Norwegian School of Economics
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# The Effect of Electricity Prices on Low-Carbon Energy Technologies

*A panel data analysis of EPO patents*

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# Abstract

In this thesis, we investigate whether electricity prices affect innovation within low-carbon energy technologies (LCE) in the period from 1978 to 2018.

2022 has brought up one of the worst energy crises the world has ever seen, causing abnormally high electricity prices. Consequently, innovation within low-carbon energy technologies is crucial. In previous research, electricity price is identified as a potential driver for green innovation. However, the scientific community also argues that policies and the stock of knowledge are important drivers.

When applying a linear model to our panel consisting of 26 OECD countries, the findings indicate that there is no effect of electricity prices on low-carbon energy innovation. Corresponding with previous research, the main driver for innovation in our model is the stock of available knowledge at the time the patent was applied for. However, for countries with higher overall patenting activity, the effect of electricity prices is positive. This indicates that electricity prices do not initiate innovation within low-carbon energy technologies, but rather affect countries where innovation is already high.

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# 1 Introduction

2022 is the year when we finally could see the end of the global COVID-19 pandemic. However, this year has been marked by abnormally high electricity prices, Russia invading Ukraine, and we are facing uncertainty related to the general economic outlook (IEA, 2021d). The negative consequences of high electricity prices are very tangible and present all around us. However, can this current crisis have a climate-friendly silver lining? Europe is working towards less dependence on Russian fossil fuel imports by speeding up the transition to clean energy. In addition, the global climate crisis contributes to the urgency of implementing this transition in near future to meet the Paris agreement. The innovation of low-carbon energy technologies (LCE) is considered a crucial part of this transition (IEA, 2021c). Considering today's global situation, we aim to analyse whether electricity prices historically have led to more innovation within LCE technologies.

In previous research, energy and electricity prices have been identified as potential drivers for green innovation. Popp (2002) finds that energy prices have a positive significant effect on energy-efficient innovation in the United States but emphasises that the stock of knowledge has an even more substantial effect on innovation. He states that "the supply of ideas, as well as the demand for new ideas, plays an important role in shaping the direction of innovation" (Popp, 2002). The knowledge stock aims to measure the available knowledge within a technology category at a given time and is considered a proxy for technical capability. Kruse and Wetzel (2016) find that the knowledge stock is a significant driver of green technological innovations, while energy prices only significantly affect some technologies.

Furthermore, a widely recognised driver of green innovation is policies. Lanjouw and Mody (1996) found that environmental innovations respond to the severity of environmental regulations, and Johnstone et al. (2010) single out policies as the key driver to green innovation. Policies are also considered to be closely linked to both electricity prices and the stock of knowledge (Kruse and Wetzel, 2016). Governments can increase electricity prices by implementing policies that increase the potential profit of successful innovations. On the other hand, governments can increase the knowledge stock by implementing policies that decrease the cost of producing innovations. (Kruse and Wetzel, 2016).

A common feature of previous research is the focus on specific energy supply technologies such as solar, wind, and biofuels. We aim to add to the literature by basing our analysis on the IEA's categorisation of LCE technologies, which reflects new trends in renewable energy innovation (IEA, 2021c). The three main building blocks of LCE technologies are LCE-supply technologies, enabling technologies and end-use technologies.

LCE-supply technologies include wind, solar, hydropower, bioenergy and energy generation of nuclear origin. Enabling technologies mainly involve carbon capture, utilisation and storage (CCUS), batteries, hydrogen and fuel cells, smart grids and other technologies for energy storage. End-use technologies are primarily used for production in agriculture, production of consumer products, electric vehicles and technologies for transportation within the aviation and maritime sector.

To limit the scope of this analysis, we choose to focus on the LCE-supply and enabling technologies. This is mainly because LCE-supply and enabling technologies represent the supply side of electricity production and can significantly impact the supply mix of electricity. End-use technologies, on the other hand, can be considered the demand side as the sales of the technologies will be affected by how the customers embrace the innovations.

Innovation within LCE-supply and enabling technologies have followed each other closely since 1978, but have moved in different directions since 2012 (IEA, 2021c). The question of what drives innovation of LCE-supply and enabling technologies remains complex as innovation activities are affected by several factors. In this analysis, we investigate whether electricity prices can explain changes in patenting activity. Additionally, we analyse whether the effect differs between LCE-supply and enabling technologies, and whether the effects vary before and after 2012. Thus, the research question of this analysis is:

*How do electricity prices affect innovation within LCE-Supply and Enabling technologies?*

To answer our research question, patents are used as a proxy for innovation. Using a linear regression model, we analyse patent applications from 26 OECD countries from 1978 to 2018.

"Patents are the data source most widely used to measure innovative activity" (van Pottelsberghe et al., 2000). Beyond the fact that patent data is readily available, there are many advantages to using patent data. There are few examples of major inventions that have not been patented, and the patent data is a rich source of information on the applicants, inventors and technology categories. Additionally, "patents cover a broad range of technologies, including those where there sometimes can be few other sources of data" (van Pottelsberghe et al., 2000).

There are, however, some drawbacks when using patent data. The value distribution of patents is skewed, meaning that some patents are highly valuable while others have no industrial application (van Pottelsberghe et al., 2000). Also, the propensity to patent differs across countries leading to some inventions not to be patented. Differences in patent regulations across countries can sometimes make it challenging to compare counts of patents. Lastly, changes in patent law can affect the trends over time (van Pottelsberghe et al., 2000).

Patents are structured into categories using the Cooperate Patent Classification (CPC). The categories for LCE-supply and enabling technologies are based on the cartography of LCE technologies from the article "Patents and the Energy Transition" (IEA, 2021c). The CPC classifications for the two categories are presented in table A1.1 in the appendix.

We expect our findings to be in line with the induced innovation hypothesis. The induced innovation theory states that "changes in one relative factor should lead to innovations that reduce the need for the relatively expensive factor" (Popp, 2002). LCE technologies contribute to facilitating and producing electricity and can be considered part of the supply mix of electricity generation. The commercial viability of these technologies will depend on the cost level relative to other non-renewable substitutes (Johnstone et al., 2010). Johnstone et al. (2010) states that an increase in electricity prices should increase the incentives to innovate within renewable energy. This is because the initial cost of electricity production using renewable energy sources is generally higher than the cost of fossil fuels. Based on this, our main hypothesis is:

*H1 = An increase in electricity price will positively affect patenting activity within LCE-supply and enabling technologies.*

The findings indicate that for the 26 OECD countries in our panel, electricity prices have no significant effect on patenting activity. However, for countries in our panel with an overall high patenting activity, the effect of electricity prices coincides with the hypothesis, indicating that patenting activity is positively affected by increasing electricity prices. Furthermore, we find no significant effect of policies. In line with the previous research, knowledge seems to be the main driver for innovative activity in our models. At last, the findings indicate that electricity prices have similar effects on patenting activity before and after 2012.

This thesis is structured in 6 parts and proceeds as follows: Section 2 describes the data and gives an understanding of how the data is structured. In section 3, the model specifications and methodical approach are explained. Section 4 presents the results of how patenting activity affects LCE-supply and enabling technologies. To strengthen our results, section 5 examines various subsets and specification choices by performing a robustness analysis. Finally, section 6 makes a concluding statement and presents suggestions for future research.

# 2 Data

To study our hypothesis, we constructed a panel dataset with the variables necessary for our research. First, we introduce the OECD REGPAT database, where we extract data on patents. Then, we present all other relevant sources of data. Next, we describe the construction of our dependent and explanatory variables and provide a thorough description of how the data is processed. Finally, our processed data is presented through descriptive statistics.

## 2.1 Data sources

### 2.1.1 OECD REGPAT Database

Our analysis is based on patent data from the OECD REGPAT database, which covers data on patent applicants to the EPO and associated regionalised data (Maraut et al., 2008). A significant advantage of REGPAT data is the possibility to join the data with other regional structured data such as GDP and electricity prices (Maraut et al., 2008). The data covers all EPO patent applications from 1977 to 2022.

