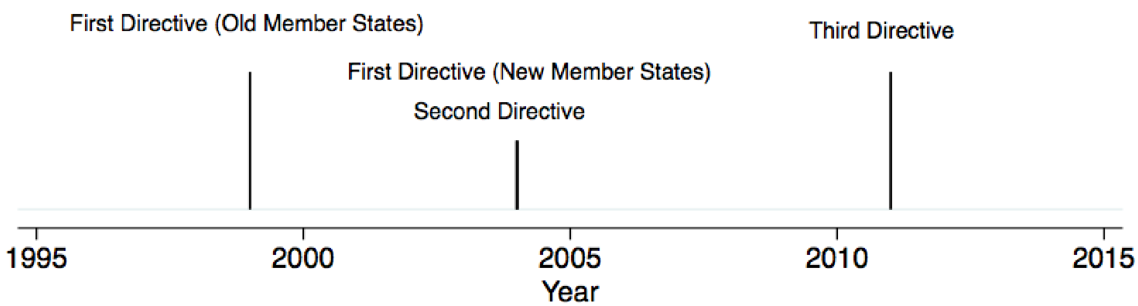
Starting from 1990s, EU Member States underwent extensive product market deregulation in a number of industries, including the electricity industry. Historically, the electricity sector has been a strictly regulated state monopoly, due to the natural monopoly characteristics displayed by crucial parts of the electricity supply chain. The electricity sector consists of (1) Electrical Power Generators producing electricity, (2) Transmission System Operators who provide long-distance transport and ensure system stability, (3) Distribution System Operators who deliver electricity directly to consumers and (4) Electricity suppliers who buy electricity from power generators and sell it to consumers, (5) Consumers and (6) Regulators [European Parliament, 2016].

In general, the transmission and distribution system networks exhibit strong natural monopoly characteristics, while both power generation and supply do not. Hence, there exists an economic rationale for maintaining a regulated monopoly in transmission and distribution while opening both generation and supply for competition, largely the aim the EU Electricity Market Regulation has. The three EU Electricity Directives (discussed in more detail below) compliment each other in their attempt to unbundle the previously vertically integrated parts of the electricity supply system, first opening power generation and later electricity supply to competition, while introducing an

Independent System Operator in both transmission and distribution to facilitate fair and equal access to the grid by power generating and supply companies [European Parliament, 2016].

Some of the early electricity market liberalizers were the United Kingdom and Norway, followed by Sweden. The United Kingdom was the first to liberalize (deregulate) its power market, starting in the early 1990s and finishing the liberalization process around 2000 (Jamasb and Pollitt [2011] and OECD [2017]). At the European Union level, work towards a liberalized electricity market started in the 1990s as a part of the broader strive towards the integration and liberalization of the EU Internal Market. The First Electricity Directive was adopted in 1996 and transposed into national regulation of the "old" Member States by 1999[3] and by the "new" Member States (that acceded to the EU in 2004 or later) by 2004[4] or 2008[5] [European Union, 1997a]. It regulated the liberalization of electricity generation allowing for free entry[6] into power generation European Union [1997b]. The second Electricity Market Directive was adopted in 2003 and transposed into national regulation by 1 July 2004[7][European Union, 2003a]. The directive further advanced competition in the electricity sector through vertical disintegration of the electricity supply chain into four distinct parts, i.e. generation, transmission, distribution and sales, primarily through requiring the member states to introduce independent transmission and distribution system operators and requiring them to ensure non-discriminatory treatment of electricity generating companies [European Union, 2003b]. The third Electricity Market Directive was agreed upon in 2009 and transposed into national legislation by 2011 [European Union, 2009a]. The third directive focused on the supply side in particular, allowing consumers to freely switch between suppliers [European Union, 2009b].

Figure 1: Timeline of Electricity Market Deregulation in Europe: EU Regulation



Source: European Union [1997b], European Union [2003b] and European Union [2009b].

Unlike the EU Regulation, the EU Directives do not directly achieve the power of law in the

[3]These include: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Portugal, Spain, Sweden.

[4]These include: Cyprus, Latvia, Lithuania, Hungary (partially), Poland, Slovenia.

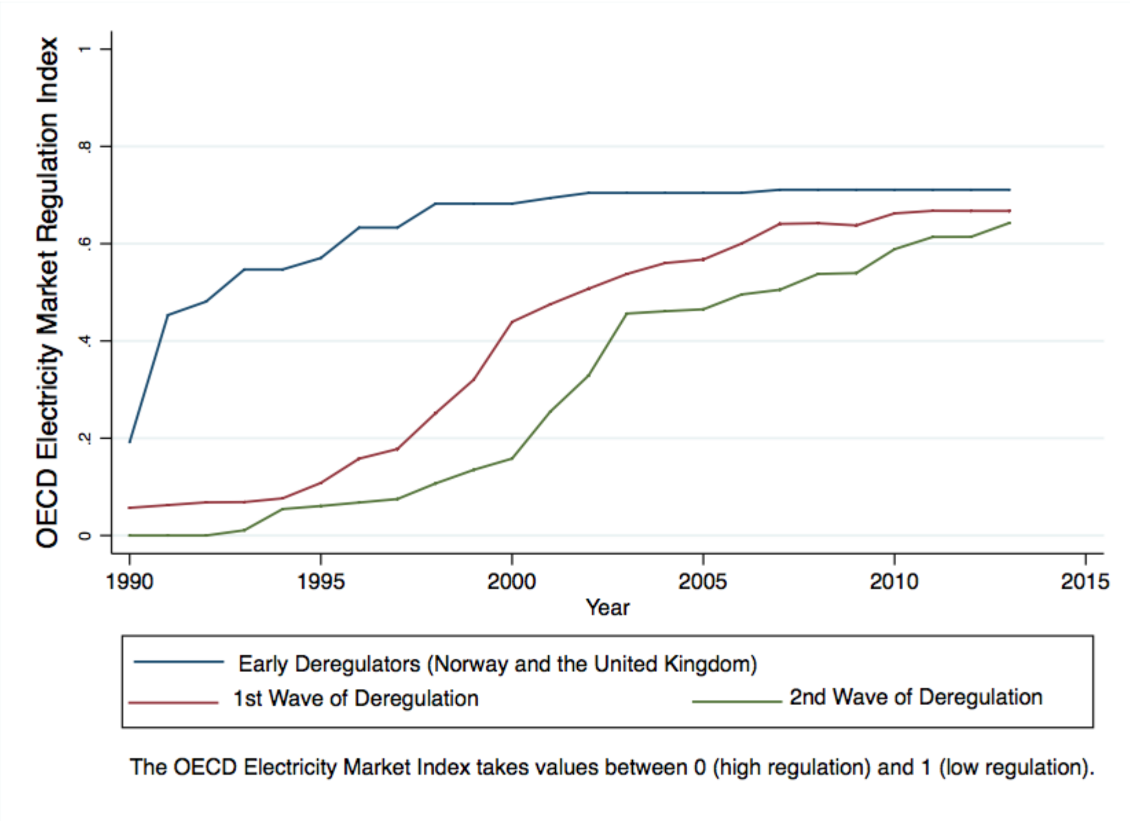
[5]These include: Estonia, Czech Republic, Hungary (partially).

[6]Power generation is still regulated in terms of capacity building.

[7]With some provisions entering into force only in 2007 and with an exception of Romania, who adopted the entirety of the rules only by 2007) and Croatia (n.d.).

member states. Rather, they are transposed into the national regulation of the member states within a certain timespan. This, arguably, allows for more freedom for the member states in terms of the disposition of the regulation. The actual state of transposition into national law can be monitored through a Product Market Regulation Index the OECD maintains (from hereon: OECD Index) for a number of industries, including the electricity sector, in order to track the competitive environment [OECD, 2017]. In contrast to the EU Electricity Market Directives, the OECD Index measures the actual change in countries regulatory environment rather than the legal obligations of the EU Directives that may or may not be implemented in the national legislation as they are intended. An overview of the OECD index by country by the EU electricity market regions is provided in the Appendix B: Data.

Figure 2: Timeline of Electricity Market Deregulation in Europe: OECD Electricity Market Regulation Index



Source: Own calculations based on the OECD [2017].

4 Theoretical Framework

In this section, I review the relevant economic theory. First, I discuss technological innovation as an information good and introduce the economic rationale of intellectual property rights. Next, I turn to the role of innovation in endogenous growth theory, discussing the development of relevant theoretical underpinnings since 1942 when Schumpeter introduced the concept of creative destruction. Then, I present a detailed review of the theory of the inverted-U shape relationship between competition and innovation as introduced by Aghion et al. [2005], the main theoretical foundation of this thesis.

4.1 Economics of Innovation and Intellectual Property Rights

Research and development is devoted to the production of knowledge. Since all technological inventions are based on knowledge, a type of information, the economic characteristics of information goods also apply to technological inventions.[8] Under competition, as pointed out by Arrow [1962], information suffers from failure of optimal allocation. This is due to three characteristics of information: its *indivisibility*, its *imperfect appropriability* and the *uncertainty* surrounding the research and development process as well as the assessment of the value of an information good in economic transactions [ibid.]. In other words, technological innovation is a nonrival good that is only partly excludable [Romer, 1990] and researching as well as trading inventions is subject to uncertainty. Under optimal allocation, knowledge would be distributed almost unlimitedly, since the cost of distribution once it has been created is negligible. However, since information is an indivisible good, it is optimal for the entity in possession of that information not to share it, as it is impossible to extract any pay for it once it is shared (in the absence of legal protection). The resulting outcome is socially suboptimal as well as potentially of little benefit to the information owner as she might not be able to exploit this information as effectively as others Arrow [1962].

Legal protection that creates a temporary monopoly hence provides (at least a partial) solution to this problem. Introducing intellectual property rights in the form of patents[9] increases the appropriability of the value of information commodities to its owner [Arrow, 1962]. Customarily, such a temporary monopoly is granted in exchange for the disclosure of information about the invention it protects. After the patent protection runs out, generally after 20 years [World Intellectual Property Organization, n.d.a], the knowledge protected by the patent enters the public domain supposedly benefiting the society [Levin et al., 1987].[10]

In the context of this thesis, renewable energy innovation in particular suffers from imperfect resource allocation due to *double externalities*. First, there are the externalities of underinvestment in renewable energy research due to the characteristics of innovation discussed above, that is imperfect appropriability, uncertainty in R&D investment and indivisibility of knowledge (innovation). Second, there is the imperfect appropriation of costs of pollution by fossil fuels. In other words, the cost of pollution is not reflected in fossil fuel prices, making renewable energy relatively more expensive and having a negative impacts on innovation in renewable energy [Nesta et al., 2014]. This means that even if the societal cost of energy from renewable sources is the same as that

[8] The terms information and knowledge will be used interchangeably in this section.

[9] As well as other intellectual property rights such as trademarks, utility patents, copyrights, industrial design rights and trade secrets etc.

[10] In reality, this *quid pro quo* works less smoothly since the information about the innovation that a patent contains has to be understandable only to someone "skilled in the art", often resulting in disclosure of insufficient or at least challenging accuracy [World Intellectual Property Organization, n.d.a].

from fossil sources, due to imperfect appropriation of negative externalities (pollution costs) fossil energy can be produced more cheaply and there is less innovation in renewable energy technologies than socially optimal.[11]

More generally, levels of energy innovation[12] will be affected by the changes in relative prices between different inputs, spurring more innovation in the now cheaper input (as well as efficiency-improving innovation in the now relatively more expensive input). This includes (but is not limited to) changes in fossil fuel prices and renewable energy subsidies (see e.g. Popp [2002] and Lanzi et al. [2011]).

4.2 Endogenous Growth and Creative Destruction

The incentive for a firm to innovate is the difference in the profit that the firm would receive when investing in innovation compared to when not investing [Gilbert, 2006]. While this concept might seem straightforward, introducing different types of market structure, innovation characteristics and R&D dynamics in a theoretical model leads to a vast range of theoretical implications and conclusions about this relationship [ibid.]. Both industrial organization theory as well as endogenous growth theory have extensively examined the theoretical implications of product market competition for R&D and innovation. While industrial organization economists typically consider profit maximizing firms in a single period setting, Grossman and Helpman [1991] argue that this fails to capture the cyclical nature of innovation where a new invention creates a temporary monopoly but is later rendered obsolete as superior technologies are introduced. Following their line of thought, an endogenous growth framework thus seems better suited for the purpose of this longitudinal study investigating the impact of market structure and competition on innovation and ultimately economic growth. In this subsection, I therefore review some of the most notable contributions to the discussion of the role of innovation in the endogenous growth theory.

The idea of innovation as a crucial determinant of economic growth is at the core of endogenous growth theory. One of the most well-established theories on the relationship between competition and innovation was introduced by Joseph Schumpeter in 1942. He argued that perfect competition is inferior when it comes to innovation and that innovation increases with firm size and with market concentration because post-innovation rents are reduced with higher competition as more firms have to compete for the same size of the market [Cohen and Levin, 1989]. Schumpeter coined the term "creative destruction" as an essential impulse of the capitalist economic system that renews itself from *within* through new methods of production or types of innovation, deeming outdated technology obsolete [Aghion and Howitt, 1992]. While the early endogenous growth models had the Schumpeterian implication of growth being maximized in a monopolistic industry, later models have been adapted to match the empirical results of innovation increasing with competition.

Aghion and Howitt [1992] were among the first to formalize the notion of creative destruction in an endogenous growth model by endogenizing industrial innovations that improve upon the quality

[11] The same applies to efficiency improving technologies in energy production from fossil fuels.

[12] Innovation in electricity generation technologies is a subset of innovation in energy technologies, thus this is relevant also for electricity innovation.

of existing products and reasoning that research in the current period depends upon expected future research. In part, because future research renders the existing products obsolete through innovation, i.e. "creative destruction". In this model, the expectation of increasing future research discourages research in the current period as the profit from current research equals the future profit from the monopoly rents of the temporary monopoly created through innovation. Hence, with more future innovation the value of these rents will be lower as they are only received until the next innovation is introduced. Thus, since more competition in a market implies more expected future innovation, in the model framework of Aghion and Howitt [1992] firms in a competitive setting will be less innovative than monopolies, in line with Schumpeter's argument about creative destruction.

Other significant contributions modeling innovation in an endogenous growth setting include Grossman and Helpman [1991], as well as Romer [1990]. Grossman and Helpman [1991] develop a model with repeated product quality improvements where there is a continuum of products (and industries), each with its individual quality-improving ladder. In this framework, patent races take place in all industries (products) simultaneously and quality-improving innovation in each industry takes place in its own (individual) pace as at any period in time inventors succeed in innovating in some industries but not in others. Thus in equilibrium, the innovation in different industries will be distributed across the quality ladder. Romer [1990] takes a different approach. Rather than modeling innovation processes with a quality ladder, he models innovation as a process in which R&D expands the range of inputs used in production. In other words, Romer [1990] models product innovation as a process of generating an ever-greater number of horizontally differentiated products.

While the three models represent two distinct types of innovation in an endogenous growth model setting, as pointed out by Grossman and Helpman [1991], the models of quality and of process innovation provide rather similar results which can directly be related to innovation in the electricity sector. Innovation in electricity, a commodity good, is aimed at improving efficiency rather than diversification. However, efficiency improvements can take place both through improved quality of products as well as refined production processes. All three models by Aghion and Howitt [1992], Grossman and Helpman [1991] and Romer [1990] share the theoretical implication that innovation is maximized in a monopolistic competition setting, due to presence of the Schumpeterian effect of creative destruction. I.e. increased product market competition decreases the temporary monopoly rents from innovating, hence reducing incentives to innovate.

Arrow [1962] models innovative behavior of monopoly firms under no threat of entry. He argues that under both, perfect competition and monopoly, the incentives for research and innovation will be below the socially optimal level and concludes, in contrast to the proponents of the Schumpeterian theory, that incentives to invest will be lower under monopoly than under perfect competition. This is because a firm in a perfectly competitive market is not earning any profit (price equals the cost) and by innovating it can gain a temporary monopoly in that technology, earning positive profit. On the other hand, a profit maximizing monopoly already earns a positive profit, hence when innovating, the monopoly firm essentially "replaces itself". Furthermore, a bias against major inventions exists within monopolistic industries and competitive markets are likely to provide greater incentives for product innovation if (i) competition in the old product is intense and (ii) innovation is drastic, i.e. it makes the old product obsolete.

While a monopoly industry that is not exposed to threat of entry has less incentives to innovate than firms in a competitive economy, firms that are exposed to threat of entry tend to invent and patent more in order to deter new competition [Gilbert and Newbery, 1982]. If an incumbent monopoly firm has a greater incentive to invest in R&D than the potential new entrants, it will attempt to prevent entry of other firms into the market through the creation of barriers to entry. This is known as the "business stealing effect". In general, any activity where rewards from acting before others are sufficiently large, compared to moving together with the other firms, can be considered as a tool for preemption of competition [Gilbert and Newbery, 1982]. Such preemption of competition might take various forms, for example capacity expansion or preemptive patenting, the latter of which is considered here. Gilbert and Newbery [1982] show that the system of granting a company a temporary monopoly in the form of a patent creates opportunities for monopoly firms to exclude potential entrants and to maintain their monopoly power. They show that a monopolist has incentives to preempt competition through patenting if the cost of innovation is less than the expected profits from preventing entry of new firms. The monopoly firms patent emerging technologies ahead of their potential competitors, thus effectively excluding them from the innovation race. Furthermore, the monopoly companies themselves fail to put patents to use at times, favoring the existing technology due to more beneficial revenue streams, thus producing "sleeping patents" and creating an efficiency loss [ibid.]. Gilbert and Newbery [1982] acknowledge, however, that there are limits to preemptive patenting, due to the very same characteristics of patents and innovation summarized in the previous subsection on Economics of Innovation and Intellectual Property Rights. These include, most importantly, uncertainty in research and innovation and the limits of the scope of patent protection, such that possibilities to "patent around" and invention exist. This makes the potential deterrence of entry through innovation and patenting very costly.

The theories of differential behavior by monopolies, depending on whether they are exposed to competition, can easily be linked to the setting of this thesis. Before negotiations on and implementation of market liberalization policies, there was no threat of other firms entering into the market. Thus, following Arrow [1962] reasoning there were lower incentives for the monopoly firms to innovate. Preemption through patenting could be relevant for electricity companies in the framework of the electricity market deregulation as it can be said that the transition from a monopoly industry with no threat of entry, like the one considered by Arrow [1962] to one exposed to potential entry by new firms as discussed by Gilbert and Newbery [1982] is exactly what happened in the European electricity sector.

4.3 Competition and Innovation: an Inverted-U Shape Relationship

Aghion et al. [2005] motivate their work with a lack of coherence between prior theoretical models and empirical results. To reconcile Schumpeterian theory with empirical results, Aghion et al. [2005] develop a theory of an inverted-U relationship between the competition level in an industry and the aggregated innovative output in that industry.[13] They argue that a firm's incentives to innovate depend upon the difference between its *post*-innovation and *pre*-innovation rents. Thus, "if more competition reduces a firm's pre-innovation rents by more than it reduces its post-innovation rents, then competition increases profits from innovating and encourages innovation to escape competition" (p. 702, Aghion et al. [2005]).

In the model by Aghion et al. [2005], the economy consists of many sectors characterized by duopolistic competition and innovation happens step-by-step.[14] At every point in time, there are two types of sectors in the economy: (i) leveled or neck-on-neck sectors, where both firms are technologically equally advanced and (ii) unleveled sectors where there is a technological leader and a laggard firm. Competition in a given industry is modeled as the extent to which the firms are able to collude.

Their first proposition states that the equilibrium R&D intensity by both firms in a neck-on-neck sector increases with higher competition in the product market. In contrast, the equilibrium research intensity of a laggard firm decreases with higher competition in the product market. The former is the "Escape-Competition" effect, where the rents from innovating increase with product market competition and hence higher product market competition encourages firms to innovate. The latter is the "Schumpeterian" effect of reduced rents to the laggard who succeeds in catching up with the leader by innovating. The overall effect of competition on innovation will thus be ambiguous as in a portion of industries higher competition will increase innovation and in others higher competition will decrease innovation. This overall effect will thus depend on the (steady state) share of leveled versus unleveled sectors, which in turn will depend on the equilibrium R&D intensity in each of the sectors.

The second proposition provides conditions under which this overall relationship follows an inverted-U shape. When the competition in the product market is low, firms in leveled industries will have little incentive to innovate and hence innovation rates will be highest when the sector is in an unleveled state. Thus, the sector will be quick to exit the unleveled state and slow to exit the leveled state, resulting in a sector with low product market competition being in the leveled state for most of the time. In contrast, when the competition in the product market is high, it is the laggard firm in the unleveled state of industry that has little incentive to innovate while the firms in the leveled state have relatively large incentive to innovate. Hence, the industry will be slow to leave the unleveled state and quick to leave the leveled state, resulting in it being in the unleveled

[13] The empirical contribution of Aghion et al.(2005) is considered below in the Empirical Research on Deregulation, Competition and Innovation section.

[14] It is assumed that the maximum gap that can be sustained between the leader and laggard is equal to 1 due to knowledge spillovers. In other words, it is assumed that there is automatic catch-up in terms of technology so that the laggard firm is never further than one step behind. This further implies that when the laggard firm innovates, i.e. moves one step up the innovation ladder, the leader does not innovate.

state most of the time. Put differently, when there is little competition in the sector initially, increases in competition would result in an increasing innovation rate while, if competition is high from the beginning, further increases in competition intensity would result in lower innovation rate.

It should be pointed out that the inverted-U relationship is expected to hold for aggregate innovation rates in an economy and not for the innovation rates of individual companies, as they respond differentially to the same level of product market competition, depending on the state (leveled or unleveled) in which they are as well as depending on whether they are the leader or the laggard in the unleveled industry.

The theory of an inverted-U relationship between competition and innovation can be applied to the setting of the European electricity sector liberalization. In this case, the industry in each country in each year constitutes one observation along the inverted-U curve. As the previously regulated state monopolies were deregulated starting from the 1990s, the change in the regulatory framework affected the market structure and the competitive environment.

5 Empirical Research on Deregulation, Competition and Innovation

As argued above, many studies investigating the link between competition and innovation suffer from issues of reverse causality between competition and innovation. Finding exogenous variation in product market competition is challenging. However, deregulation of previously highly regulated markets provides one such option. This chapter thus discusses some of the contributions to the competition-innovation literature that study the introduction of competition to previously monopolized markets through deregulation and privatization. This is similar to the approach of this thesis that also uses the exogenous change in regulatory environments as a proxy measure of introducing competition to the market.

Using deregulation of electricity markets in the UK, Jamasb and Pollitt [2005] show that innovation decreased as a result of market liberalization. The authors explain this by short-term profit maximization, i.e. a "Schumpeterian" effect of expected post-innovation rents decreasing more than the pre-innovation rents. Nesta et al. [2014] study the interaction of competition and renewable energy policies in a subset of European countries and show that innovation increases post-deregulation in a subset of technologies, namely renewable energy technologies. They explain this by arguing that conventional energy innovation (i.e. innovation in "brown technologies") is more concentrated among large utilities and incumbent players in the sector since these technologies are more concentrated (e.g. large coal power plants), while renewable energy technologies (such as solar, wind or geothermal) are typically more distributed.

In the United States, Sanyal and Ghosh [2013] observe a drop in patent filings by upstream electric equipment manufacturers around 1992, when the Energy Policy Act was introduced, contrary to booming patenting activity in many other industries at the same time. Unlike Jamasb and Pollitt [2011], Nesta et al. [2014] and this thesis, Sanyal and Ghosh [2013] study the effect of electricity market deregulation in a vertical industry setting, focusing on the impact of electricity market deregulation on its upstream technologies. Using a difference-in-difference design they find that electricity market deregulation is responsible for the decrease in patenting within these technologies. They argue that the overall effect can be explained by three mechanisms, (i) a pure competition effect, corresponding to the Schumpeterian effect in Aghion et al. [2005], (ii) an escape-competition effect, equal to the escape-competition in Aghion et al. [2005] and (iii) an appropriation effect, due to entry of new firms into the upstream market. The latter effect is specific to the vertical setup studied and is comprised of two components: increased bargaining power by upstream firms and demand-push from increased demand due to new entries in the downstream market. Their findings suggest that the negative competition effect dominates the positive competition effect, that there is a positive appropriation effect and that a considerable share of the negative effect remains unexplained.

In general, to date, there are only few studies of the impact of market liberalization in the electricity sector. Yet, there exist studies of other sectors that have been exposed to similar liberalization policies. For instance, Calderini and Garrone [2001] study liberalization of the Telecommunications industry in 17 European countries. The authors point out that liberalization of the telecommunications industry has spurred a fierce debate about whether market incentives are sufficient to sustain appropriate technological development. Therefore, they study to what extent and in what ways opening the market to entry has changed firms R&D investments. They argue, based on their findings, that firms switch their R&D activity towards activities that yield more short-term returns. Like Jamasb and Pollitt [2011], Calderini and Garrone [2001] explain this short-term focus with Schumpeterian effects as the firms switch their focus from long-term to short-term profit maximization. They use scientific publications as proxy for basic research and patents as proxy for applied research and show that the focus of R&D activity has switched from basic to applied research. More specifically, they find that, while scientific publications by incumbent telecommunications firms decreased, patenting by these firms increased.

In addition to studies focusing on a single sector, several studies assess the cross-industry impact of regulatory reforms. Aghion et al. [2005] test their proposition of an inverted-U shape relationship between competition and innovation in a cross-industry panel over firms in the United Kingdom. To deal with the discussed endogeneity issues, they instrument a competition measure with major policy reforms, including the reforms of the European Single Market as well as national reforms such as Thacher-Era Privatizations that vary across time and industries, allowing for causal interpretation of results. They measure competition as (1 - Lerner index)[15], using citation weighted patents as the innovation measure. Their results suggest that there indeed exists an inverted-U shape relationship between competition and innovation. They report the extremum of the inverted-U shape to lie near the median of the distribution (at 0.95). A median value of 0.95 for the competition measure (1- Lerner Index) implies that the median value of the Lerner index in this dataset is 0.05, meaning that on average industries in the dataset are highly competitive.

[15]A Lerner index ranges between 0 and 1, where 0 implies high competition and 1 implies low competition. Later in this thesis, I modify my regulation measure to follow the same structure for ease of comparison.

Aghion et al. [2002] show that the same relationship holds for the top four innovating industries in their sample.

In another study, Aghion et al. [2009] test the inverted-U relationship in a different setting, studying the effects of (greenfield)[16] firm entry on innovation and productivity of domestic firms. The study finds that the response of domestic incumbent firms to greenfield firm entry at the technological frontier is heterogeneous across industries. They argue for a causal effect, where technological frontier industries are subject to a positive relationship between foreign firm entry, innovation and productivity growth, while no such relationship prevails in laggard industries. They theorize that in industries where the domestic firms are technologically developed and thus close to the technological frontier to which the entrant firms belong, as the *new* firms enter, innovation will increase as explained by the neck-to-neck competition effect in Aghion et al.[2005]. Incumbents will be increasing their innovation activity as "escape-entry"[17] effect dominates, given that firms know they can escape entry of foreign firms as they innovate. In contrast, in laggard industries, innovation decreases with the entry of new firms as incumbents maximize short term profits knowing that the threat of new entry reduces expected rents from investing in innovative activity. This effect is similar to the Schumpeterian appropriability effect, where the appropriable returns from innovation decrease (for an individual firm) as more firms enter the market.

Carlin et al. [2004] make use of the natural experiment provided by the introduction of free-market economy to former socialist countries in Eastern Europe and Central Asia. Using a set of 4000 firms over 24 transition economies, they find that a minimum rivalry of at least 5 firms within an industry is necessary to facilitate innovation and growth. They also note some (relatively weak) evidence that presence of a few firms has a stronger effect on performance than presence of many firms. This observation is in line with the inverted-U shape found in Aghion et al. [2005]. More specifically they find that some market power in combination with some pressure from foreign firms boosts innovation. In addition to estimating the impact of market reforms in innovation, the authors also investigate how both competition and innovation impact growth. Carlin et al. [2004] find that innovation is a major determinant of growth, yet, particularly for young firms, competition acts as another driver of growth. While the authors argue that the specific mechanisms through which innovation, competition and growth interact are not entirely clear, they conclude that the firms studied nevertheless seem to follow a Schumpeterian-type competitive process. A drawback of this study is that it relies upon self-reported company survey data.

In sum, the results of economic research, that uses deregulation, privatization and market liberalization as exogenous variation in product market competition to study its impact on innovation, point in different directions, suggesting that further research is warranted. The usage of both supranational (e.g. EU Single Market Program) as well as national regulation (Thacher-Era Privatizations in the United Kingdom) as exogenous change supports my choice of OECD electricity

[16] Greenfield firm entry captures firms that enter the U.K, market by setting up new production facilities in the country (market). Data on entries by internationally operative firms from the United States is used, as authors argue that they are more likely to operate on the technology frontier.

[17] The escape-entry effect is similar to the escape-competition effect discussed above in the summary of Aghion et al. [2005].

market regulation index as an exogenous measure of regulatory change as it captures EU-wide as well as national regulation, with the largest share of reforms carried out on the supranational level.

6 Data

In this section, I describe the data used in the study. I start with a discussion of various competition measures, continue by describing my competition measure - the OECD Electricity Market Regulation Index - and argue that regulation in itself might be a better measure of competition than the available competition measures. Thereafter, I discuss how well patent counts measure innovation as well as the possible strategies for selecting the relevant patents for this study and other covariates that might affect variation in patent counts. I conclude with a brief discussion of countries included in the sample and covariates included in the empirical analysis.

6.1 Measuring Competition in the Electricity Market

Typical measures of market concentration include (i) the Hirschmann-Herfindahl Index[18] as well as (ii) the Lerner index.[19] In their study, Aghion et al. [2005] use the Lerner Index[20] and argue that it is a better concentration measure than the Hirschmann-Herfindahl Index as it does not require a definition of a relevant geographical and product market. However, no sufficient financial data was available to me that would allow for calculation of any of the two indexes. While Eurostat [2017] collects five indirect indicators of competition in the electricity generation sector, all of these display significant flaws and are therefore not used here. This is discussed in more detail in Appendix A: Extensions, where I also extend the study to include an instrumental variable approach using regulation as an instrument for competition.

Challenges might arise when trying to fit the inverted-U shape relationship to the electricity sector as the electricity sector still remains highly concentrated with the market share of the largest firm on average being 59 per cent Eurostat [2017]. Therefore, even if the inverted-U relationship were theoretically present in the sector, it might not be testable because the values might cover an insufficiently large part of the scale of competition and thus not include the extremum of the inverted-U shape. Then again, such a finding would not be completely out of line with Aghion et al. [2005] who mainly observe variation at the top end of their competition scale only (see the section Empirical Research on Deregulation, Competition and Innovation above).

To capture changes in the competitive environment in the Electricity generation sector, I thus use the change in regulation, similar to the studies considered in section Empirical Research on Deregulation, Competition and Innovation. More precisely, I use OECD Product Market Index [OECD, 2017] for the Electricity Sector. In contrast to the EU Electricity Market Directives, the

[18]Herfinhdal-Hirshman Index (HHI) describes market concentration. It is the sum of squared market shares of individual companies and assumes values between zero and 10,000, with high values indicating high market concentration and low values indicating high market fragmentation.

[19]Theoretically, the Lerner index measures a firms market power by calculating as following: (Market Price - Marginal Cost) / Market Price = (P-MC)/P.

[20]In the study by Aghion et al. [2005] measured as: (Operating Profit - Financial Cost)/ Sales.

OECD Index measures the actual change in countries' regulatory environment rather than the legal obligations by the EU Directives that may or may not be implemented in the national legislation as they are intended. For these reasons, I opt to use the OECD Index rather than the EU legislation as my measure of change in the competitive environment.

I use the OECD index, originally coded between 0 (low regulation) and 6 (high regulation), in an inverted version to facilitate the interpretation of results and further normalize it to take values between 0 (high regulation) and 1 (low regulation). The data compiled by the OECD is primarily based on a questionnaire filled out by national governments.[21] The OECD Product Market Index for the electricity sector covers production, transmission, distribution as well as supply, without specific data available for each. Since I cannot distinguish regulatory changes in power generation from transmission or distribution, I study how the changes in all of these affected innovation by electrical power generation companies. Nevertheless, most of the EU regulation mainly affected power generation and not transmission or distribution as the later two remain regulated monopolies to date. The index is available for 22 out of 29 OECD countries included in this study for the time period from 1980 to 2013 and for the remaining 7 countries[22] only in 2013.