Patent applications to EPO are relatively expensive compared to filing for patents through other national patent offices in Europe (Johnstone et al., 2010). However, filing for EPO patents is more economical and efficient than filing for the same patent at multiple national patent offices. This causes a natural elimination of low-value inventions to EPO and assures that only relevant patents of a particular value are included in our analysis (Johnstone et al., 2010).

### 2.1.2 IEA Energy Prices and Taxes Statistics Database

Data on electricity prices are retrieved from the IEA Energy Prices and Taxes Statistics Database (IEA, 2021a). The database provides detailed OECD country statistics on energy prices and taxes for different energy sources (IEA, 2020). We have extracted data on household electricity prices, presented in US Dollars per MWh of electricity. The prices are converted using average annual purchasing power parity (PPP), which accounts for the general price differences of goods and services across countries (IEA, 2020).

### 2.1.3 Share of Electricity Production from Renewables

Data on electricity production from renewables is retrieved from Our world in data (2022). Renewable electricity sources include hydropower, solar, wind, biomass waste, geothermal, wave, and tidal sources. The data covers almost all OECD countries from 1985 to 2021. Our world in data (2022) bases its data on the Global Electricity Review from Ember, an independent non-profit climate and energy think tank, which provides analysis and policy solutions.

### 2.1.4 OECD Data - Gross Domestic Product

The data on the gross domestic product (GDP) is retrieved from OECD (2022) and covers data for all OECD countries from 1960 to 2021. We have extracted GDP presented in million US dollars to include information about countries' economic activity and wealth.

### 2.1.5 OECD Environment Statistics Database

The OECD Environment Statistics Database provides data on policy-relevant environmental statistics (OECD, 2016). The data includes 28 OECD countries from 1990 to 2022. We extract data on the environmental policy stringency index for the 26 countries in our panel data.

## 2.2 Construction of variables

### 2.2.1 Dependent variable

For our model, the dependent variables are counts of patent applications within LCE-supply and enabling technologies. To construct the dependent variables, we extracted all EPO patents with CPC classifications within the two technologies. As one patent can have CPC classifications within both categories, a fraction was constructed. This was done to find the share of LCE-supply and enabling classifications for each patent and avoid double counting. For instance, if a patent has one enabling classification and three LCE-supply classifications, the patent will be 0.25 enabling and 0.75 LCE-supply. Due to the risk of delay in the enrollment of new patents, we removed the last four years of the dataset. Further, the first year was set to 1978 as an outcome of missing data for previous years. Our dataset thus ranges from 1978 to 2018.

One patent can be filed by several applicants, which makes it possible for patents to be linked to multiple applicant addresses. To avoid double counting of patents, a fraction was constructed to divide the share of each patent correctly among its applicants. The data were further grouped by country and year to get the total count of patents within the two categories, per country per year.

The structure of our dependent variables results in zero values for the patent count in some countries. There are two potential reasons for zero values. Firstly, we can not exclude the possibility of true missing values. This can be the case if patent applications are excluded from the database, or if information about the applicants' addresses is missing. Secondly, the patent count results in zero values for countries if there are no patent applications in the given year. If this is the case, the zeroes can be considered true values. We assume that the second reason applies to our data.

### 2.2.2 Electricity prices

The relationship between electricity prices and innovation depends on the technologies in question. For some specific markets, for instance, the car industry, the relationship between green innovation and electricity price is straightforward to detect. For instance, Aghion et al. (2016) finds that increased electricity prices give significantly less "clean" innovations, and consequently more "dirty" innovation. On the other hand, increased fossil fuel prices will have the opposite effect.

However, we expect electricity prices to have a positive effect on patenting activity within LCE-supply and enabling technologies. This is based on the theory of induced innovation (Popp, 2002). As previously discussed, the initial cost of electricity production using renewable energy sources is generally higher than the cost of fossil fuels (Johnstone et al., 2010). Consequently, increased electricity prices can improve the profit from using renewable energy sources.

For our panel data analysis, we want to account for the differences in electricity prices between countries. Therefore, we import electricity prices on a country level from 1978 to 2018. The data is converted using annual purchasing power parity (PPP) to equalise the difference in price levels between countries (IEA, 2020).

### 2.2.3 Knowledge stock

Popp (2002) finds that energy prices and the quality of knowledge available to inventors are important factors for inducing innovation. Researchers have been able to find links between current and future research, meaning that previous inventions matter for new innovations (Popp, 2002). Therefore, we include a knowledge stock to consider the available knowledge for the two technologies at the time the patent was applied for.

As our analysis focuses on the differences between LCE-supply technologies and enabling technologies, we have created technology-specific knowledge stocks for each of the two categories.

The knowledge stock is constructed based on the method of Kruse and Wetzel (2016). This method does not account for the value of different patents. One patent can be more useful to new innovations than others. However, as previously discussed, EPO applications are in general more valuable than patents filed in a single country, due to their higher costs. As our panel data only consist of “high-value patents”, we follow the method of Kruse and Wetzel (2016) and choose not to include a value measure of patents in the knowledge stock.

We construct the knowledge stock based on the perpetual inventory method, following the previous work of Kruse and Wetzel (2016) and Peri (2005). The method constructs a stock of knowledge by using the formula below.

$$K_{\text{ijt}} = P_{\text{ijt}} + (1 - \delta)K_{\text{ijt-1}} \tag{2.1}$$

The knowledge stock, represented by $K_{\text{ijt}}$, for country $i$, technology $j$ at time $t$, calculates the number of patents accumulated up to the year of interest. $P_{\text{ijt}}$ is the number of patents within LCE supply technologies or enabling technologies. Following Kruse and Wetzel (2016) and Peri (2005) the depreciation rate of previous knowledge, represented by $\delta$, is set equal to 10%. "The depreciation rate accounts for the fact that knowledge becomes obsolete as time goes by" (Kruse and Wetzel, 2016).

To account for knowledge accumulated in the years before our starting year 1978, we construct $\mathrm{K}_{\text{ij0}}$.

$$K_{\text{ij0}} = P_{\text{ij0}}/(\delta + g) \tag{2.2}$$

$P_{\text{ij0}}$ is the number of patents in 1978, our starting year. Furthermore, the growth rate of accumulated knowledge before 1978 is accounted for with $g$ and is set to 15%. $\delta$ represent the depreciation of knowledge and is again set at 10% (Kruse and Wetzel, 2016).

### 2.2.4 Control variables

In addition to the variables discussed above, there are other factors that might affect patenting activity within LCE-supply and enabling technologies.

Renewables play a crucial role in the transition to clean energy, and renewable power is considered one of the main solutions to avoid the average global temperature increasing more than 1.5°C (IEA, 2022). A country's share of electricity from renewables indicates its position in the clean energy transition. It is reasonable to assume that countries with a high share of electricity production from renewables, also will have a higher patenting activity within LCE-supply and enabling technologies. Hence, we include the share of electricity production from renewables for each country in our data.

Further, patenting activity differs widely across the countries in our panel. We want to give more weight to countries with a large impact on the world's patenting activity. These are also countries with high overall economic activity. GDP measured in millions of dollars per year is included to control for this.

"It has been widely recognized that for environmental innovations in particular, policy support is an important trigger" (Kemp et al., 1997 as cited in Peters et al. 2012). Therefore, we include a variable for environmental policy stringency in the robustness section. OECD defines stringency as "the degree to which environmental policies put an explicit or implicit price on pollution or environmentally harmful behaviour" (OECD, 2016). The stringency index is an internationally-comparable measure for each country's stringency of environmental policy (OECD, 2016).

## 2.3 Data cleaning

The EPO REGPAT database (Maraut et al., 2008) contains data on 36 OECD countries in total. Table A2.1 in the appendix provides an overview of all countries and the number of patent applications within LCE-supply and enabling technologies. We remove the 10 countries with less than 100 patents in total as it is unlikely to find a relationship to electricity prices when the count of patents fluctuates around zero. Additionally, it creates more noise in our model. After removing these countries, we are left with 26 OECD countries for our analysis, shown in table 2.1.