6.2 Patents as a Measurement of Innovation

R&D investment is a common way to measure innovation (see for example Griliches [1980]). However, R&D investment data is not alway widely available, particularly for private companies. Additionally, government subsidized private research and development is shown to not to have as large an impact on innovation as that employed by private companies themselves [Popp, 2002]. Another measure of innovation used in economic studies is the number of employees that are involved in R&D within a firm or an industry (e.g. [Scherer, 1967]). However, these two are just proxy measures of input rather than output.

Patents are likely a good approximation of innovation because they measure the outcome of the innovation process rather than the input. A patent is a legal title that grants the patent applicant (usually the inventor) exclusive rights to her invention. According to WIPO, exclusive rights to an invention imply that the patent owner has an exclusive right to decide over the commercial use of the invention that the patent protects, including but not limited to production, distribution and licensing [World Intellectual Property Organization, n.d.a]. Since a patent provides territorial legal protection, when seeking a patent, the patent applicant must indicate in which countries she is seeking protection [ibid.].

Furthermore, WIPO highlights three key requirements that an innovation must meet to be granted a patent protection [World Intellectual Property Organization, n.d.a] : First, there must be a novelty element, i.e. the innovation must entail new knowledge which is not known as *"prior art"*, that is the previous state of technology within an industry. Second, the invention must involve

[21]The latest questionnaire available is from 2013: `http://www.oecd.org/eco/reform/PMR-Questionnaire-2013.pdf`, methodological description of index compilation: `http://www.oecd-ilibrary.org/docserver/download/215182844604.pdf?expires=1508934308&id=id&accname=guest&checksum=593B9BCD8580ABF8F8A0CFAE408C8F`

[22]These countries are: Bulgaria, Croatia, Cyprus, Latvia, Lithuania, Malta, Romania.

an *"inventive step"*, i.e. it must be non-obvious. Third, the invention must be industrially *useful*, that is, e.g. it cannot be just a theoretical model.[23]

Unlike other innovation indicators, the records of patented innovation are maintained in openly available databases, allowing for the data to be used in scientific studies. As an approximation of innovation rates in the electricity sector I therefore use patent data from the European Patent Office PATSTAT database [European Patent Office, 2017c]. This database includes worldwide patent application data as well as data on patent-related legal events.

Certain shortcomings are, however, associated with using patents as proxy for innovation. First, many innovations are not patented. Nevertheless, patents capture the inventions valued most by the inventors, which are also likely to have higher economic value. Second, patents are highly heterogeneous with regards to the value of the underlying technology. This leads to patent value being highly skewed, with few highly valuable patents [Trajtenberg, 1990]. Various options for accounting for this heterogeneity exist, the most relevant of which are reviewed and tested in the Robustness Analysis section, subsection Accounting for Variation in Patent Value.

6.3 Matching Patents to Firms

Generally, there are two ways to approach the selection of relevant patents: (i) Linking patents to the electricity generation sector, (ii) Linking electrical power generating firms to their patents. Both selection strategies are severely complicated by the fact that there is no industry classification available for patents in any of the patent databases.[24]

In my main data selection strategy, I select the European Power Generation firms from the ORBIS company database [Van Dijk, Bureau, 2011].[25] In this way, I get closest to selecting firms that were affected by the deregulation policy. The European companies are more likely to be affected by the EU regulation in their decision making process regarding innovation, while companies that have their main activity elsewhere might feel less of an impact.[26] This distinction makes sense as technologies, especially more valuable ones, once invented, are typically patented in many countries. Subsequently, I link the European firms to their patents using the OECD HAN database.

No common identifiers (such as a company ID) are shared by the PATSTAT and ORBIS databases. However, both databases include data such as the applicants name[27] and the name of

[23] A patent application entails a cost dependent on the geographical scope for which the patent applicant seeks protection. Furthermore, filing a patent application is a lengthy process that requires legal knowledge. During patent application process all "prior art" (prior technological state) must be stated in the patent application, typically done by patent office employees with specialized knowledge on a handful of patent classes in cooperation with the patent applicant and her patent attorney.

[24] While Eurostat [Looy et al., 2015] in cooperation with KU Leuven maintain a correspondence table between patent classification classes and a selection of industry classification codes, neither electricity nor energy more generally are included in this concordance table or any other concordance table known to me. Instead, patents are divided in thousands of highly specialized subclasses, following International Patent Classification (IPC) code system [World Intellectual Property Organization, 2017].

[25] I select the relevant geographic area and NACE Rev 2 industry classification code (NACE Rev 2 code used is 3511 - Production of electricity). I only select the companies that are classified under 3511 - Production of electricity as their primary industry classification code and thus have electricity generation as their primary activity.

[26] Since the European Companies are likely the ones actually having most of their operations placed in Europe, i.e. producing electricity in Europe, they should be more directly affected by the regulatory changes.

[27] Often a company or a research organization.

the inventor. This data is not standardized and might therefore differ.[28] The ORBIS database also provides data on patents for a subsection of companies. This is a subset of ORBIS companies that OECD has linked to their patents in the PATSTAT database, creating the OECD HAN (Harmonized Applicant Names) Database. Thus for a subset of companies all their patents can be identified. The HAN Database relies upon an algorithm that takes the following actions: (1) it performs the search country by country, (2) the harmonization of the names is based on a country-specific dictionary,[29] (3) The OECD HAN database uses a fuzzy string match algorithm based on strings and tokens (Dernis [n.d.] and Eurostat - OECD [n.d.]).[30] (4) Furthermore, the OECD sets high matching thresholds for high precision.[31]

I use this pre-identified set of companies and their patents, available through the HAN Database and also on Orbis (some data is also stored in PATSTAT). It should be noted that a large share of companies do not have any patents at all, a pattern that is generally prevalent in different industries [Aghion et al., 2005]. The ORBIS data only includes the priority patent, that is, the patent from the first patent office where it was applied for. These patents might be owned by one subsidiary in a group, which could be in another country. Thus reporting the number of companies per country could be misleading and assigning all these patents to a single country could lead to biased results. For these reasons, I increase the dataset by extending it to all patents within the same patent family. Thus I create a dataset of granted patents within the relevant technologies that are owned by the power generation firms.[32] I use a narrow definition of a patent family, that is the DOCDB patent family where all patents cover a single invention. [33]

[28]For example company name in Orbis would state "SYDKRAFT NUCLEAR POWER AB" while the inventors name in PATSTAT would read "Sydkraft Aktiebolag", clearly referring to the same company but making matching the companies in the industry to their patents more challenging. Additionally, also within PATSTAT this entry varies in the same manner between patents belonging to the same firm. Therefore, I initially intended to use a fuzzy string match approach, where similar strings can be matched based on their similarity score. This approach to patent application linkage to patent applicant data in some other database is discussed at length in Raffo and Lhuillery [2009] who has developed a methodology for an unbiased match of fuzzy string variables with a special application to patent data. However, the same issues as above arise, that is the difficulty of selecting the relevant patents or the respective IPC classes. As no reliable way (based on previous literature and existing data) could be found to select the IPC classes in which electricity generating companies patent, this strategy was rejected.

[29]Such a dictionary takes into account country-specific alphabet characters, indications of legal forms and other things, for more detailed description see Eurostat/KU Leuven dictionaries by Magerman et al. (2009). Data Production Methods for Harmonized Patent Indicators: Patentee Name Harmonization. EUROSTAT Working Paper and Studies, Luxembourg, on which the OECD vocabularies are built on.

[30]Compared to the OECD HAN database, a fuzzy string match using a bigram matching algorithm could potentially improve the dataset through decreased number of falsely negative matches as it decreases the false negatives while allowing for more falsely positive matches that can thereafter be manually rejected. See Raffo, 2009 for an extended discussion. He also notes that using bigram algorithms produces unbiased results while a token/string algorithm (such as the one used by the OECD) may lead to a biased sample [Raffo and Lhuillery, 2009].

[31]OECD claims that this minimizes both false positives and false negatives, however, a trade-off generally exists as high matching scores would typically reduce false positives at the expense of an increased number of false negatives [Raffo and Lhuillery, 2009]. They nevertheless also carry out manual controls to improve precision.

[32]It takes about 3 to 4 years for an EPO patent to be granted. National patents are likely to be granted within a shorter time frame. While there is a slight possibility that a minimal share of data is truncated, other results of this thesis seem to be robust to that. In the Robustness Analysis section, where patents are weighted by their citations, the dataset is narrowed down to cover years up to 2010. As the relationship also holds in this dataset, data truncation seems to not be an issue. Furthermore, the Energy Patent Dataset (also found in Robustness Analysis) is based on selected patent applications rather than granted patents. Since it confirms the results from the main dataset, truncation concerns should be further minimized. As an additional attempt to alleviate the concerns of potential truncation affecting results, I run the same regression using the main dataset of European firms and choose a shorter time frame (from 1990 to 2010). This dataset confirms my results as the significance of the coefficients remains unchanged and they further increase in magnitude.

[33]There are two types of patent families maintained in PATSTAT. The DOCDB patent families cover the same technology while the INPADOC families cover same or related technologies, that share at least one priority [Martinez, 2010]. Thus, by using the more narrow DOCDB family, I ensure that I do not extend my dataset to technologies outside those relevant for electricity generation, which would be a potential risk if using the broader INPADOC

6.4 Patent Counts

Innovation rates in this study are measured by patent counts that are aggregated by year and by country. The counts are based on the "Earliest filing date" (also known as the "priority date"), that is the date when the patent protecting the particular innovation was first filed somewhere in the world. This date is chosen as it is the date closest to the actual innovation date [European Patent Office, 2017a]. An alternative could have been to use the application filing date, that is the filing date of the particular patent application considered [European Patent Office, 2017a]. This would be the date when the innovation is introduced to the country in question.[34] An overview of patent counts by European electricity generation firms by country over time is included in Appendix B: Data.

6.5 Selected Countries

Countries studied include all of the EU-28 countries as well as Norway, i.e. 29 countries that are all currently subject to EU electricity market policies.[35] I further exclude the time period before 1991 for the post-socialist countries, i.e. Estonia, Latvia, Lithuania, Poland, Slovakia, Czech Republic, Slovenia, Croatia, Hungary, Bulgaria, Romania. Both Slovakia and the Czech Republic lack data up to 1994, that is prior to disintegration of Czechoslovakia their patents were recorded jointly and hence cannot be assigned to either of the countries.

6.6 Covariates

As discussed in section Economics of Innovation and Intellectual Property Rights, innovative behavior is affected by changes in relative prices of different factor inputs. Based on prior studies, the most important explanatory variables to include are (i) Changes in fossil fuel prices. Since fossil fuel prices (Oil, Gas, Coal) are highly correlated, I only include an oil price index. The price index used is the Brent oil price index [BP, 2017].[36] Furthermore, I include (ii) country level electricity demand from the United Nations Energy Statistics Database [UN Statistics Division, 2017]. Since electricity cannot be stored, overall demand is somewhat less interesting a measure than peak demand. Nevertheless, it is the best available approximation. Lastly, (iii) renewable energy supporting policies such as renewable energy subsidies or carbon taxes are intended (and work) to increase innovation in certain technologies. The International Energy Agency maintains a Renewable energy policy database [OECD/IEA, 2016] where it records country level data on renewable energy policies. For the relevant geographical region and time frame, there are records of over one hundred renewable energy policies. I include country level dummy variables, where the dummy takes a value of 1 the year that a renewable energy policy is introduced for the first time in a country and every year thereafter. This approach accounts for a general switch towards

family.

[34] The data is checked for missing values of "First filing date" and even though some (few) missing values are reported, these cannot be imputed by "Application filing date" as in these cases all date variables are missing.

[35] Norway was early to deregulate its market and it has adopted EU Electricity market regulation [European Commission, n.d.].

[36] Other oil price indexes are highly correlated.

renewable energy policies in a country, rather than measures the effect of each individual policy which is not interesting here. The impact of the energy policies and subsidies is complicated to measure, not least because they cover a wide range of policy tools and technologies and because these policy initiatives display considerable heterogeneity in their geographical and time scope. I focus on the first/initial policy change on the national level, in an attempt to capture a more general change in the national sentiment regarding renewable energy subsidies. It is important to note that the timing of this variable varies considerably across countries even if the distribution of the corresponding variable is somewhat skewed towards the earlier years. It is assumed that companies respond to actual changes in the national policy rather than global agreements. As rational agents, they only respond to actual changes in input prices (and therefore policy initiatives that might actually impact these). While deviations from this assumption might hypothetically introduce bias to the below estimations, it ought to be reiterated that the relationship of interest for this thesis is less concerned with the effect of idiosyncratic energy policies on the company level and rather focused on accounting for the role of general regulatory attention to the electricity generation sector.

7 Empirical Strategy

The Electricity Market Liberalization reforms in the European Union are particularly well suited for the purpose of my study as (i) the electricity market regulation across the EU has been harmonized through the three Electricity Market Directives discussed in the Regulatory Framework section. In other words, all countries were subject to the same treatment: they started off as monopolies, were all subject to the three Directives converging to a liberalized market.[37] (ii) Thus, the only variation in the electricity market regulation across countries is with respect to the timing of the reforms in each country, which does exhibit quite a lot of variation. (iii) The EU electricity market reforms were exogenous to the national markets, as the motivation was the introduction of competition in the markets as well as integration in the context of the European Single Market program. Furthermore, the precise timing of implementation of these reforms on the national level was not motivated by innovation concerns in the sector rather than competition concerns. (iv) While exogenous to innovation, these reforms were aimed at introducing competition to the national electricity markets. As argued in the section Empirical Research on Deregulation, Competition and Innovation, there is a close relationship between product market regulation and the competition conditions in that market. (v) Electricity is a homogeneous good, hence innovation in the sector is likely to be directed towards improving efficiency rather than differentiation, which is in line with the theoretical model in Aghion et al. [2005].

I use an unbalanced panel of 29 countries and 24 years and choose a fixed effects model. I cluster my data by country, including country fixed effects to account for country specific variation

[37] Some countries, i.e. Great Britain and Norway liberalized their electricity markets before the EU-wide deregulation reforms. However, these also eventually converged to the same regulation. In general, the OECD Product Market Index captures the regulatory change in a consistent way, making the cross-country observations comparable.

in innovation. Year fixed effects are also included to account for variation in patent counts as a result of aggregate trends. By using a fixed effects model, I thus measure the average effect of regulation across countries. For determining the effect of the product market regulation on innovation, I use the OECD Electricity Market Regulation Index as the independent variable and the number of patents as the dependent variable and estimate the following model:

$$(1)\ Num.ofpatents_{ct} = \beta_0 + \beta_1 OECD\_index_{ct} + \beta_2 OECD\_index^2_{ct} + \mathbf{bX_{ct}} + \lambda_c + \alpha_t + \epsilon_{ct}$$

where $Num.ofpatents_{ct}$ is the number of patents per year and country, β_0 is a constant, $OECD\_index_{ct}$ is the OECD electricity market regulation index, $OECD\_index^2_{ct}$ is the square of OECD electricity market regulation index, X_{ct} is a vector of covariates, λ_c captures the country fixed-effects, α_t captures the year fixed-effects and ϵ_{ct} is the error term.

I include both, a linear and a squared term, as it is the standard way of testing for an inverted-U shape relationship [Lind and Mehlum, 2010] and applied also by Aghion et al. [2005]. When interpreting the regression results, the two coefficients of the linear and the squared term must be interpreted jointly, as can easily be seen from the first order derivative of the equation.[38] Such a model should capture an inverted-U shape relationship if the linear and squared term are both jointly significant and the coefficient of the linear term is positive, while the coefficient of the squared term is negative. Intuitively, the linear term will originally dominate, whereas for higher values of the respective variable the square will dominate, wearing off the linear relationship at some point and turning it into an inverted-U shape.

However, Lind and Mehlum [2010] argue that joint significance and presence of an extreme point are neither necessary nor sufficient criteria for concluding presence of an (inverted) U-shape relationship. The extreme point might be outside the data range. This is possible in my dataset as deregulation of an industry does not automatically lead to perfect (or even close to perfect) competition. This is supported by the data that show that the electricity generation sector is still highly concentrated. Lind and Mehlum [2010] also argue that there should be an additional criterion, namely sufficient steepness of the curve at the both ends of the U-shape relationship. For this they propose to carry out two t-tests testing the slope at both ends of the curve.[39] Additional to the t-statistic for less steep end of the inverted-U curve[40], I report the extremum and the Fieller interval for extreme point.[41]

Most of the time innovation does not happen spontaneously. Rather, it follows as an outcome of a lengthy R&D process. Bearing this procedural nature of firm-level innovation in mind, I make certain assumptions regarding the timing of both electricity market liberalization reforms as well as

[38] $(\delta Numberofpatents_{ct}/\delta OECD\_index_{ct}) = \beta_1 + 2\beta_2 OECD\_index_{ct}$

[39] These additional criteria are therefore tested using *utest*, a STATA command design by Lind and Mehlum to test the criteria for a U shaped or inverted-U shaped relationship.