Further, some countries in our panel have missing data for certain years, meaning that these countries have shorter time periods in the analysis. For example, Poland has missing data for electricity prices before 1990, while Hungary has missing data for GDP before 1991. Missing values for electricity prices, GDP and share of renewables in electricity supply are removed, as it is reasonable to assume that the missing values exist, but are not captured in the data. We cannot set these values to zero and will rather eliminate them from our data.

Box plots of patents for the 26 remaining countries are presented in figure 2.1. The median value for the 26 countries is respectively 9 and 6 patents for LCE-supply and enabling technologies. When removing all observations with zero patents, the medians increases to 19 and 15, indicating that a majority of the countries have a stable low patent count. On the other side, we observe upper outliers with patent counts over 1,000. Thus, our data is very skewed. Nevertheless, we keep all upper outliers in our data, as these observations represent the main drivers of innovation.

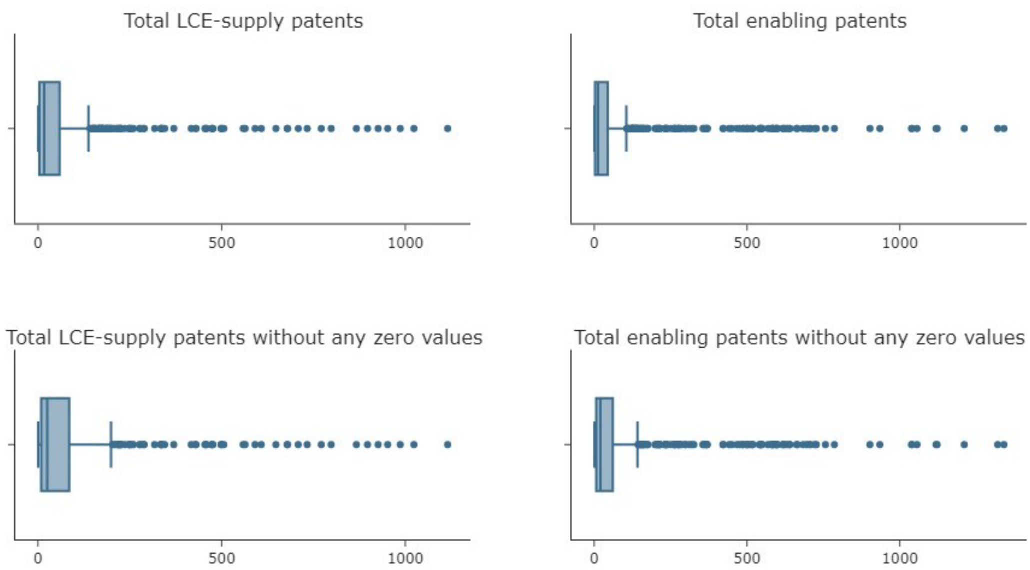


**Figure 2.1:** Boxplot of patent counts for 26 OECD countries (1978 - 2018)

**Table 2.1:** Number of LCE technology patents per country

| Countries | 1978-1986 | 1986-1994 | 1994-2002 | 2002-2010 | 2010-2018 | Total |
|---|---|---|---|---|---|---|
| AT | 75 | 82 | 115 | 331 | 582 | 1187 |
| AU | 46 | 32 | 119 | 280 | 325 | 803 |
| BE | 58 | 33 | 104 | 268 | 595 | 1059 |
| CA | 29 | 129 | 309 | 666 | 694 | 1829 |
| CH | 163 | 174 | 388 | 1112 | 1799 | 3638 |
| DE | 1039 | 1211 | 2558 | 6312 | 9852 | 20974 |
| DK | 21 | 49 | 182 | 909 | 1983 | 3144 |
| ES | 14 | 25 | 69 | 518 | 799 | 1426 |
| FI | 11 | 55 | 85 | 250 | 486 | 888 |
| FR | 721 | 615 | 738 | 2025 | 3893 | 7994 |
| GB | 302 | 301 | 458 | 1136 | 1842 | 4041 |
| HU | 16 | 10 | 6 | 25 | 51 | 111 |
| IE | 4 | 5 | 19 | 124 | 162 | 316 |
| IL | 18 | 27 | 76 | 221 | 328 | 671 |
| IT | 66 | 150 | 251 | 785 | 1022 | 2276 |
| JP | 476 | 1254 | 3924 | 7740 | 12441 | 25837 |
| KR | 0 | 3 | 158 | 2071 | 6001 | 8235 |
| LU | 20 | 21 | 38 | 61 | 108 | 248 |
| NL | 94 | 115 | 271 | 749 | 1142 | 2372 |
| NO | 11 | 15 | 78 | 233 | 239 | 576 |
| NZ | 0 | 10 | 14 | 41 | 90 | 156 |
| PL | 1 | 2 | 3 | 44 | 156 | 207 |
| PT | 1 | 3 | 9 | 36 | 58 | 108 |
| SE | 149 | 122 | 291 | 395 | 652 | 1610 |
| TR | 0 | 0 | 4 | 35 | 75 | 115 |
| US | 1509 | 2079 | 3461 | 8964 | 10617 | 26633 |

AT = Austria, AU = Australia, CA = Canada, CH = Czech Republic, DE = Germany, DK = Denmark, ES = Spain, FI = Finland, FR = France, GB = Great Britain, HU = Hungary, IE = Ireland, IL = Israel, IT = Italy, JP = Japan, KR = South Korea, LU = Luxembourg, NO = Norway, NL = New Zealand, PL = Poland, SE = Sweden, TR = Turkey, US = The United States

Table 2.1 presents an overview of the total number of LCE-supply and enabling patents applied for within each country. The time period spans from 1978-2018, and the total patent count is calculated per 8 years. At last, the column "total" displays the total number of patent applications for each country across the entire time period.

## 2.4 Descriptive statistics

Table 2.2 shows descriptive statistics for the variables in our panel data. The dependent variables are counts of patents within LCE-supply and enabling technologies. LCE-supply technologies include technologies within wind, solar, geothermal energy, hydro, marine, biofuels, fuel from waste and other technologies related to energy generation. Enabling technologies include cross-cutting energy systems like CCUS, batteries, hydrogen and fuel cells and smart grids. On average, the OECD countries in our panel apply for 50 LCE-supply patents and 59 enabling patents per year. The median values are however less than 10 patents for both categories, meaning that for most countries the average patenting activity is much lower.

The knowledge stock, as previously presented in Equation 2.1, is a constructed measure of the available knowledge within each category at a given time. The average knowledge stock is around 55 for both categories, which can provide a better understanding of the scale for the knowledge stocks. Due to the depreciation rate, one unit increase in the knowledge stock equals more than one patent.

**Table 2.2:** Descriptive statistic

| Statistic | Units | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Supply patents | count | 1,066 | 49.8 | 121.7 | 0.0 | 1,115.3 |
| Enabling patents | count | 1,066 | 59.5 | 161.5 | 0.0 | 1,340.6 |
| Knowledge stock supply | count | 1,066 | 52.4 | 131.8 | 0.0 | 1,193.2 |
| Knowledge stock enabling | count | 1,066 | 61.0 | 169.4 | 0.0 | 1,422.3 |
| Electricity price | USD/ MWh | 1,002 | 148.1 | 76.9 | 19.1 | 417.7 |
| GDP | $1MM | 1,041 | 1,070,737 | 2,272,336 | 3,840 | 20,533,058 |
| Share of renewables | ratio | 884 | 26.6 | 26.9 | 0.01 | 99.6 |
| Stringency | index | 754 | 2.1 | 1.1 | 0.0 | 4.6 |

### 2.4.1 Trends in LCE technologies

Patenting activity for LCE technologies has gone through several changes the recent years. We observe a general shift in new technologies to more reliance on electrical power, more consumer-oriented solutions and more distributed resources (IEA, 2021c). However, the new drivers for innovation are mainly in the enabling and end-use categories, while there have been fewer new patents within the supply category. The world is still in need of innovation for supply technologies to increase the share of renewables in global electricity generation, which is currently at 29% (2020) (IEA, 2021b).