[40] I carry out two t-tests for each of the ends of the inverted-U shape, however, I only report the one with the lowest t-statistic.

[41] The Fieller interval is a confidence interval for the ratio of two normally distributed estimates, see Lind and Mehlum [2010] for derivation.

innovation and patenting. Namely, I assume that the information about the planned market reforms is known to the firms well ahead of the time of the actual implementation. This is likely, as the national liberalization reforms resulted from the transposition of EU-level directives into national law and were therefore implemented following a rigorous planning procedure. Furthermore, I assume that the firms time their R&D efforts so as to reach the desired innovation level at a specific point in time, anticipating the change in the regulatory and competitive landscape. This is consistent with the presumed characteristics of rationally optimizing firms introduced in the theoretical framework. For these two reasons, the model specification does not include any leads or lags.

Many studies that use patent data (including Aghion et al. [2005]) use Poisson or Negative binomial model designs[42] because these designs are useful in approximating the distribution of nonnegative count data such as patent counts [Hausman et al., 1984]. The Poisson regression model differs from the OLS model in its assumption of Poisson distributed data, usually being right-skewed. This is usually a good approximation for low values of count data. However, for higher value count data (as is the case here), this distribution is reasonably well approximated by a normal distribution. As a Poisson regression models coefficients as a change in the natural logarithm of the outcome variable, the interpretation is not straightforward. Given that the residual errors in my specification are indeed approximately normally distributed[43] and I do not aim to make out of sample predictions, I therefore refrain from using the Poisson model and use the easier-to-interpret OLS model instead.[44]

8 Results

In this section, I present the main results of my study showing the effect of deregulation and competition in the electricity sector on innovation by European power generating firms in Europe. The set of European firms holds 21 559 patents. The table Descriptive Statistics (1) below presents summary statistics of the dependent variable as well as the main independent variable of interest and the covariates. The number of patents is zero-inflated due to many countries having zero patents in some years. The OECD electricity regulation index, as explained above, is transformed such that the observations take value between 0 (fully regulated sector) and 1 (fully deregulated sector). While variation only occurs in the lower 85 per cent of the possible range, the data is relatively normally distributed within that range, with a mean of 0.44. The global Oil Price Index exhibits considerable variation across time. The electricity demand also exhibits large variation, as size of countries included in the study varies greatly. The third covariate included is a country specific dummy that turns to 1 when the first renewable energy policy was introduced. The table

[42]Negative binomial regression is an extension of the Poisson regression that relaxes the assumption of no overdispersion of data [Hausman et al., 1984].

[43]The distribution of the residuals can be seen in table Distribution of the Residuals.

[44]When estimating a Poisson fixed effects regression with the main dataset (European Firms), the significance level and the sign of coefficients remains unchanged. When estimating a Poisson fixed effects regression with the Global firms dataset (from the Robustness Analysis section), the significance of the squared term increases from 10 to 1 per cent significance level. (Not reported)

below summarizes the number of countries where the REP dummy =1 in a given year. The distribution is somewhat skewed towards higher values as most renewable energy policies were introduced in more recent years.

Table 1: Descriptive Statistics (1)

Dataset (1990-2013)	Min	25%	Median	75%	Max	Std. Dev.	Country-Year Obs.
Number of patents	0	14	27	52	167	29	525
OECD_index	0	0.11	0.43	0.62	0.85	0.28	525
Oil Price Index ($/bbl)	13	19	28	72	112	34	525
Electricity Demand (mkWh)	1980	28684	60965	126439	532424	131832	522
REP dummy = 1	2	5	11	20	28	9	24

As discussed in the Data section above, I expect the effect of European electricity market deregulation to be most pronounced among European firms as they are the ones actually operating within the geographical area exposed to this regulatory change. Indeed, coefficients of the linear and quadratic OECD index terms are significant at the 1 per cent level for both specifications: column (1) which does not include other covariates and column (2) where all 3 covariates are included. Both the linear and quadratic OECD Electricity Market Regulation Index terms have the expected signs, i.e. the linear term has a positive coefficient while the squared term has a negative coefficient, indicating the presence of an inverted-U shape relationship between OECD index and number of patents. The size of the effect of the linear term increases slightly after inclusion of the additional covariates (from 31.79 in column (1) to 33.43 in column (2)) while the size of the effect of the squared term decreases somewhat in its magnitude (from -41.76 to -36.22). As will be seen in the section Robustness Analysis, subsection Results where I extend the analysis to firms globally, the effect is indeed economically most significant for the European firms.[45,46]

Also the covariates included have a statistically significant effect on innovation. Higher oil prices have a considerable positive effect on innovation, presumably through change in the relative input prices, as it becomes more attractive to invest in renewable energy innovation. Increase in the country-level electricity demand has a statistically significant negative effect on innovation. This could be explained with higher demand alleviating competitive pressures in the market. Decreasing demand, on the other hand, increases competition as the same firms compete for a smaller overall market. Overall, the model seems to be a good fit, as evidenced by the within-country R^2 of around 94 per cent in both specifications. This shows that my model is good at explaining the variation within the panel units, i.e. the countries.

[45] For comparison, regressions with only the linear OECD index variable are included in Appendix A: Extensions. It is clear that the inverted-U shape fits the data better than a linear relationship since the coefficient in the linear regressions is of much smaller magnitude for all three datasets and exhibits less significance for the main dataset.

[46] The inverted-U shape relationship is not expected to hold on the company level as argued in Competition and Innovation: an Inverted-U Shape Relationship and confirmed in a regression with a company-level outcome variable. (not reported)

Table 2: OLS FE Regression Results: European Electrical Power Generation Firms

VARIABLES	(1) Number of patents	(2) Number of patents
OECD_index	31.79***	33.43***
	(5.565)	(6.442)
OECD_index^2	-41.76***	-36.22***
	(6.437)	(7.437)
Oil Price Index		0.547***
		(0.0379)
Electricity Demand		-8.43e-05***
		(2.96e-05)
REP dummies		YES
Constant	5.421***	0.781
	(1.790)	(3.490)
Observations	525	522
Within R^2	0.931	0.947
Number of countries	29	29
Country FE	YES	YES
Year FE	YES	YES
F-statistic	255.2	172.6

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the table Testing for the Presence of an Inverted U-Shape Relationship below, I carry out further tests for the presence of an inverted-U shape relationship in the regressions presented in table OLS FE Regression Results: European Electrical Power Generation Firms above. T-tests for both column (1) and column (2) provide additional strong support for presence of an inverted-U relationship, with a large t-statistic of 5.71 (p-value 9.89e-09) and 3.87 (p-value 0.0000616) respectively. The extreme point is calculated to be at 0.38 for column (1) with a 95 per cent Fieller interval for the extreme point between 0.31 and 0.46. The extreme point is calculated to be at 0.46 for column (2) with a 95 per cent Fieller interval for the extreme point between 0.37 and 0.59. This means that for the main specification of the main dataset the extreme point lays at 0.46, i.e. slightly above the mean of the OECD index in this dataset.

Table 3: Testing for the Presence of an Inverted U-Shape Relationship

Specification: $f(x) = x^2$	(1)	(2)
Extreme point	0.38	0.46
Overall test of presence of an Inverted-U shape:		
t-value	5.71	3.87
P>|t|	9.89e-09	0.00006
95% Fieller interval for extreme point:	[0.31; 0.46]	[0.37; 0.59]

9 Robustness Analysis

In this section, I provide two robustness checks additional to the main analysis above: (i) using two different data selection methods, i.e. testing the strength of the relationship in two additional datasets and (ii) adjusting patent data by their forward citations to account for variation in patent value.

9.1 Inverted-U Shape Relationship in Other Datasets

I carry out further tests of the sensitivity of the inverted-U shape relationship using two other datasets. That is, I test (i) the effect of regulation and competition in European electricity sector on European patents by Global companies. I also test (ii) the effect of regulation and competition in the electricity sector on innovation in energy patents more generally, based on a selection of relevant patent classes in the International Patent Classification (IPC).

9.1.1 Data

(i) To select patents by Global firms, I simply extend my geographical criteria in the ORBIS company database to include companies from the entire world and then match these companies to their patents in Europe. (ii) In an attempt to select relevant patents based on the patent classification codes, I rely upon previous studies, including Johnstone et al. [2010] for renewable technologies and Lanzi et al. [2011] for fossil-fuel technologies. I thus follow the same methodology of patent selection as Lanzi et al. [2012], who likewise study determinants of innovation in the electricity generation sector. The list of all patent IPC codes included in the set can be found in the Appendix B: Data. This data, however, includes patent classes that cover the energy sector more broadly and hence could be used also for, e.g. heat generation. This is a more general problem for a data selection strategy based on patent classification codes, as any classification codes will always include patents from various industries, even if some industries patent more frequently in certain patent classification code classes than others. The overall effect of electricity market liberalization in this data set is likely ambiguous. On the one hand, the effect might be less pronounced due to the selection of patents being broader than just the electric power generating industry. On the other hand, this data selection method might capture more relevant innovative activity by other stakeholders, such as universities and research centers, that were also affected by the regulatory change.

9.1.2 Results

The table Descriptive Statistics (2) below shows the distribution of patents in these two datasets. Like in the main dataset, the number of patents per year and country is zero-inflated in the Global Firms dataset, while no zero values are present in the Energy Patents dataset even if the data is still right-skewed. The size of the data set in terms of the total number of patents increases when using these two data selection methods, as compared to the main dataset. The set of Global Firms in total hold 38 118 patents. The main dataset, the patents held by European Firms, is a strict subset of this dataset. The data set based on selected relevant Energy patent classes is the largest of the three, with 1 086 752 observations.

Table 4: Descriptive Statistics (2)

Dataset (1990-2013)	Min	25%	Median	75%	Max	Std. Dev.	Country-Year Obs.
Num. of pat. (Global Firms)	0	18	47	108	207	49	525
Num. of pat. (Energy Pat. Classes)	3	518	1657	3004	5111	1266	525

The table OLS FE Regression Results: Global Electrical Power Generation Firms below presents results based on the dataset of European patents by firms globally. Like for the European firm patents in the main Results section, the coefficient of the linear term is positive and that of the squared term is negative, i.e. they both have the expected signs. The coefficient of the linear OECD index is significant at the 1 per cent level in both specifications, while the coefficient of the quadratic term is significant at 1 per cent in column (1) with the significance level decreasing to 10 per cent after including covariates in column(2). Thus, the presence of the inverted-U shape in this dataset is somewhat more uncertain. However, this is in line with the non-European firms being less affected by the European regulation, as discussed in the Data section. The effect size of both the linear and the squared term decreases considerably after inclusion of covariates (from 36.39 to 26.76 for the linear term and from -32.89 to -16.57). The effect is smaller in magnitude than in the main dataset even if this dataset has over 50 per cent more patent observations. Like in the main dataset, the within R^2 is very high, meaning that the model accounts for the vast majority of variation in patenting over time within the countries.

Table 5: OLS FE Regression Results: Global Electrical Power Generation Firms

VARIABLES	(1) Number of patents	(2) Number of patents
OECD_index	36.39***	26.76***
	(6.828)	(8.246)
OECD_index^2	-32.89***	-16.57*
	(7.897)	(9.520)
Oil Price Index		1.176***
		(0.0485)
Electricity Demand		-8.22e-05**
		(3.79e-05)
REP dummies		YES
Constant	3.101	-16.96***
	(2.196)	(4.468)
Observations	525	522
Within R^2	0.971	0.975
Number of countries	29	29
Country FE	YES	YES
Year FE	YES	YES
F-statistic	624.9	383.8

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the table Testing for the Presence of an Inverted U-Shape Relationship below, I carry out further tests for the presence of an inverted-U shape relationship in the table OLS FE Regression Results: Global Electrical Power Generation Firms above. A t-test for column (1) provides further support for presence of an inverted-U relationship in this specification, with a t-statistic of 2.72 (p-value 0.003) and an extreme point at 0.55. The 95 per cent Fieller interval for the extreme point is between 0.43 and 0.78. However, after the inclusion of covariates in column (2), i.e. the main specification, the t-statistic has a low value of 0.49 (with p-value 0.311). The extreme point is shifted closer to the competitive end of the scale and is now located at 0.81 with a 95 per cent Fieller interval for the extreme point reaching well outside the defined range, rising some concerns regarding the existence of an inverted-U relationship in this dataset.

Table 6: Testing for the Presence of an Inverted U-Shape Relationship

Specification: $f(x) = x^2$	(1)	(2)
Extreme point	0.55	0.81
Overall test of presence of an Inverted-U shape:		
t-value	2.72	0.49
P>|t|	0.003	0.311
95% Fieller interval for extreme point:	[0.43; 0.78]	[-Inf;0.50] U [-2.99;+Inf*]
		*Outside the defined range

As can be seen in the table OLS FE Regression Results: Energy Patent Classes below, electricity market deregulation appears to have a significant effect on innovation in the energy sector more broadly. Both the linear and quadratic OECD Electricity Market Regulation Index terms are significant at the 1 per cent significance threshold and have the expected signs, i.e. the linear term has a positive coefficient while the squared term has a negative coefficient. This indicates presence of an inverted-U shape relationship between the OECD index and the number of patents. Coefficients for both the linear and quadratic OECD Index terms are significant both without covariates (column (1)) as well as after the inclusion of the relevant covariates (column (2)), even if the magnitude of the effect decreases somewhat in the latter specification (from 1587 to 1447 for the linear term and from -1,608 -1,064 for the squared term). When comparing the size of effect to the main results, proportionally to the size of the two datasets it is somewhat less pronounced for both terms. The size of the coefficient of the linear term is 44 times larger in this dataset and the size of the coefficient of the squared term is 30 times larger, while the size of this dataset is about 50 times the size of the main dataset. It was discussed in the Data section above that selection of relevant patents by this methodology, i.e. by selecting the relevant patent classes could have an ambiguous impact on the overall effect. Indeed, the effect appears to be smaller in magnitude when using this broader dataset. Nonetheless, the inverted-U shape still appears to be present in this dataset. Like in the main dataset, the covariates are both significant and have the expected signs and the within R^2 is very high, meaning that the model accounts for the vast majority of variation in patenting over time within the countries.

Table 7: OLS FE Regression Results: Energy Patent Classes

VARIABLES	(1) Number of patents	(2) Number of patents
OECD_index	1,581***	1,447***
	(218.2)	(257.2)
OECD_index^2	-1,608***	-1,064***
	(252.3)	(297.0)
Oil Price Index		29.42***
		(1.513)
Electricity Demand		-0.00507***
		(0.00118)
REP dummies		YES
Constant	357.3***	93.85
	(70.17)	(139.4)
Observations	525	522
Within R^2	0.950	0.960
Number of countries	29	29
Country FE	YES	YES
Year FE	YES	YES
F-statistic	360.4	233.9

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the table Testing for the Presence of an Inverted U-Shape Relationship below, I further test the presence of an inverted-U shape relationship in the table OLS FE Regression Results: Energy Patent Classes above. T-tests for steepness of the slope further support the presence of an inverted-U relationship in the data at the 1 per cent significance level for specification in column (1) and at the 5 per cent significance level for specification in column (2) with t-value of 4.73 respectively 1.69. Furthermore, I report the extreme point which is located at 0.49 for column (1) and 0.68 for column (2). The 95 per cent Fieller interval for the extreme point is reported to be between 0.46 and 0.60 for column (1) and between 0.52 and 1.11 for column (2), i.e. outside the possible range, thus far being the only concern regarding the existence of an inverted-U relationship in this dataset as column (2) represents the main specification.