We observe that the three categories have experienced very different paths since 2000. As seen in Figure 2.2, patenting activity within LCE-supply and enabling technologies have followed each other closely since 1978, but have started to move in different directions in more recent years. For instance, enabling technologies constituted 34% of all LCE patents in 2019, up from 27% in 2000. On the other hand, LCE-supply technologies have decreased since their peak in 2012, representing only 17% of total LCE patents in 2019 (IEA, 2021c).

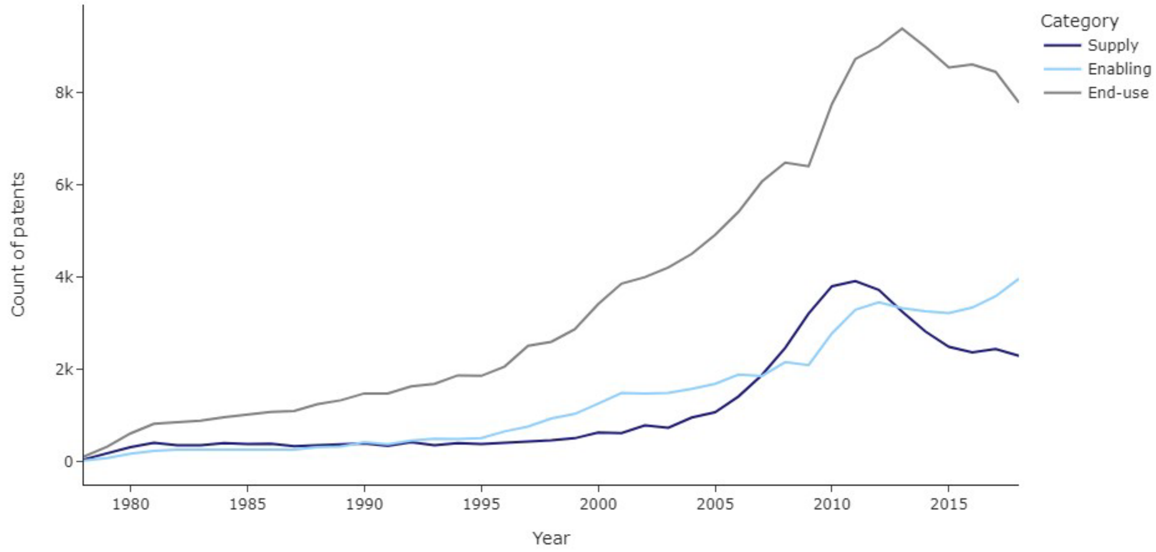


**Figure 2.2:** Trends in LCE Technologies 1978-2018

As stated, to limit the scope of this analysis we choose to only include LCE-supply and enabling technologies in the analysis. There are various reasons for LCE-supply and enabling technologies to be moving in different directions since 2012. One potential reason is that developing innovations for mature technologies is more challenging and provides less value, causing a decrease in innovation for supply technologies (Kruse and Wetzel, 2016). Another potential reason is that the supply side of energy underwent a general decline in recent years. This theory is supported by the similar decline in fossil fuel exploration and extraction technologies in the same period (IEA, 2021c). For patents with CPC classifications within both categories, we observe a trend of patents having a higher share of CPC classifications within enabling technologies. The upward trend for enabling technologies may be caused by the increasing need for more flexible systems when the electricity supply varies. (IEA, 2021c).

### 2.4.2 LCE innovation across countries

Figure 2.3 and 2.4 illustrate how different countries' patenting activity has evolved over the time period. The United States, Japan and Germany account for 68% of the total patenting activity within LCE-supply and enabling patent applications. The other countries generally have a much lower patenting activity between zero and a hundred patents per year.

As noted above, LCE-supply technologies have dramatically decreased since around 2012 while enabling technologies have experienced a slight increase. For LCE-supply technologies, it is evident that the trends in figure 2.2 are mainly driven by the United States, Japan and Germany. The other countries in our sample have remained relatively stable even after 2012. However, the increase since 2012 in enabling technologies seems to be mainly driven by Korea. Figure 2.4 seems to indicate that enabling technologies also had a decrease in several countries, but due to the strong growth in Korea, the overall trend in Table 2.2 is slightly upwards.