Table 8: Testing for the Presence of an Inverted U-Shape Relationship

Specification: $f(x) = x^2$	(1)	(2)
Extreme point	0.49	0.68
Overall test of presence of an Inverted-U shape:		
t-value	4.73	1.69
P>|t|	1.50e-06	0.0456
95% Fieller interval for extreme point:	[0.42; 0.60]	[0.52; 1.11*]

*Outside the defined range

9.2 Accounting for Variation in Patent Value

9.2.1 Data

As noted in the main Data section above, patents are highly heterogeneous in their value. To account for this, studies have used a range of tools. Some, for example, adjust for the size of the patent family, i.e. the total number of countries in which the invention is protected by a patent (e.g. Lanjouw et al. [1998]). However, adjusting for the size of the family would account for the value of the patent to the inventor rather than its value in terms of new knowledge contribution (as value to the inventor could also stem from preventing a competitor from using the particular invention). Additionally, the different patent jurisdictions vary greatly with respect to the market size [Van Zeebroeck, 2011]. Therefore, other studies only select patents that belong to the triadic patent families, i.e. are patented at the three largest patenting office: European Patent Office, Japan Patent Office and United States Patent and Trademark Office. For example, Nesta et al. [2014] use this methodology. Since I explicitly focus on European patents, this methodology cannot be applied here. Furthermore, Lanjouw et al. [1998] also use patent renewal rates to account for the value of patents. The rationale behind this is that, while patents are granted for a time up to 20 years, a fee must be paid every couple of years to maintain the validity of a patent. However, size of fees and the period after which a patent must be renewed vary across patent offices and jurisdictions (Compare e.g. European Patent Office [2017b] and World Intellectual Property Organization [n.d.b]). As my dataset is relatively recent, renewal rates could only be accessed for a subset of it. Like patent family size, renewal rates are only an indirect measure of the inventive value of the technology protected by the patent as they capture the value of the invention to the patent owner rather than the value of the invention in terms of knowledge contributed.

A more convincing approach to accounting for value of patent-protected inventions is weighting the patents by their citations. When a patent is granted it includes backward citations, i.e. citations to patents filed earlier that are related to the current invention, they represent the "prior art" within the relevant technology. These citations are added to the patent documentation by the patent examiner, in consultation with the patent applicant and her patent attorney [OECD, 2009]. As noted above, it is important to include all relevant citations because a patent is only valid for truly new inventive activity, that exceeds the realm of the prior art. For that same reason, the patent applicant has an incentive to ensure that no unnecessary citations are included. Therefore, the patent backward citations should be a good indicator of prior knowledge that was used by the inventor in developing the new technology [Popp, 2002]. By this reasoning, if a patent has been frequently cited in later patent applications, then the knowledge included in that patent has been particularly useful. Several studies have tried to assess the exact relationship between patent citations and the value of the underlying invention. One of the first significant contributions was by [Trajtenberg, 1990]. He shows that there is a close relationship between number of patent citations and the social benefit from innovation. Furthermore, he finds that the relationship is nonlinear, i.e.

that patent value increases more than linearly in the number of citations. Other studies (e.g. Hall et al. [2005] and Kogan et al. [2017]) relate patents to stock market value of firms and likewise find that patent value is disproportionately concentrated to highly cited patents. In a cross-industry study, Hall et al. [2005] find that there are large differences in impact of citations on market value in different industries [ibid.]. Thus no universal weighting scheme can appropriately be applied to citations. However, on average Hall et al. [2005] find that firms having two to three times the median number of citations per patent display a 35 per cent premium in stock market. Aghion et al. [2005], whose theoretical framework I rely upon in this thesis, do not elaborate on their specific approach to citations, other than explaining that they do weight the number of patents by the average number of citations in an industry.

A study by Popp [2002] provides probably the most advanced approach to adjusting patent value by using its forward citations. Due to citation truncation issues (as more recent patents will be naturally cited less times to date than older patents), simple patent citation counts are not a realistic reflection of the patent value, i.e. the value that a patent adds to the knowledge stock. Therefore, Popp [2002] suggests to consider the probability of a citation that is dependent on the number of citations to date as well as patenting propensity within a certain technology over time. That is, Popp [2002] accounts for probability of a citation for each individual patent, but also weights this value by the average citation propensity within the particular technology over time.

The strategy applied by Popp [2002] presupposes specialist knowledge of which patent classification codes belong to the same technology classes, a knowledge which I do not possess.[47] Since I cannot use the strategy proposed by Popp [2002], I apply a slightly simplified approach, by weighting the patent counts by citations of patents in the year the priority patent was filed and in the five subsequent years. Because it takes up to 18 month until a patent is published, as well as up to six months until the patent data is updated in the database, the patent data is thus likely not complete for years 2016 and 2017. This reduces the length of my dataset to years between 1990 and 2010. According to Popp [2002], most citations come in the years closely after the innovation, thus I in this way still capture the majority of heterogeneity in patent value. More specifically, I normalize the patent value by the forward citations of their *narrow patent family*, i.e. DOCDB family, a narrow definition of a patent family, where all patents cover a single invention.[48] Weighting by patent family citations thus means that I account for all citations that refer to the very same technology.

9.2.2 Empirical Strategy

As explained above, patents vary greatly with respect to their value and this variation is best accounted for by weighting patents with the number of their forward citations, i.e. number of times when patents were cited by more recent patents, thus likely having contributed useful knowledge to

[47] In theory, this approach could be used for one of my datasets: the Dataset of Energy Patents. However, since this is not my main dataset I do not apply this patent-citation weighting method.

[48] There are two types of patent families: DOCDB family includes all patents across all countries that cover a single invention and INPADOC family covers patents that directly or indirectly share at least one priority patent Martinez [2010].

this invention. As argued in the Data section, the impact of patent citations on patent value varies across industries and hence there is no one "right" way to weight them. However, studies in general arrive to a conclusion that patents with a higher number of citations are disproportionately more valuable, than those with lower number of citations. Hence, these patents should be given more weight in terms of innovative value. I therefore include 4 different specifications in terms of weights assigned to citations in my robustness analysis. These include: linear weights, where the patent itself as well as the citations are each assigned a value of 1, i.e. (i) $1 + \sum(cit)$ (also Trajtenberg [1990] includes linear weights for comparison); steeper weights were each patent lacking citations is assigned a value of 1 and the value of citations is scaled by 1.5 times the number of citations: (ii) $1+1.5*\sum(cit)$, thus the more cited patents being given proportionally more value and exponential weights i.e. (iii) $1+\exp(0.5*\sum(cit))$, where highly cited patents are rewarded even more. Finally, as e.g. Popp [2002] argues that patents with no citations have low value in terms of knowledge contributed to future research, I include a weighting function that assigns zero value to patents without citations: (v) $\sum(cit)$.

9.2.3 Results

Table Distribution of 5 Years of Forward Citations (1990-2010) below provides an overview of distribution of patent citations in the year of the priority patent filing. In general, the number of citations is right skewed and zero-inflated. Over half of the patents have zero citations, meaning that they were of relatively little use for subsequent innovation (at least in the five years following the invention) and only about one and a half per cent of patents had six citations (the highest value in this dataset). This confirms the findings of the previous studies. Furthermore, as mentioned above, Popp [2002] argues that patent value for future innovation diminishes over time and that most citations occur in the years immediately after the original patent has been filed. Thus these citations are likely to still be a good approximation of patent value.

Table 9: Distribution of 5 Years of Forward Citations (1990-2010)

Sum of citations	Frequency	Percent	Cumulative
0	5,500	34.43	34.43
1	2,979	19.19	54.62
2	2,445	15.75	70.37
3	2,127	13.70	84.07
4	1,183	7.62	91.69
5	943	6.07	97.76
6	347	2.24	100.00
Total	15,524	100.00	

In the table OLS FE Results: European Electrical Power Generation Firms, Citation-Weighted Patents below, I weigh the patents with the number of forward citations in the five years following the initial patent. As discussed, previous studies have shown that there is a clear link between number of forward citations of a patent and the value of the underlying invention. However, the precise relationship between citations and the value of patents is unclear. As can be seen in the table OLS FE Results: European Electrical Power Generation Firms, Citation-Weighted Patents, the significance level of the results is rather insensitive to inclusion of different weights. For all specifications, the results have the expected sign. It should be pointed out that the magnitude of these coefficients is not directly comparable to each other or to the coefficients in the main results table due to the weights assigned and the differing time frame. Nevertheless, they provide further support for presence of an inverted U-shape relationship between competition and innovation in the European electricity sector.

Table 10: OLS FE Results: European Electrical Power Generation Firms, Citation-Weighted Patents

(1990-2010)	(1)	(2)	(3)	(4)
$cit\_w\_pat =$	$1 + \sum(cit)$	$1 + 1.5 * \sum(cit)$	$1 + \exp(0.5 * \sum(cit))$	$\sum(cit)$
OECD_index	59.10***	72.82***	81.86***	27.45***
	(15.77)	(20.68)	(26.20)	(10.14)
OECD_index^2	-59.48***	-72.62***	-81.83***	-26.28**
	(18.46)	(24.22)	(30.68)	(11.87)
Oil Price Index	2.962***	3.903***	4.557***	1.882***
	(0.141)	(0.185)	(0.234)	(0.0907)
Electricity Demand	-0.000194**	-0.000242**	-0.000310**	-9.52e-05**
	(7.50e-05)	(9.84e-05)	(0.000125)	(4.83e-05)
REP dummies	YES	YES	YES	YES
Constant	-45.28***	-62.83***	-66.42***	-35.10***
	(9.059)	(11.88)	(15.05)	(5.826)
Observations	449	449	449	449
R-squared	0.948	0.951	0.956	0.959
Number of countries	22	22	22	22
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Weighted $\sum$(patents)	33665	44057	56252	20783
F-statistic	161.2	174.8	194.0	210.4

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the table Testing for the Presence of an Inverted U-Shape Relationship below, the additional t-test results and the estimated extremum for each specification are reported. In all specifications, the extremum is between 0.49 and 0.52 and the 95 per cent Fieller interval for the extremum is clearly within the data range. These values of the extreme point can be compared to that in the main results, where the extremum is reported at 0.46, i.e. in a slightly more regulated market.

Table 11: Testing for the Presence of an Inverted U-Shape Relationship

Specification: $f(x) = x^2$	(1) $1 + \sum(cit)$	(2) $1 + 1.5 * \sum(cit)$	(3) $1 + \exp(0.5 * \sum(cit))$	(4) $\sum(cit)$
Extreme point	0.50	0.49	0.50	0.52
Overall test of presence of an Inverse U shape:				
t-value	2.37	2.56	1.95	1.55
P>|t|	0.009	0.005	0.0258	0.0611
95% Fieller interval for extreme point:	[0.35; 0.80]	[0.36; 0.74]	[0.38; 0.90]	[0.41; 2.78*]

*Outside the defined range

10 Discussion and Policy Implications

To summarize, the results seem to point towards the existence of an inverted-U shape relationship between regulation and innovation. The impact, as expected, is strongest on the innovation conducted by European firms. The significance and the magnitude of the OECD electricity market regulatory index appears to be robust to the inclusion of additional variables in this main dataset. While the observed effect in the two additional datasets included in the Robustness Analysis is of somewhat lower magnitude, the relationship is nevertheless robust to change in data selection methodology. When adjusting patent value by forward citations, the coefficients of both the linear and the squared OECD electricity market regulatory index remain significant at the 1 per cent significance level when using both linear and exponential weighting schemes.

These findings contribute to the competition-innovation literature in two important ways: (i) They shed some more light on the relationship between product market regulation, competition and innovation by further exploring the theory of an inverted-U shape relationship between competition and innovation by Aghion et al. [2005], suggesting that this relationship might also hold in a single-industry, cross-country setting. (ii) This thesis also contributes to the literature focusing on electricity market deregulation in particular. Relatively few studies exist to date, especially ones studying the EU electricity market, and most of these find a negative effect of deregulation. My results suggest that there might exist and inverted-U shaped relationship, emphasizing the need for further research.

Furthermore, the thesis yields practical policy implications. Identifying innovation incentives is generally important in order to be able to implement appropriate regulation and support economy-wide growth. More specifically, facilitating increased innovation in the electricity sector has been put forward by the European Commission as one of the major goals within the latest legislative proposal concerning the Energy Union [European Commission, 2016]. Understanding the innovation determinants in the electricity sector, in this case the impact of regulation and competition, is crucial due to pressing need for technological progress in the area in order to deal with issues such as air pollution and the global warming. As discussed in this thesis, the social returns to innovation are higher than the individual returns and this is even more the case in the energy sector, due to the negative externalities of fossil energy. Hence, empirical studies on this topic can further inform the decisions of the policy makers.

In recent years, the economic dynamics discussed in this thesis have gained more prominence with antitrust and competition authorities. Concerns of reduced innovation are used by regulatory bodies, such as the European Commission and National Competition Authorities, in the evaluation of mergers and anti-competitive behavior.[49] Thus, this thesis contributes to the literature that can help regulatory bodies to make more informed decisions regarding merger clearance or antitrust action against firms suspect to presumed anti-competitive behavior.

This thesis focuses on measuring the innovation carried out directly by power generating firms. It remains beyond the scope of this thesis to assess the overall changes in electricity innovation that may have resulted from the deregulation of the electricity markets. It could be the case that firms, instead of innovating themselves, rely upon research institutions and specialized R&D firms to carry out research and innovation on their behalf and thereafter license the technologies from them. Such behavior is not captured in the dataset used in this thesis and could be a focal point of future research. To further test the validity of the results of this thesis, a similar study of another sector that underwent comparable deregulation could be carried out, e.g. the telecommunications industry.

Some ambiguity remains as to how well the OECD Electricity market regulation index approximates the actual competitive environment in the electricity market. As discussed in the Empirical Research on Deregulation, Competition and Innovation section, a number of studies use market deregulation as a proxy measure of changes in the competitive environment. Furthermore, the very idea of EU electricity market liberalization was to introduce competition in the sector. Nevertheless, the question remains to what extent this has been achieved. Therefore, testing the sensitivity of results by using other competition measures that more precisely reflect the true competitive environment in the market could potentially improve the validity of the results.

There might be other theoretical explanations for the empirically observed pattern in patenting behavior over time than those proposed by Aghion et al. [2005]. For example, Arrow [1962]'s model predicts that monopolies invent less, but only when they are not exposed to entry. Once the market is opened up and the dominant firms are exposed to threats of competition from new entrants, they might choose to temporarily increase their innovative and patenting activity by engaging in preemption of competition as described in Gilbert and Newbery [1982] but decrease again once they have succeed in keeping competition out or once the potential entrants succeed in entering the market. However, this does not have to contradict the theory by Aghion et al. [2005] which maintains that firms consider the difference in their pre- and post- innovation results.

To conclude, this thesis makes a cautious argument that the relationship between the stringency of product market regulation and innovation follows an inverted-U shape. That the true

[49] E.g. in the 2017 DuPont-Dow merger, the European Commission demanded considerable divestments as a part of the remedies package in order to clear the merger and cited innovation concerns as the reason for this [European Commission, 2017]. On the contrary, the Federal Trade Commission in the US cleared the 2001 acquisition of Novazyme Pharmaceuticals, Inc. by Genzyme Corporation citing the acquiring corporations ability to take an important drug owned by the acquired company to the market as the principal reason for clearance [Federal Trade Commission, 2004].

explanation behind this relationship is introduction of competition is likely but not certain and might merit future research in other sectors and using different competition measures.

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A Extensions

Appendix A: Extensions includes the following extensions: (i) Models with Linear Term Only and (ii) Instrumental Variable Approach.

Models with Linear Term Only

For comparison, I include a fixed effects regression using only the linear OECD Electricity Market Regulation term, as the majority of previous empirical studies have used a linear term, as discussed in the Empirical Research on Deregulation, Competition and Innovation section. The OLS model with only linear term has the following specification:

$$(2)\ Num.ofpatents_{ct} = \beta_0 + \beta_1 OECD\_index_{ct} + \mathbf{bX_{ct}} + \lambda_c + \alpha_t + \epsilon_{ct}$$

where $Num.ofpatents_{ct}$ is the number of patents per year and country, β_0 is a constant, $OECD\_index_{ct}$ is the OECD electricity market regulation index, X_{ct} is a vector of covariates, λ_c captures the country fixed-effects, α_t captures the year fixed-effects and ϵ_{ct} is the error term.

Table 12: OLS FE Regression Results: European Electrical Power Generating Firms

VARIABLES	(1) Number of patents	(2) Number of patents
OECD_index	1.807	7.018**
	(3.232)	(3.562)
Oil Price Index		0.560***
		(0.0387)
Electricity Demand		-0.000128***
		(2.90e-05)
REP dummies		YES
Constant	6.934***	5.425
	(1.850)	(3.441)
Observations	525	522
Within R^2	0.925	0.944
Number of countries	29	29
Country FE	YES	YES
Year FE	YES	YES
F-statistic	242.9	167.4

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: OLS FE Regression Results: Global Electrical Power Generating Firms

VARIABLES	(1) Number of patents	(2) Number of patents
OECD_index	12.78***	14.68***
	(3.869)	(4.458)
Oil Price Index		1.183***
		(0.0485)
Electricity Demand		-0.000102***
		(3.62e-05)
REP dummies		YES
Constant	4.292*	-14.83***
	(2.215)	(4.307)
Observations	525	522
Within R^2	0.970	0.975
Number of countries	29	29
Country FE	YES	YES
Year FE	YES	YES
F-statistic	628.5	390.5

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: OLS FE Regression Results: Energy Patent Classes

VARIABLES	(1) Number of patents	(2) Number of patents
OECD_index	427.1***	671.4***
	(126.5)	(140.6)
Oil Price Index		29.83***
		(1.528)
Electricity Demand		-0.00635***
		(0.00114)
REP dummies		YES
Constant	415.6***	230.3*
	(72.43)	(135.8)
Observations	525	522
Within R^2	0.946	0.959
Number of countries	29	29
Country FE	YES	YES
Year FE	YES	YES
F-statistic	344.8	232.7

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Instrumental Variable Approach

In this subsection, I use a 2SLS IV regression specification, instrumenting the other available competition measures (from Eurostat) by the OECD product market index.

Data

Eurostat [2017] collects five (indirect) indicators of competition in the Power generation sector: (i) Number of main producers (with over 5 per cent market share), (ii) Cumulative market share in generation of these main producers, (iii) Cumulative market share in capacity of the main producers, (iv) Market share of the largest producer and (v) number of producers contributing 95 per cent of total production. Eurostat only reports data on competition in the electricity sector since 1999 for the old EU member states and since 2004 for the new member states. That is, these competition indicators are only available for the time period *after* the initial wave of deregulation. This further restricts the range of variation in competition that is observed. The electricity market indicators recorded by Eurostat are very indirect measures of the competitive conditions in the national power generation sectors.

As stated in the main Data section of this thesis, the competition indicators recorded by Eurostat are rather indirect: (i) the market share of the largest producer does not tell the whole story about market concentration; (ii) the cumulative share of these main producers in generation, adds just a little more information and likewise, tells little about the distribution of market shares between the producers; (iii) the cumulative market share in capacity is arguable even less related to the current competitive landscape within the market and hence is not used in my empirical analysis; (iv) the number of main producers (with at least 5 per cent market share) does not provide information about distribution of market shares among these main producers and (v) the number of producers providing 95 per cent of total likewise does not show the distribution. Furthermore it is distorted by large numbers of small suppliers in certain countries, e.g. Denmark, where the value of this indicator reaches up to 1600 while in most other countries there are no more than a couple of firms. Thus this indicator is not comparable across countries and furthermore can be a misleading indicator within a country as the number of firms might be high but many of them are small and hence contribute little to competition in the market. Hence, this measure is dropped as well so that three competition indicators remain: (i) Market Share of the Largest Producer, (ii) Cumulative Market Share of Main Producers in Generation and (iii) Number of Main Producers (with at least 5 per cent market share). For more coherence between the theoretical framework and the empirical results of this thesis, I invert two of the competition measures, the market share of the largest producer as well as cumulative market share of main producers. I furthermore normalize these measures to take a value between 0 (high regulation) and 1 (low regulation), that way imitating Aghion et al. [2005]'s independent variable (Learner index) in terms of scale and direction. The remaining competition measure (number of main producers), in theory, should form the inverted-U relationship without any transformation and is furthermore a count variable, values of which cannot be normalized.

Empirical Strategy

I use an instrumental variable approach in this section due to the reverse causality between competition and innovation, as discussed above. The independent variable, i.e. the measure of competition is assumed to be endogenous and thus correlated with the error term. An instrumental variable must fulfill two criteria, it must be (i) valid and (ii) relevant [Angrist and Pischke, 2009]. Validity of an instrument requires that the exclusion restriction holds. The exclusion restriction for an instrumental variable presupposes two things: (i) the instrument must be as good as randomly assigned (i.e. there can be no correlation between the instrument and the error term), (ii) the instrument an effect on the dependent variable (variable of interest) other than through the first stage (i.e. other than through the endogenous variable) [ibid.]. Furthermore, the instrument must be relevant, i.e. the first stage should have coefficients that are significantly different from zero. While relevance of an instrument can be tested, the exclusion restriction cannot. Therefore a theoretical argument for the validity of the instrument must be made. In this thesis, I argue that the deregulation was an exogenous change imposed by the European Union on the national electricity sectors. Furthermore, the assumption is that the only likely channel of effect of regulation on innovation is through competition. This is also likely to hold because the regulation considered was designed to have a direct and specific impact on product market competition. The relevance of an instrument can, however, be tested. Hence, I include first stage results below. The strength of the first stage, as well as the size of the F-statistic of the first stage, according to Angrist and Pischke [2009] are the most important measures of the quality of the instrument. Following Angrist and Pischke [2009], I instrument the linear competition variable and the squared separately, with competition being instrumented by linear OECD regulation index and the competition squared being instrumented with the squared OECD regulation index. I use a 2SLS IV approach and specify the following model:

The first stage:

$$(3)\ Competition_{ct} = \beta_{10} + \beta_{11} OECD\_index_{ct} + \beta_{12} OECD\_index^2_{ct} + \mathbf{bX_{ct}} + \lambda_c + \alpha_t + \epsilon_{ct}$$

where $Num.ofpatents_{ct}$ is the number of patents per year and country, β_0 is a constant, $OECD\_index_{ct}$ is the OECD electricity market regulation index, $OECD\_index^2_{ct}$ is the square of OECD electricity market regulation index, X_{ct} is a vector of covariates, λ_c captures the country fixed-effects, α_t captures the year fixed-effects and ϵ_{ct} is the error term.

The reduced form:

$$(4)\ Num.ofpatents_{ct} = \beta_{20} + \beta_{21} OECD\_index_{ct} + \beta_{22} OECD\_index^2_{ct} + \mathbf{bX_{ct}} + \lambda_c + \alpha_t + \epsilon_{ct}$$

where $Num.ofpatents_{ct}$ is the number of patents per year and country, β_0 is a constant, $OECD\_index_{ct}$ is the OECD electricity market regulation index, $OECD\_index^2_{ct}$ is the square of OECD electricity market regulation index, X_{ct} is a vector of covariates, λ_c captures the country fixed-effects, α_t captures the year fixed-effects and ϵ_{ct} is the error term.

2SLS IV Regression Results

Like with the OECD electricity market regulation index above[50], the variation of the (1- Market Share of the Largest Producer) only occurs in the lower 85 per cent of the possible range. Likewise, (1- Cumulative Market Share of Main Producers) ranges between 0 and 0.63, only covering high market concentration. Number of main producers ranges between 1 and 9. All measures are somewhat left-skewed within the covered range.

Table 15: Descriptive Statistics (3)

Dataset (1990-2013)	Min	25%	Median	75%	Max	Std. Dev.	Country-Year Obs.
1-MSLargestProd*	0	0.19	0.53	0.69	0.85	0.26	296
MainProd	1	2	3	4	9	1.7	282
1-CumMSGenMainEntit*	0	0.13	0.26	0.36	0.63	0.15	169

*Note that these measures are inverted, i.e. this table illustrates 1-MS.

In the table First Stage Results below, I present the first stage results. The linear and the squared term are instrumented for separately. The market share of the largest producer has the expected sign but is not statistically significant. The squared term of this competition measure is significant but has a sign opposite to the one expected. The number of main firms (with over 5 per cent market share) likewise shows no significance in the linear term and also in the quadratic term. The third measure, cumulative market share of the main firms has a highly significant linear term, however it has an opposite sign to what was expected. Finally, the squared cumulative market share of main firms is both of wrong sign and statistically insignificant. Furthermore, the F-statistic is rather low for all regressions. Only (1-MSLargestProd) has an F-statistic larger than the rule of thumb, which suggests that the F-statistic should be at least 10. Likewise, the explained within-country variation of this first stage model is relatively low for all competition measures with within R^2 ranging between 0.25 and 0.58. Also covariates exhibit less significance and sometimes have different-than-expected results. In general, the first stage results suggest that the OECD electricity market regulation index is not a particularly good instrument for any of the competition measures used here. As argued above, this is more likely due to these measures being crude approximations of the actual competition in the market.

[50]Descriptive Statistics (1).

Table 16: First Stage Results

VARIABLES	(1) 1-MSLargestProd	(2) (1-MSLargestProd)^2	(3) MainProd	(4) MainProd^2	(5) 1-CumMSGenMainEntit	(6) (1-CumMSGenMainEntit)^2
OECD_index	0.0797		0.546		-0.349***	
	(0.0526)		(0.710)		(0.117)	
OECD_index^2		0.126**		3.190		-0.102
		(0.0617)		(7.394)		(0.0774)
Electricity Demand	1.76e-06***	1.97e-06***	-7.16e-06	-6.65e-05	1.91e-06*	9.26e-07
	(5.18e-07)	(4.85e-07)	(6.53e-06)	(5.72e-05)	(1.01e-06)	(6.50e-07)
Oil Price Index	5.40e-05	-0.000455	0.00348	0.0239	0.00180***	0.000987***
	(0.000325)	(0.000310)	(0.00481)	(0.0415)	(0.000543)	(0.000360)
Constant	0.182***	0.00959	3.397***	17.87***	0.0578	-0.0807
	(0.0625)	(0.0572)	(0.755)	(6.439)	(0.139)	(0.0895)
Observations	296	296	282	282	169	169
Within R^2	0.586	0.526	0.312	0.255	0.253	0.224
Number of Countries	27	27	29	29	28	28
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
REP dummies	YES	YES	YES	YES	YES	YES
F-statistic	11.74	9.199	3.649	2.743	2.651	2.258

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Like expected, the results on the relationship between competition and innovation are less certain (see table 2SLS IV FE Regression Results: European Electrical Power Generating Firms below). However, all linear as well as squared terms have the expected sign. As discussed in the data section, the competition measurements used here leave more to wish for. Likewise, the competition measurements are only available from 1999 (or 2004 for the newer EU member states) thus only covering a shorter time period *after* the initial deregulation had taken place. Hence, the lack of significance in the results might be due to imprecise competition measure rather than other reasons, e.g. regulation being a weak instrument for competition.[51]

[51] This holds true for the other two datasets as well (not reported).

Table 17: 2SLS IV FE Regression Results: European Electrical Power Generating Firms

VARIABLES	(1) Num. of patents	(2) Num. of patents	(3) Num. of patents
1-MSLargestProd	1,130		
	(1,331)		
$(1\text{-MSLargestProd})^2$	-1,336		
	(1,486)		
MainProd		221.3	
		(5,593)	
MainProd^2		-59.49	
		(1,311)	
CumMSGenMainEntit			128.5
			(135.4)
$\text{CumMSGenMainEntit}^2$			-233.4
			(329.3)
Electricity Demand	0.000452	-0.00240	-0.000120
	(0.000745)	(0.0471)	(0.000145)
Oil Price Index	-0.0448	1.096	0.701***
	(0.564)	(12.97)	(0.133)
Constant	-164.7	329.1	-15.02
	(237.8)	(4,400)	(29.81)
Observations	296	282	169
Number of countries	27	29	28
Country FE	YES	YES	YES
Year FE	YES	YES	YES
REP dummies	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B Data

Appendix: Data includes the following subsections: (i) OECD Product Market Regulation Index by European Electricity Market Region[52], (ii) Country Level Patent Counts[53], (iii) Country Level Patent Counts Plotted Against the OECD Electricity Market Regulation Index[54], (iv) Overview of Selected International Patent Classification Classes and (v) Distribution of residuals.

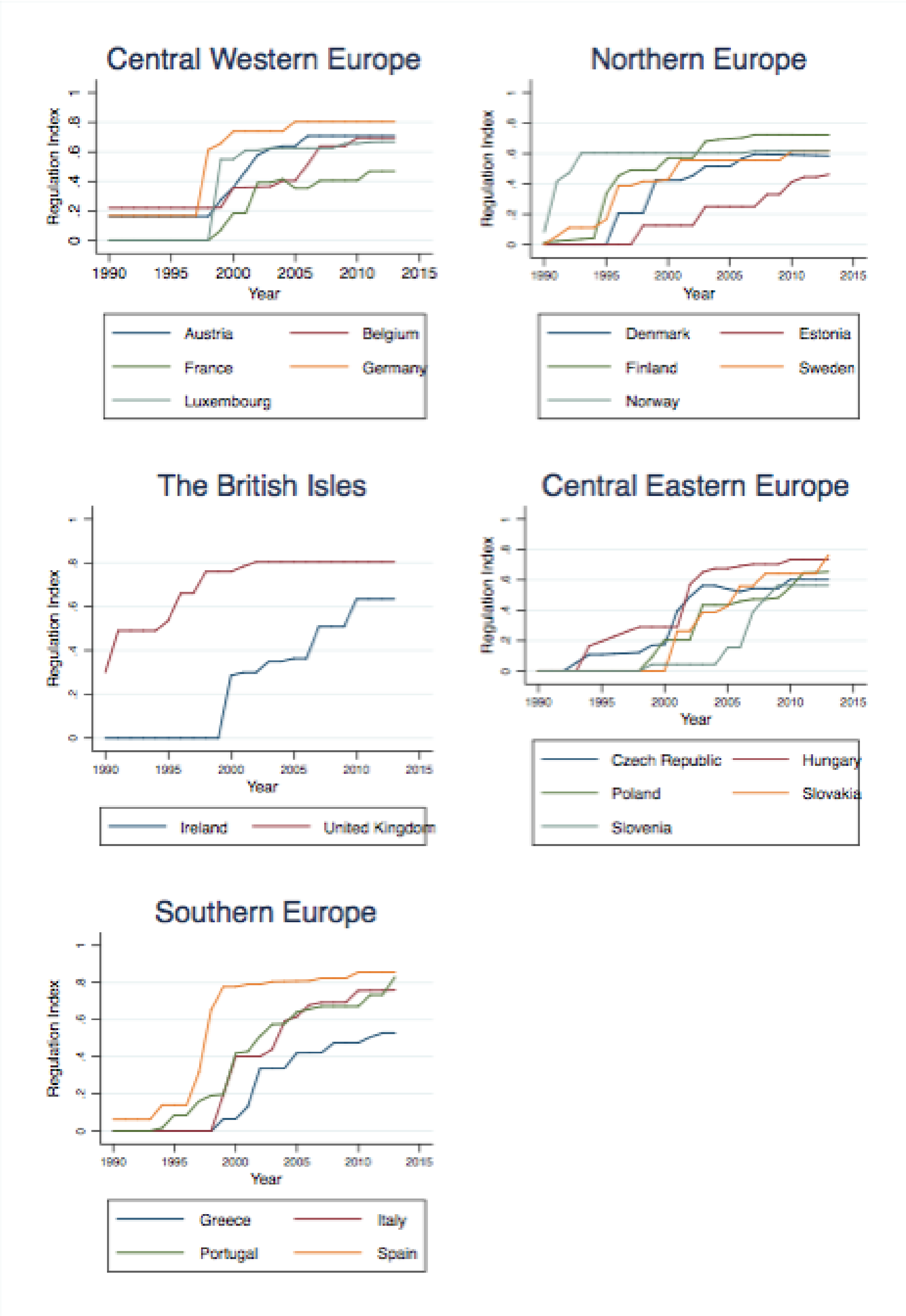
[52]Countries that do not have OECD Electricity Market Index for the entire time period are excluded.

[53]The patent counts are based on the main data specification used in this thesis, i.e. "Patents by European Power Generation Companies".

[54]The patent counts are based on the main data specification used in this thesis, i.e. "Patents by European Power Generation Companies". Countries that do not have OECD Electricity Market Index available for the entire time period are excluded.