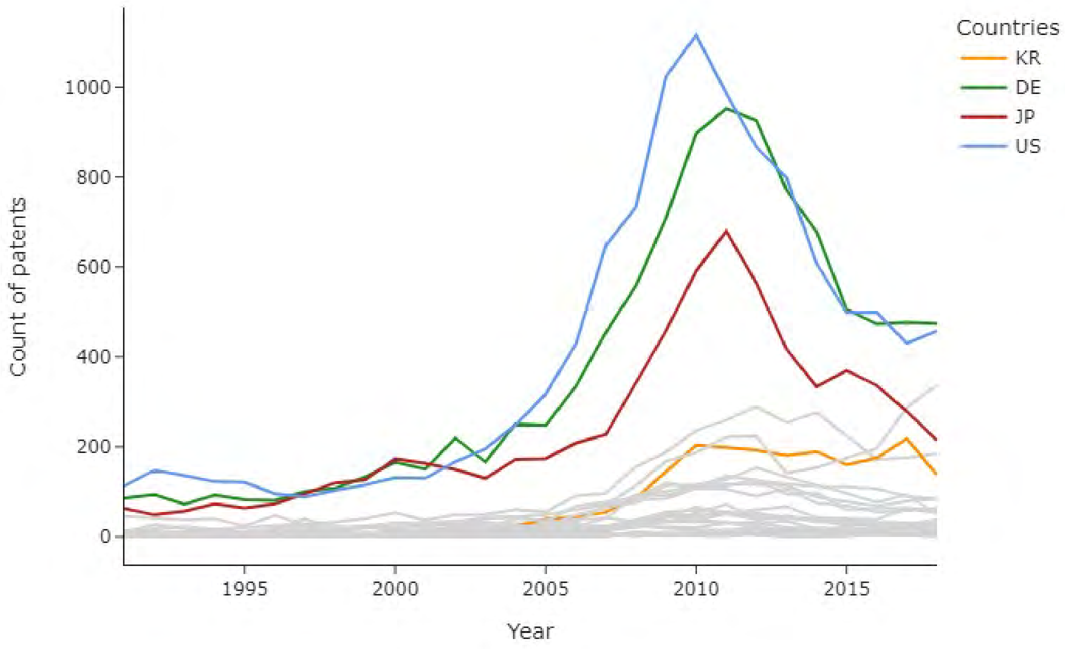


**Figure 2.3:** LCE-supply patent applications by country

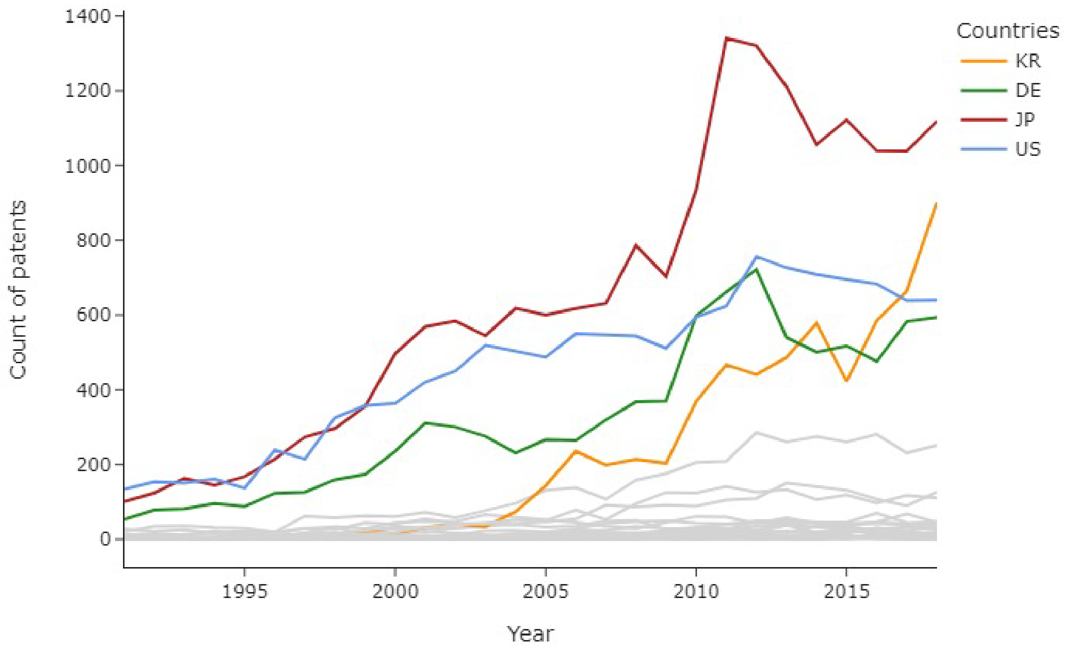


**Figure 2.4:** Enabling patent applications by country

### 2.4.3 Electricity prices

Electricity prices from 1978 to 2018 are visualized in figure 2.5. The average price throughout the time period is 148 dollars per MWh. In 2.5, The United States, Germany and Japan are highlighted, while the other countries are shown in grey to demonstrate the overall trend in electricity prices. The United States has had a relatively flat trend over the time period, while Germany has experienced a rapid price increase since around 2000. Japan represents a more average price level throughout the time period.

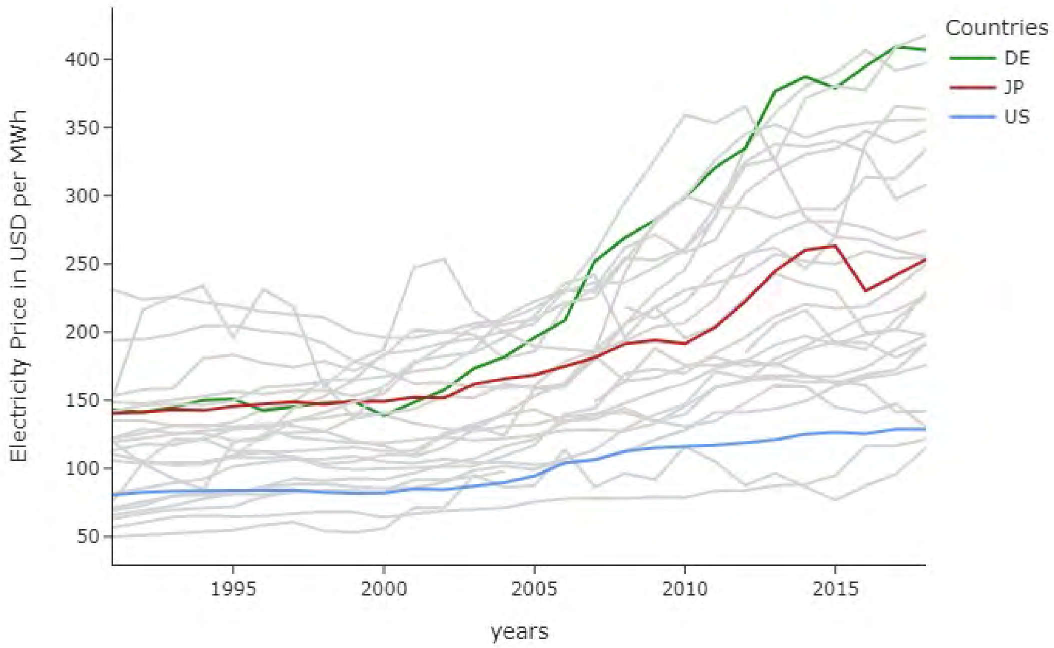


**Figure 2.5:** Electricity prices by country

### 2.4.4 Relationship between LCE technologies and electricity prices

To visualize the relationship between patenting activity and electricity prices, we create scatterplots. Plots for the countries with the highest patenting activity, the United States, Japan and Germany are presented in figure 2.6. The patent counts are displayed on the x-axis, and electricity prices lagged by one year are shown on the y-axis. The electricity prices are converted using annual purchasing power parity (PPP).

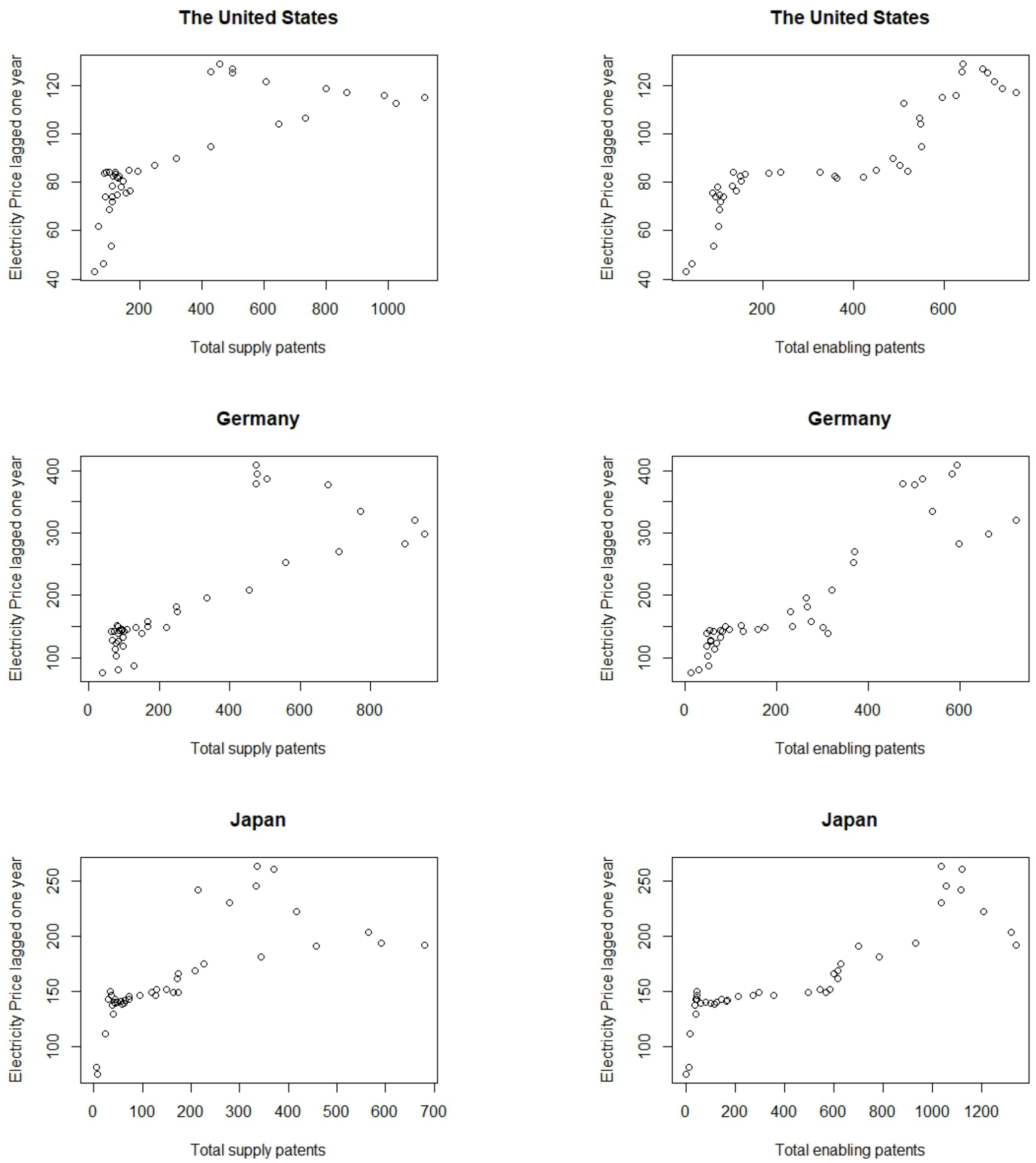


**Figure 2.6:** Scatterplots for countries with the highest patent activity (1978-2018)

The scatterplots for the United States, Germany and Japan indicate that the two variables might be related to some extent. However, we cannot draw any conclusions based on these plots because the relationship could be caused by other explanatory variables. As the observations from these three countries are considered outliers, we create scatterplots for more average countries in our panel.