OECD Product Market Regulation Index by European Electricity Market Region[55]

Figure 3: OECD Product Market Regulation Index by European Electricity Market Region

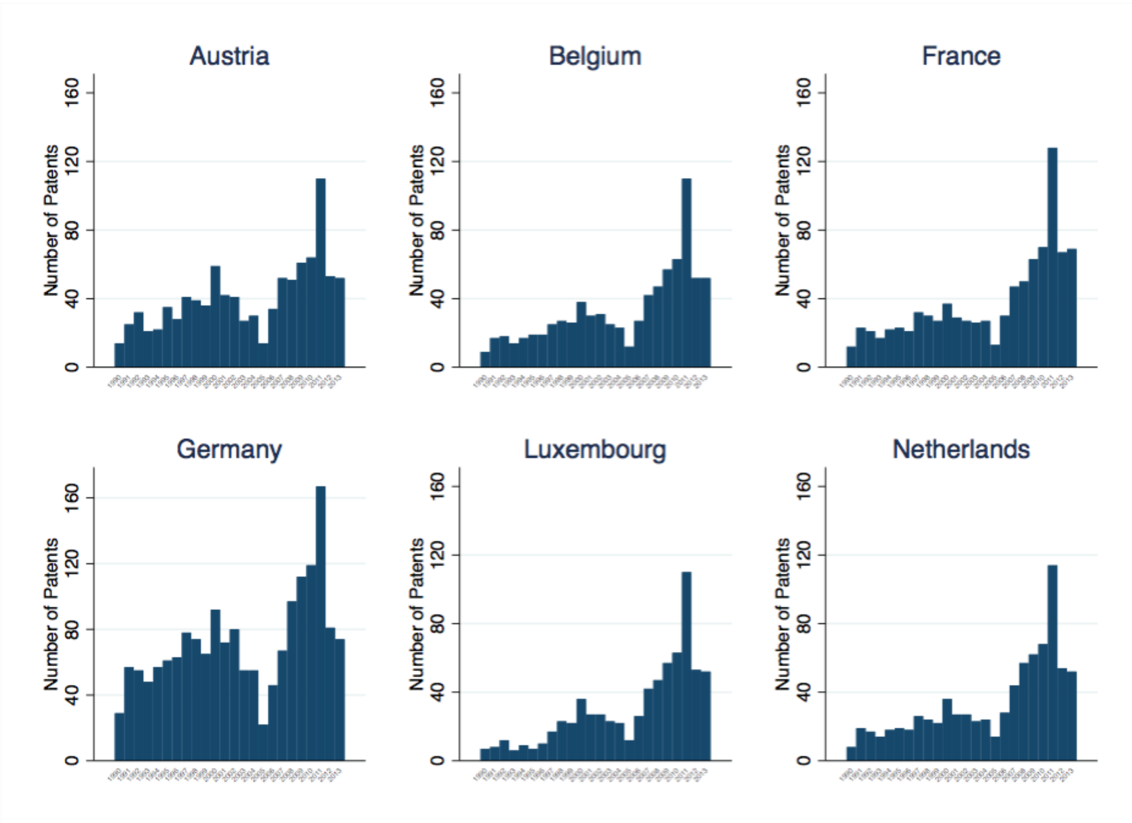


Source: Own calculations based on the OECD [2017].

[55] Countries that do not have OECD Electricity Market Index for the entire time period are excluded.

Country Level Patent Counts[56]

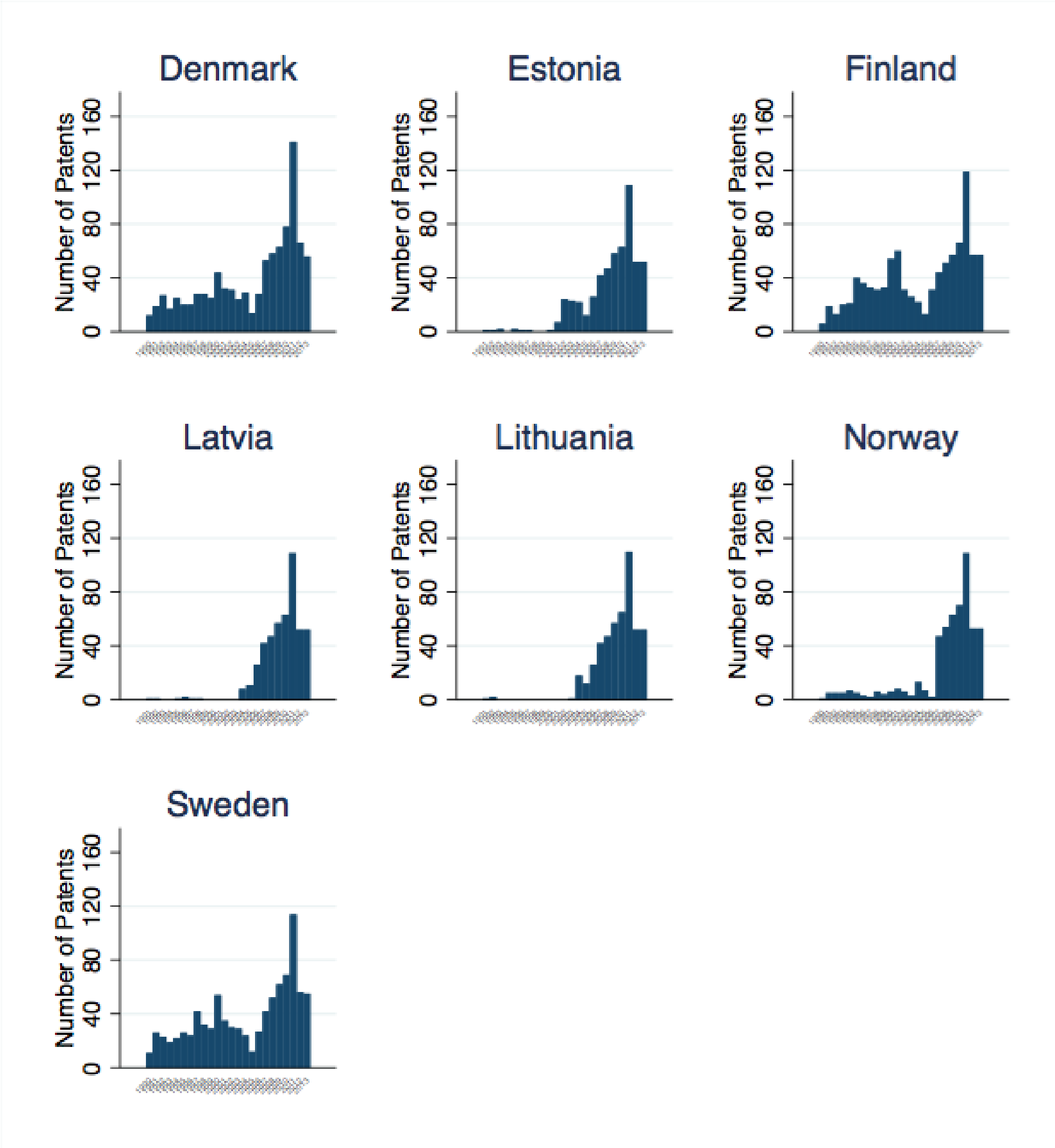
Figure 4: Patent Counts: Central Western Europe



Source: Own calculations using data from the European Patent Office [2017c].

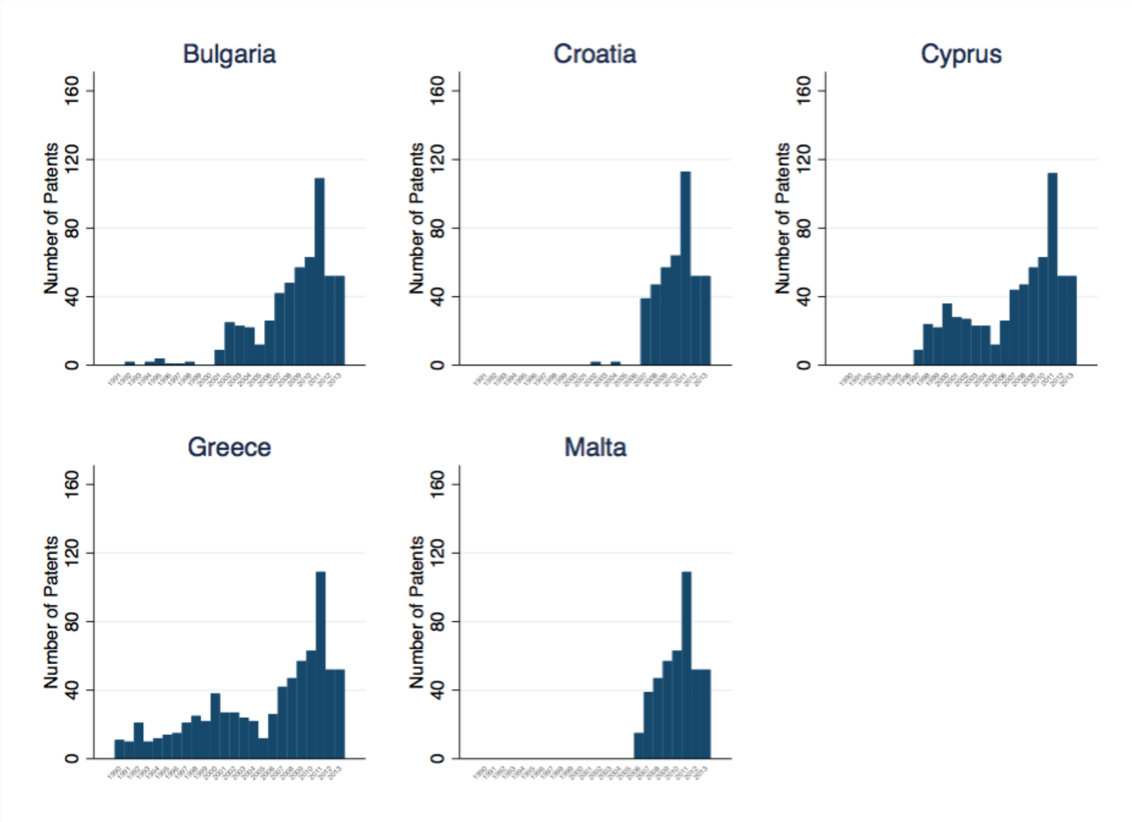
[56]The patent counts are based on the main data specification used in this thesis, i.e. "Patents by European Power Generation Companies".

Figure 5: Patent Counts: Northern Europe



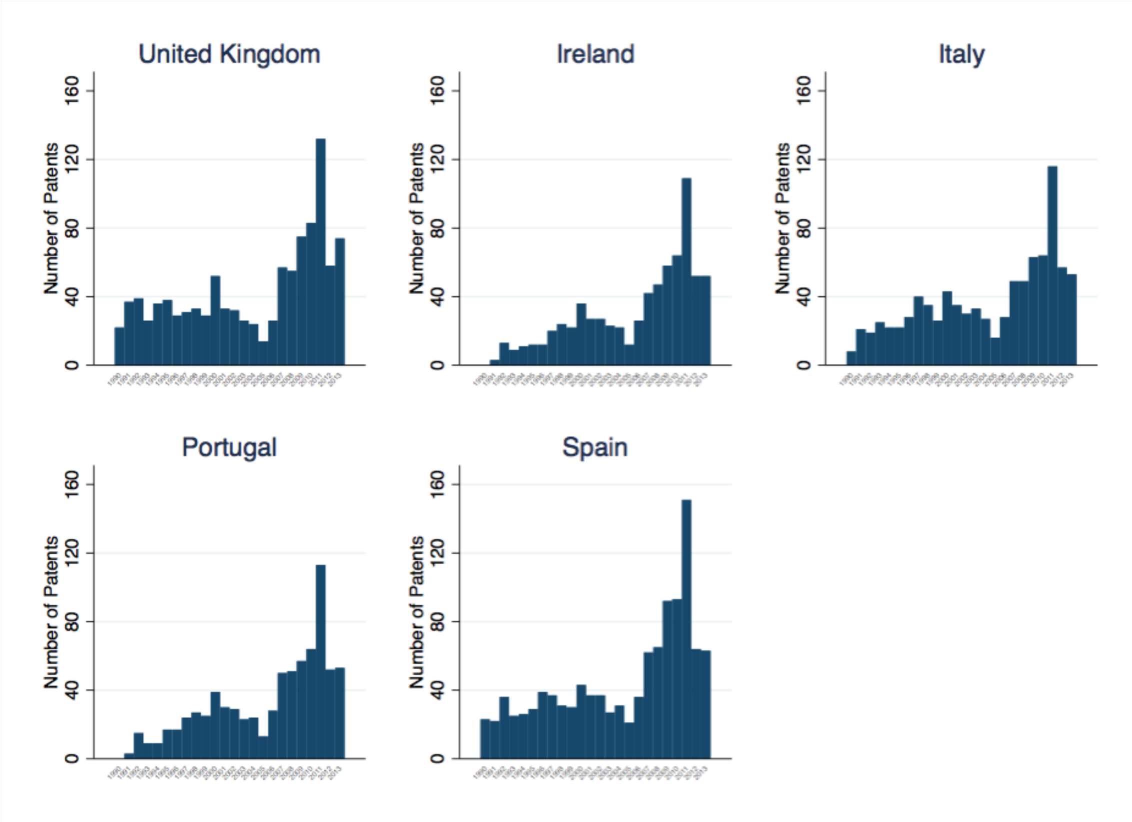
Source: Own calculations using data from the European Patent Office [2017c].

Figure 6: Patent Counts: South Eastern Europe



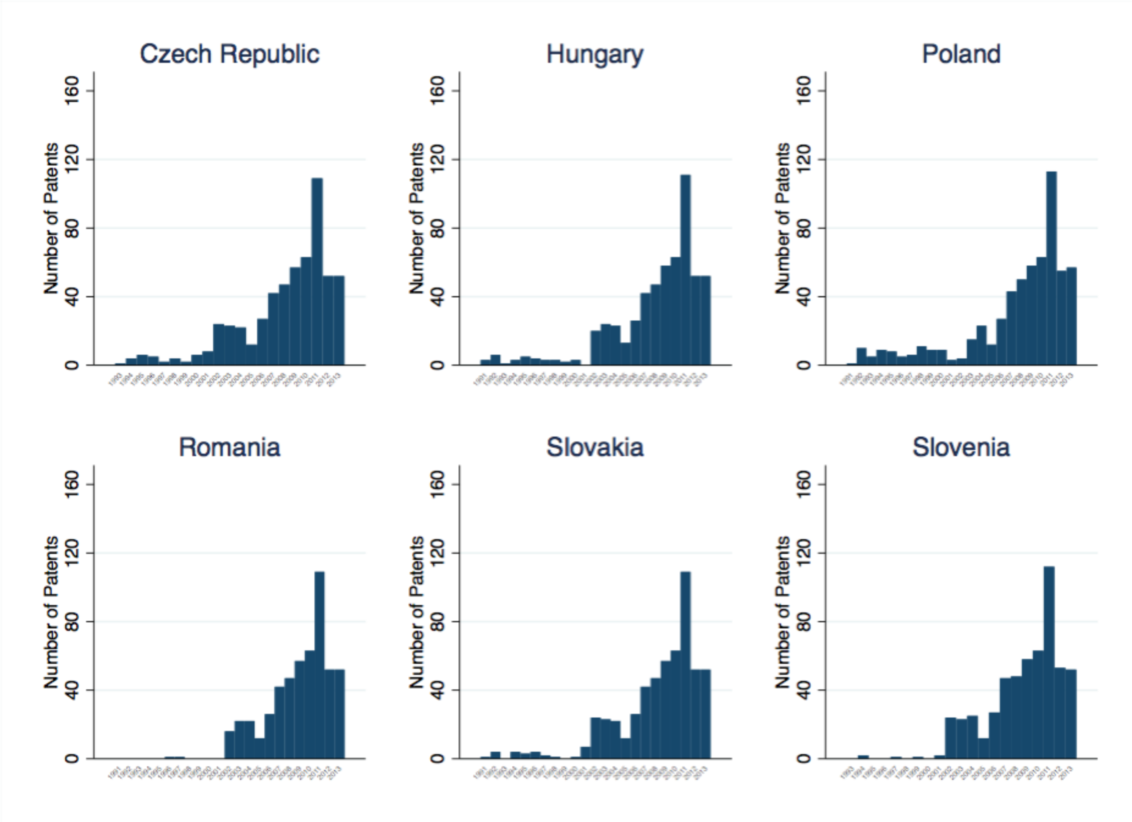
Source: Own calculations using data from the European Patent Office [2017c].

Figure 7: Patent Counts: The British Isles, Apennine Peninsula and Iberian Peninsula



Source: Own calculations using data from the European Patent Office [2017c].

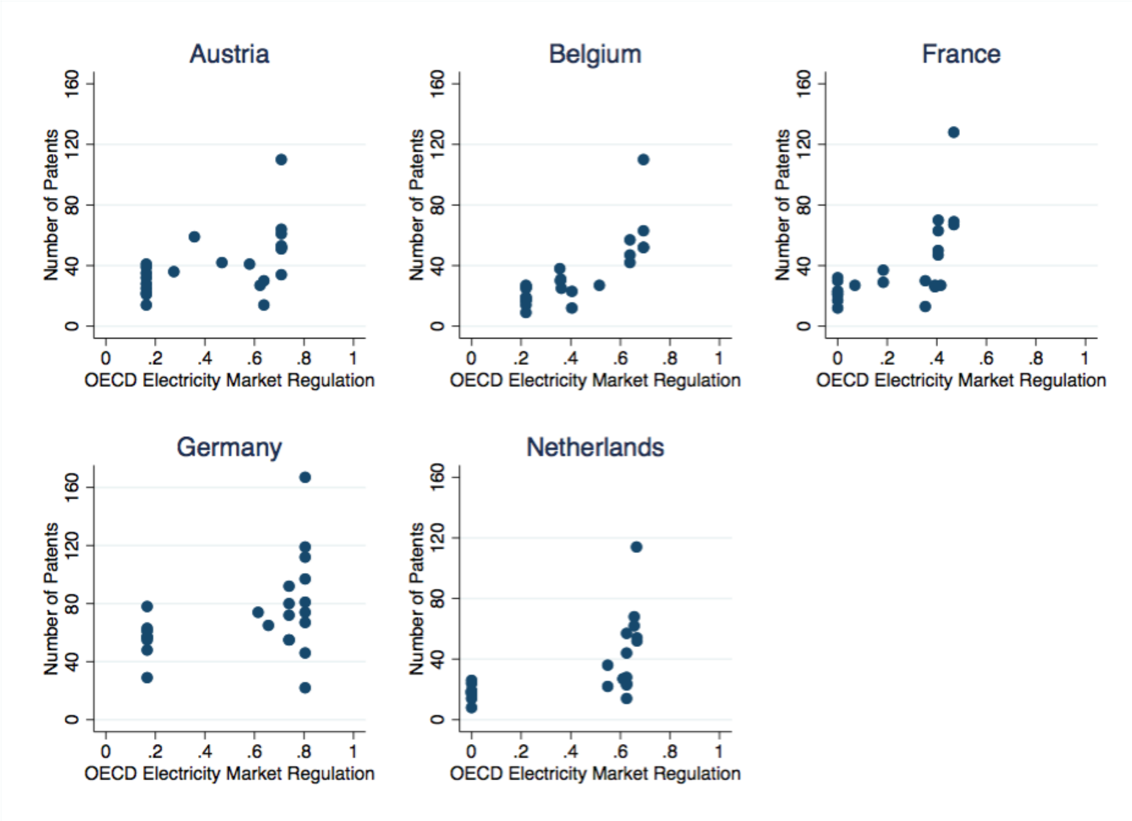
Figure 8: Patent Counts: Central Eastern Europe



Source: Own calculations using data from the European Patent Office [2017c].

Country Level Patent Counts Plotted Against the OECD Electricity Market Regulation Index[57]

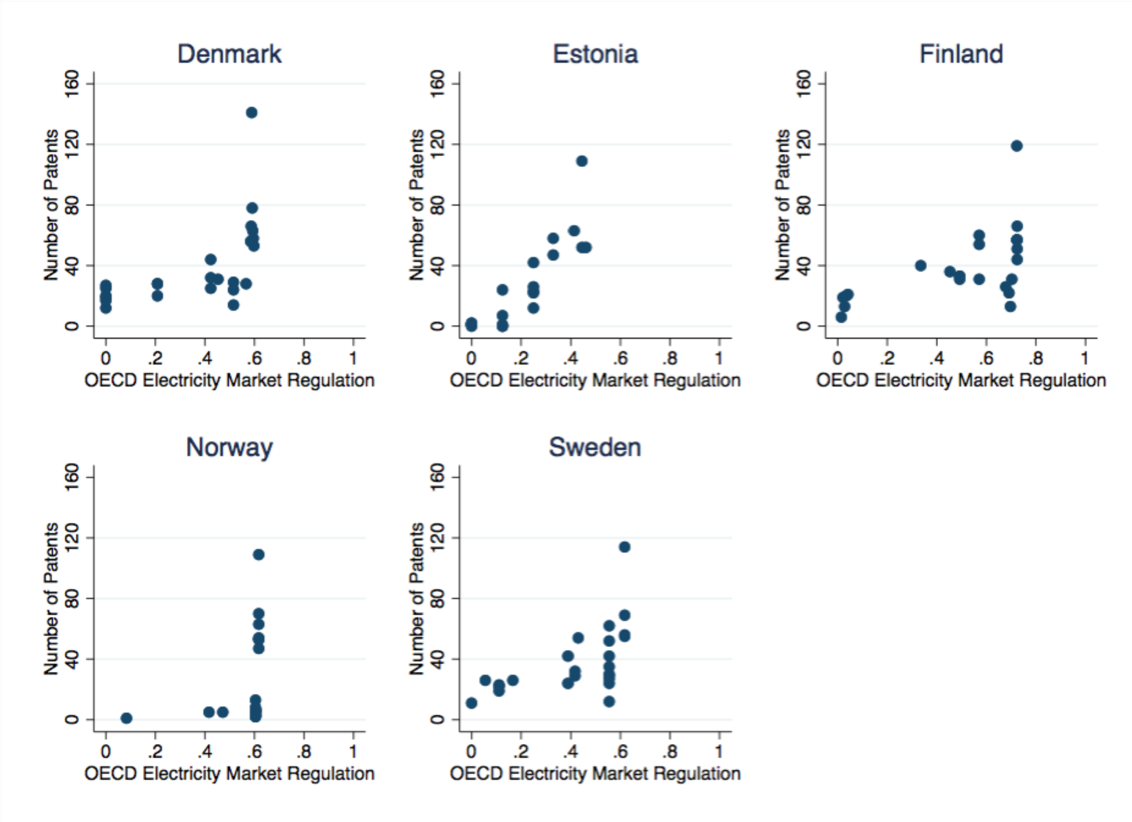
Figure 9: Patents and Regulatory Index: Central Western Europe



Source: Own calculations using data from the European Patent Office [2017c] and the OECD [2017].

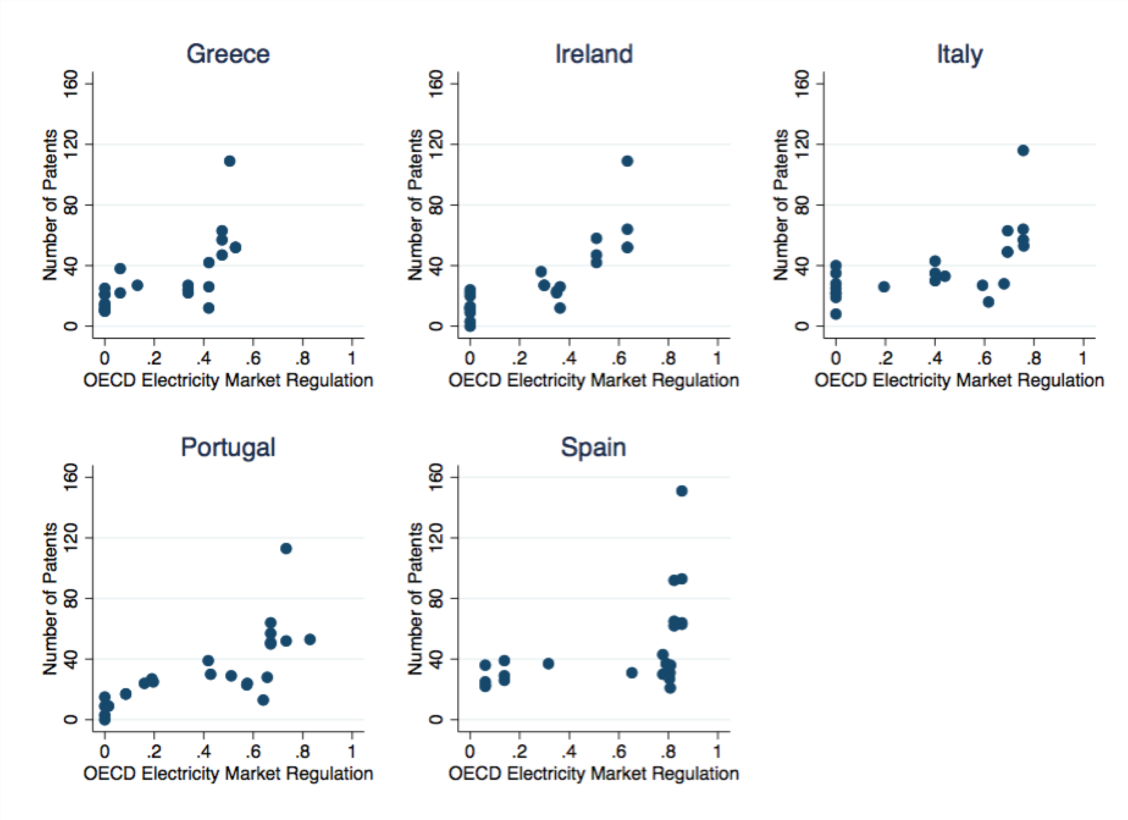
[57]The patent counts are based on the main data specification used in this thesis, i.e. "Patents by European Power Generation Companies". Countries that do not have OECD Electricity Market Index available for the entire time period are excluded.

Figure 10: Patents and Regulatory Index: Northern Europe



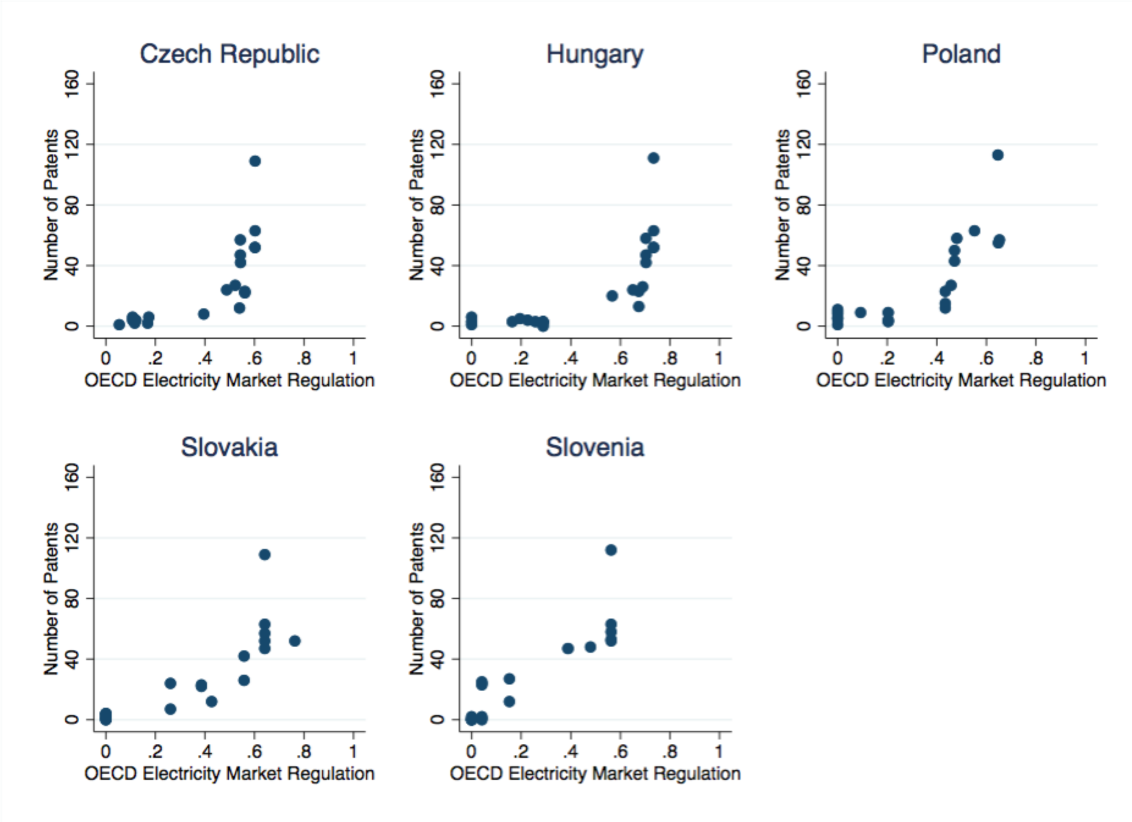
Source: Own calculations using data from the European Patent Office [2017c] and the OECD [2017].

Figure 11: Patents and Regulatory Index: Southern Europe and the British Isles



Source: Own calculations using data from theEuropean Patent Office [2017c] and the OECD [2017].

Figure 12: Patents and Regulatory Index: Central Eastern Europe



Source: Own calculations using data from the European Patent Office [2017c] and the OECD [2017].

Overview of Selected International Patent Classification Classes

Table 18: Selected International Patent Classification Classes

Technology Class	International Patent Classification Codes
Biomass	F02B43/08; C10L5/44; B01J41/16; C10L5/42; C10L5/43;C10L1/14
Geothermal	F24J3/02; F24J3/06; F03G4/06; F24J3/01;F03G4/02; F24J3/03; F03G4/01; F24J3/07; H02N10/00; F24J3/05; F03G4/00; F03G4/05; F24J3/00; F24J3/04; F24J3/08; F03G4/04;F03G4/03
Hydro	F03B17/06; F03B13/08; F02C6/14; F03D9/00; E02B3/02; F01D1/00; F03D9/02; B62D5/06; F03B13/10; F03B13/00; F03B3/00; F03B3/04; E02B3/00; H02K7/18; B62D5/093
Ocean	F03B13/15; F03B13/12; F03B13/18; F03B13/16; F03B13/17; F03B13/14; F03G7/04; F03B13/22; F03B13/21; F03B13/20; F03B13/13; F03G7/05; F03B7/00; F03B13/24; F03B13/19; F03B13/23
Solar	F24J2/49; F24J2/15; H01L31/042; F03G6/04;F24J2/26; F24J2/00; F24J2/03; F24J2/23; F24J2/10; F24J2/33; F24J2/11; F24J2/20; F24J2/28; F24J2/30; F24J2/13; F24J2/05; F24J2/38; F24J2/37; F24J2/50; F24J2/14; F24J2/06; F24J2/08; F24J2/18; F03G6/02; F24J2/39; F03G6/00; F25B27/00; F24J2/40; F24J2/24; F03G6/03; F03G6/05; E04D13/18; F24J2/43; F24J2/41; F24J2/27; F03G6/07; F24J2/53; F24J2/45; F03G6/01; F24J2/34; F26B3/28; F24J2/12; F24J2/07; B60L8/00; F24J2/04; F24J2/31; F24J2/54; H02N6/00; H02N6/06; F24J2/19; F24J2/42; F24J2/46; F24J2/47; F24J2/29; F24J2/36; F24J2/52; F24J2/32; F24J2/01; F24J2/48; F24J2/35; F24J2/44; F24J2/02; F24J2/17; F24J2/09; F24J2/51; F24J2/16; F24J2/21; F24J2/22; F03G6/08; F24J2/25
Waste	F02G5/04; F02G5/02; F23G7/10; F02G5/03; F23G5/46; C10L5/48; C10L5/47; F25B27/02; F02G5/00; C10L5/46; F02G5/01; C10J3/86; F12K25/14; H01M8/06
Wind	F03D11/00; F03D7/05; F03D5/02;B63H13/00; B60L8/00; F03D3/03; F03D5/06; F03D1/00; F03D1/05; F03D3/01; F03D3/00; F03D1/04; F03D9/01; F03D9/00; F03D11/04;F03D5/03; F03D3/04; F03D7/01; F03D5/05; F03D5/04; F03D5/01; F03D11/02; F03D7/04; F03D11/03; F03D7/03; F03D1/06; F03D3/05; F03D1/03; F03D11/01; F03D7/06; F03D3/02; F03D5/00; F03D3/06; F03D7/00; F03D1/02; F03D7/02; F03D9/02; F03D1/01
Coal gasification	C10J3
Improved burners	F23C1; F23C5/24; F23C6; F23B10; F23B30; F23B70; F23B70; F23D1; F23D7; F23D17
Fluidized bed combustion	B01J8/20-22; B01J8/24-30; F27B15; F23C10
Improved boilers for steam generation	F22B31; F22B33/14-16
Improved steam engines	F27B15; F01K5; F01K23
Superheaters	F22G
Improved gas turbines	F02C7/08-105; F02C7/12-143; F02C7/30
Combined cycles	F01K23/02-10; F02C3/20-36; F02C6/10-12
Improved compressed-ignition engines	F02B1/12-14; F02B3/06-10; F02B7; F02B7; F02B13/02-04; F02B49
Cogeneration	F01K17/06; F01K27; F02C6/18; F02G5; F25B27/02

Distribution of the Residuals

Figure 13: Distribution of the Residuals