Plots for Denmark, Austria and the Netherlands are presented in table 2.7, where the variables appear to be positively correlated. The curves vary for the different countries, and it is hard to determine whether a linear relationship exists. For these countries, one can see that for lower electricity prices the patenting activity fluctuates around zero. However, when reaching a certain price level the innovative activity seems to increase. This indicates that there might be different price levels for different countries that trigger innovation. However, the linear relationship is clearer when taking the natural logarithm of the two variables. In figure 2.7 the scatterplots with log-transformed variables are seen on the right-hand side.

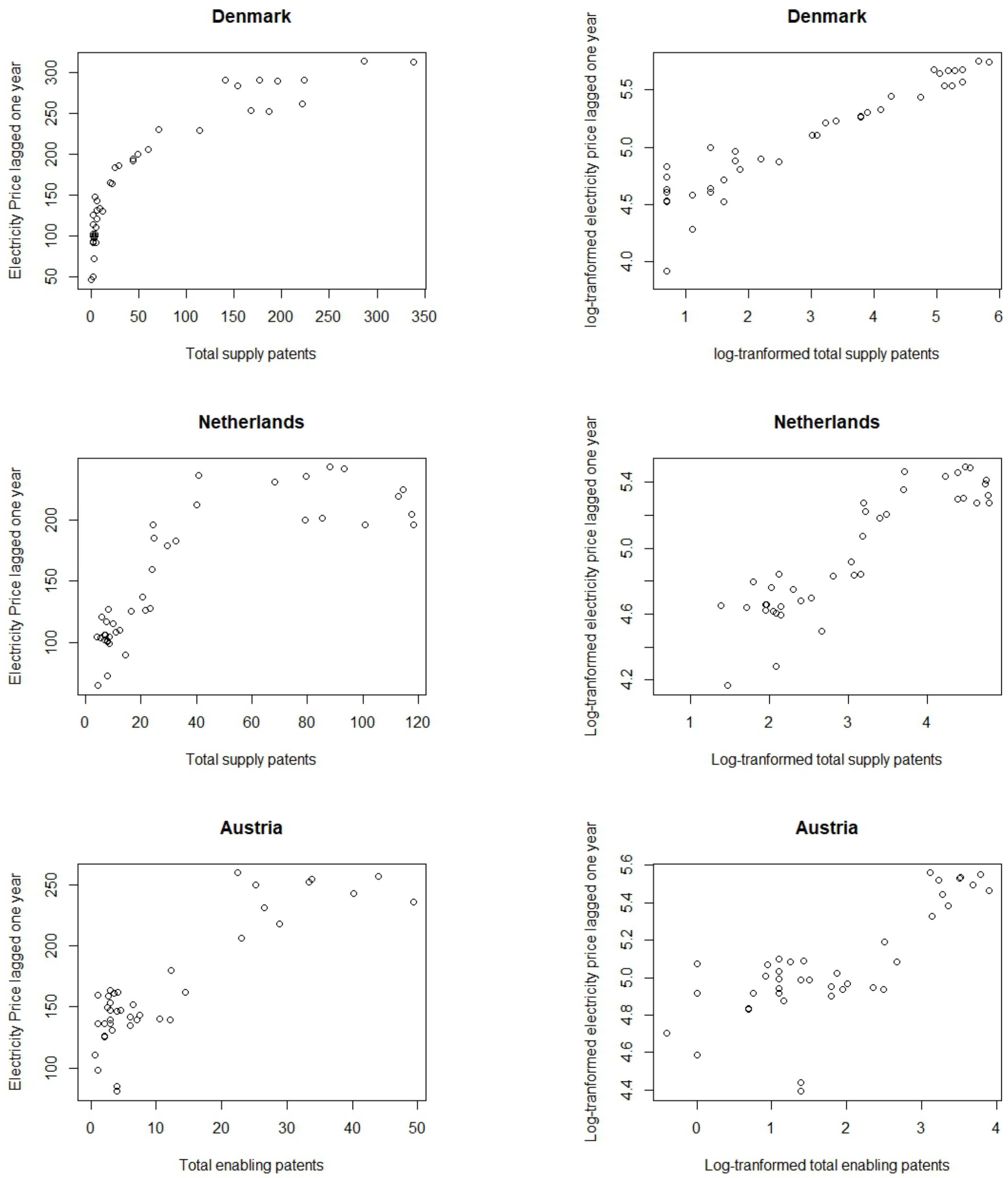


**Figure 2.7:** Scatterplots for countries with average patenting activity (1978-2018)

Further, the correlation coefficients are shown in table 2.3. The correlation between the two variables is close to 1, indicating a linear relationship. However, we cannot interpret too much of the correlation other than the fact that a relationship exists.

**Table 2.3:** Correlation between electricity price and patenting activity

| Country | Corr supply and electricity prices | Corr enabling and electricity prices |
|---|---|---|
| Denmark | 0.89 | 0.91 |
| Austria | 0.82 | 0.87 |
| Netherlands | 0.82 | 0.90 |

# 3 Methodology

## 3.1 Model specifications

As stated, this paper aims to analyse the effect of electricity prices on innovation within LCE-supply and enabling technologies. We use a linear regression model for our research.

To test our hypothesis, our model is defined by the following equation:

$$PAT_{\text{ijt}} = \beta_1 PRICE_{\text{it-1}} + \beta_2 K_{(\text{supply})\text{it-1}} + \beta_3 K_{(\text{enabling})\text{it-1}} + \beta_4 RENEW_{\text{it-1}} + \beta_5 YEAR_{\text{i}} + \alpha_{\text{i}} + u_{\text{it}} \tag{3.1}$$

where $PAT$ is the patent count for category $j$, country $i$ at time $t$. $PRICE$ is a variable for the electricity price. The variable is lagged by one year, due to the fact that innovation caused by a price increase cannot happen simultaneously with the increase. $K$ represents the knowledge stock for LCE-supply and enabling technologies. The knowledge stock is lagged by two years due to simultaneity problems. The two technical categories are closely related, and we expect that increasing the available knowledge will lead to more frequent innovation activity for both categories. Therefore, we include both knowledge stocks in our model.

$RENEW$ measures the share of green technologies in the supply mix for energy generation. As all our variables have a general increase over time, the relationship with time is not random. Therefore, our main model includes a linear time trend, represented by $YEAR$. This allows us to control for an increase in the dependent variable, which is not explained by other variables. We also include a model with a quadratic time trend, which will be further discussed in section 4. Patenting activity within LCE-supply and enabling technologies are mainly driven by some large countries, being the United States, Japan and Germany. These countries also have higher economic growth, measured by GDP. To account for the differences in patenting activity, the model is weighted by GDP to give more weight to the countries with higher patenting activity. The weights represent each country's $i$ GDP at time $t$.

All of our regressions include country-fixed effects resulting from the Hausman test in Appendix A6.2. Implementing a fixed effects model is a standard method to remove unobserved effects (Wooldridge, 2018, p. 462 - 465). For our model, any time-constant country-specific effects will be removed and captured in the unobserved effects $\alpha_{\mathrm{i}}$. Countries have general differences in patenting activity and other unobserved effects that might be correlated with our dependent variables. Therefore including the country-fixed effects reduce the chance of the model being biased.

Further, over the 41 years of data, there might be significant effects related to specific points in time. Therefore, a model with time-fixed effects instead of a linear time trend is included. The inclusion of time-fixed effects in the model allows us to both control for unobservable variables that change over time but are constant over countries, and control for factors that differ across countries but are constant over time (Hanck et al., 2021). Regressions for both time-fixed effects and a linear time trend are included because it is not apparent whether a time-fixed effect or a time trend is most appropriate. However, our data is limited, so the two-way fixed effects model seems too strict.

## 3.2 The 2012 model

This model is created to further understand the shift in trends for patenting activity after 2012. By doing so, we check whether the relationship between electricity prices and patenting activity has changed. The model is an adjustment of the main model, where we include a dummy variable for years after 2012 and an interaction term. All other variables remain equal to our main model.

$$\begin{aligned} PAT_{\mathrm{ijt}} = \beta_1 PRICE_{\mathrm{it\text{-}1}} + \beta_2 K_{(\mathrm{supply})\mathrm{it\text{-}1}} + \beta_3 K_{(\mathrm{enabling})\mathrm{it\text{-}1}} + \\ \beta_4 RENEW_{\mathrm{it\text{-}1}} + \beta_5 YEAR_{\mathrm{i}} + \beta_6 D_1 + \beta_7 D_1 * PRICE_{\mathrm{it\text{-}1}} + \alpha_{\mathrm{i}} + u_{\mathrm{it}} \end{aligned} \tag{3.2}$$

$$D_1 = 1 \text{ if year} > 2012,\ 0 \text{ if year} < 2012$$

The dummy variable $D_1$ is given the value 0 for years before 2012 and 1 for the years after. $D_1 * PRICE_{it\text{-}1}$ represent the interaction term. This variable provides a measure of the change in the effect of electricity prices on patenting activity for years after 2012. Adding an interaction term changes the interpretation of the model slightly. The $PRICE_{it}$ coefficient now represents the effect of electricity prices for years before 2012. Adding

$PRICE_{it}$ with the coefficient for the interaction term will provide the estimated effect of electricity price for years after 2012.

## 3.3 Potential challenges with the models

The model has a high risk of endogeneity, which could cause biased estimations (Wooldridge, 2018, p. 87). First, we might have omitted one or more relevant variables from our model. Fixed effects reduce omitted variable bias, but endogeneity could still be present in the model. Another endogeneity concern is simultaneity. The problem arises when one or more of the explanatory variables is jointly determined with the dependent variable (Wooldridge, 2018, p. 534). As our knowledge stock variables are a function of the dependent variables, we add a one-year lag to reduce the simultaneity problem. This changes the construction of the two knowledge stocks to equation 3.3.

$$K_{\text{ijt - 1}} = P_{\text{ijt - 1}} + (1 - \delta)K_{\text{ijt-2}} \tag{3.3}$$

Other potential problems are related to the assumption that the errors, $u_{\text{it}}$, should be homoskedastic and serially uncorrelated (Wooldridge, 2018, p. 462 - 465). After running the Breusch-Pagan and the Durbin-Watson test, we found the presence of both heteroskedasticity and autocorrelation; see Appendix A6.4 and A6.3. Using a weighted regression can help reduce some of the heteroskedasticity present in the model. However, each country in the model has specific characteristics that apply to all observations from that country. Therefore, using the normal standard errors can provide strongly misleading results (Zach, 2021). To adjust for this, we include clustered standard errors, where each country represents one cluster. The clustered standard errors are implemented in all regressions and account for heteroskedasticity across countries.

At last, our variables are strictly positive, which often leads to heteroskedastic or skewed distributions. This can be seen in the Appendix A3.1 for our dependent variable, which is left skewed towards zero. "Taking the natural logarithm of such variables can help reduce these problems if not eliminate them " (Wooldridge, 2018, p. 187). Furthermore, it changes the coefficients into elasticities, making it easier to interpret the effects of electricity price on the number of LCE-supply and enabling patents. Therefore, we include a model where the variables $PAT$ and $PRICE$ are log-transformed.

On the other hand, taking the natural logarithm of observations with zero values is not possible. As our model includes several years with zero patents, these values are transformed into missing values in the log-log model, leaving us with fewer observations for both technologies. However, these zero values are assumed to be actual zero values and not missing values that affect the model.

Changing the zero values to missing values also leaves us with a more unbalanced panel. An unbalanced panel is when there are missing values in at least some cross-sectional units in the sample (Wooldridge, 2018, p. 468 -469). If the reason for missing data in an unbalanced panel is correlated with the idiosyncratic error $u_{\mathrm{it}}$, it can cause biased estimators. As our missing values in the log-log model are actually true zero values, the reason for the missing values is likely correlated with the error term.

Due to the problems related to zero values, the log-log model does not seem fitting for this analysis. The choice of a Poisson model could reduce the problem of zero observations. However, the Poisson model would not be optimal for our data as our patent count is not an integer but constructed as a share. Our main model is therefore a linear level-level model despite its limitations.

# 4 Results

This section presents the results on whether electricity prices affect patenting activity within LCE-supply and enabling technologies. The model is estimated separately for the two technologies in order to analyse the differences between them.

Table 4.1 presents the regression model with the count of LCE-supply patents as the dependent variable, and Table 4.2 presents the regression for enabling patents. All models are weighted by GDP and include clustered standard errors and country-fixed effects.

**Table 4.1:** Regressions results - LCE-supply technologies

| | *Dependent variable:* | | | | | | |
|---|---|---|---|---|---|---|---|
| | Supply | | | | | | Log-supply |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $PRICE_{it\text{-}1}$ | 1.770*** | −0.382 | −0.224 | −0.292 | −0.245*** | 0.097 | |
| | (0.641) | (0.920) | (0.714) | (0.788) | (0.043) | (0.293) | |
| $\log(PRICE_{it\text{-}1})$ | | | | | | | 0.096 |
| | | | | | | | (0.702) |
| $K_{supply}$ | | | | | 0.864*** | 0.865*** | 0.001*** |
| | | | | | (0.016) | (0.020) | (0.0001) |
| $K_{enabling}$ | | | | | −0.075*** | −0.095*** | −0.001** |
| | | | | | (0.012) | (0.018) | (0.0004) |
| $RENEW_{it\text{-}1}$ | | | | | | −3.840 | −0.014 |
| | | | | | | (3.200) | (0.015) |
| $YEAR_i$ | | | 13.237*** | 10.629** | 1.786*** | 1.786*** | 0.080*** |
| | | | (4.806) | (4.367) | (0.405) | (0.545) | (0.024) |
| ${YEAR_i}^2$ | | | | 0.059 | | | |
| | | | | (0.067) | | | |
| Constant | −308.123** | −161.129* | −294.427*** | −261.053** | −0.041 | 196.457 | 1.125 |
| | (120.426) | (90.315) | (98.078) | (126.136) | (5.125) | (163.860) | (2.165) |
| Observations | 976 | 976 | 976 | 976 | 976 | 815 | 703 |
| Adjusted $R^2$ | 0.479 | 0.765 | 0.578 | 0.578 | 0.930 | 0.930 | 0.900 |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | No | Yes | No | No | No | No | No |
| *Note:* | | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 4.2:** Regressions results - Enabling technologies

| | *Dependent variable:* | | | | | | |
|---|---|---|---|---|---|---|---|
| | Enabling | | | | | | Log-enabling |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $PRICE_{it\text{-}1}$ | 2.029*** | −0.986 | −0.727 | −0.980 | −0.188** | −0.143 | |
| | (0.780) | (0.711) | (0.609) | (0.653) | (0.094) | (0.116) | |
| $\log(PRICE_{it\text{-}1})$ | | | | | | | −0.090 |
| | | | | | | | (0.345) |
| $K_{(supply)it\text{-}1}$ | | | | | 0.057*** | 0.061*** | −0.0002** |
| | | | | | (0.013) | (0.015) | (0.0001) |
| $K_{(enabling)it\text{-}1}$ | | | | | 0.812*** | 0.798*** | 0.0003* |
| | | | | | (0.018) | (0.018) | (0.0002) |
| $RENEW_{it\text{-}1}$ | | | | | | −0.507 | −0.012 |
| | | | | | | (0.478) | (0.007) |
| $YEAR$ | | | 18.299*** | 8.637 | 1.350*** | 1.443** | 0.083*** |
| | | | (4.222) | (5.462) | (0.482) | (0.624) | (0.013) |
| $YEAR^2$ | | | | 0.219** | | | |
| | | | | (0.092) | | | |
| Constant | −364.263** | −184.797* | −345.330*** | −221.654* | −0.151 | 22.303 | 1.299 |
| | (146.564) | (97.284) | (109.738) | (125.053) | (8.313) | (27.835) | (1.304) |
| Observations | 976 | 976 | 976 | 976 | 976 | 815 | 692 |
| Adjusted $R^2$ | 0.625 | 0.802 | 0.784 | 0.788 | 0.972 | 0.971 | 0.947 |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | No | Yes | No | No | No | No | No |
| *Note:* | | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

Model (1) is considered the naive model, including only electricity price and country-fixed effects. Without including any control variables, the *PRICE* coefficient is positively significant for both LCE-supply and enabling technologies. The results indicate that a 1 dollar increase in electricity prices per MWh leads to an increase of 1.7 supply patents and 2 enabling patents per country per year.

Model (2) adds time-fixed effects in addition to country-fixed effects. This reduces the effect of the *PRICE* coefficient as well as it turns negative for both LCE-supply and enabling patents. However, the two-way fixed effect seems too strict for our estimations due to our limited data.

Model (3) includes country-fixed effects with a linear time trend to control for the overall increase in patents which is not explained by other variables. The time trend is positively significant and indicates that the relationship with time is important. Further, the time trend seems to capture most of the effects related to time. As stated in the methodology section, controlling for time trends appears to be suited for our model.

Model (4) includes country-fixed effects with a quadratic time trend. For LCE-supply technologies, it seems that most of the effect is captured in the linear time trend. This is due to the significant coefficient *YEAR* at the 5% significance level. Further, the change in coefficients for *PRICE* from a linear to quadratic time trend is minimal. However, for enabling technologies the coefficient indicating a quadratic time trend has a significant effect. On the other hand, the coefficient for electricity price does not change much. As the results of both enabling and LCE-supply regressions showing minimal effect of including a quadratic time trend, we chose to use a linear time trend in all our models.

Model (5) builds on model (3) with linear time trend and country-fixed effects. In addition, model (5) includes the knowledge stocks for the two categories. Controlling for available knowledge makes the coefficient for *PRICE* negative and significant for both LCE-supply and enabling technologies. However, the observed effect is small. Both patent counts are positively affected by their own knowledge stock, as a one-unit increase in knowledge increases the patent counts by 0.8. $K_{enabling}$ has a slightly negative effect on LCE-supply patents, while $K_{supply}$ has a small positive effect on the enabling patent count.

Model (6) is considered our main model and includes a control variable for the share of renewables in the electricity supply mix. Including the variable *RENEW* reduces our data by 7 years, leaving us with 815 observations. The coefficients for *PRICE* are no longer significant for either LCE-supply or enabling patents. The coefficients for the two knowledge stocks are still significant, but the effect remains the same as in model (5).

Model (7) is a log-log model, where both the count of patents and electricity prices are log-transformed. As discussed, log-transformed variables can create a better distribution of our observations. Considering the fact that a log-log model loses all zero values and reduces the number of observations by over 100 patents, we will not move further with this model. With the log-log model, the effect of electricity prices remains the same as in model (6). However, we observe that the effect of knowledge disappears.

# 5 Robustness Analysis

In this section, we test our results by widening our analysis. First, we include a variable for environmental policy, before taking a closer look at how the effect of electricity prices might vary for countries with higher patenting activity. Further, we investigate the observed shift in patenting activity after 2012. At last, we check how different time lags and weights affect our model.

## 5.1 Environmental policy stringency

Environmental policies are in previous research recognized as a potential driver for green innovation. However, environmental policies are closely linked to electricity prices and the stock of knowledge. As Kruse and Wetzel (2016) explains, governments can increase electricity prices by implementing policies like emission taxes. This is because a large share of electricity is generated from fossil fuels. Additionally, governments can increase the stock of knowledge by for example implementing tax incentives for investments and government-sponsored R&D (Kruse and Wetzel, 2016). Consequently, the variable for environmental policy stringency is not included in our main model.

However, in order to test the robustness of our results, we include a control variable for environmental policy stringency. As previously discussed, the stringency index measures "the degree to which environmental policies put an explicit or implicit price on pollution or environmentally harmful behaviour"(OECD, 2016). Models with a variable for stringency are presented in table 5.1. The database dates back to 1990, meaning that we lose several observations. Hence, this model only has 723 observations compared to the previous 815 observations.

**Table 5.1:** Regression results - Including environmental policy stringency

| | *Dependent variable:* | |
|---|---|---|
| | Supply | Enabling |
| | (1) | (2) |
| $PRICE_{it\text{-}1}$ | 0.177 | −0.128 |
| | (0.341) | (0.125) |
| $K_{(supply)it\text{-}1}$ | 0.864*** | 0.065*** |
| | (0.020) | (0.015) |
| $K_{(enabling)it\text{-}1}$ | −0.114*** | 0.779*** |
| | (0.023) | (0.023) |
| $RENEW_{it\text{-}1}$ | −4.522 | −0.508 |
| | (3.680) | (0.400) |
| $STRINGENCY_{it}$ | −1.519 | −10.747 |
| | (11.633) | (7.689) |
| $YEAR$ | 2.061 | 2.483*** |
| | (1.272) | (0.742) |
| Constant | 219.900 | 13.908 |
| | (177.435) | (21.911) |
| Observations | 723 | 723 |
| Adjusted $R^2$ | 0.929 | 0.970 |
| Country fixed effects | Yes | Yes |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

The results for the two categories are quite similar to our previous findings. The coefficient for *PRICE* is close to zero and not significant when including all countries. The coefficient for *STRINGENCY* is negative and not significant. This is somewhat surprising compared to previous findings. For instance, Johnstone et al. (2010) finds that environmental policies play a significant role for patent applications. However, Johnstone et al. include several types of policy instruments and found that the effect on patenting activity varies between these. As our index for environmental policy stringency is an overall measure of policies, it will not reflect the effect of particular policies. Furthermore, the time period in Johnstone et al. (2010) spans from 1978 to 2003. Due to this, the significant decrease in LCE-supply technologies is not captured in his data. This could have a substantial effect on the results and might reduce the importance of policies for innovation in the model.

## 5.2 Testing different subsets

As previously discussed, patenting activity varies between countries. The United States, Japan and Germany have an extremely high patenting activity compared to other OECD countries. To investigate whether the effect of electricity prices varies among countries, we create two subsets. One including only the United States, Japan and Germany and one including the remaining countries. The results are presented in table 5.2. All models in the table are identical to our main model with a linear time trend and country-fixed effects.

**Table 5.2:** Regression results - Testing different subsets

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Supply | | Enabling | |
| | (1) | (2) | (3) | (4) |
| | US, JP, DE | 23 countries | US, JP, DE | 23 countries |
| $PRICE_{it\text{-}1}$ | 3.089*** | −0.094* | 0.424** | −0.092 |
| | (1.164) | (0.050) | (0.202) | (0.077) |
| $K_{(supply)it\text{-}1}$ | 0.805*** | 0.890*** | 0.051*** | 0.018 |
| | (0.044) | (0.018) | (0.012) | (0.017) |
| $K_{(enabling)it\text{-}1}$ | −0.412*** | −0.058*** | 0.715*** | 0.966*** |
| | (0.106) | (0.015) | (0.042) | (0.037) |
| $RENEW_{it\text{-}1}$ | −33.216*** | −0.363 | −5.955*** | −0.058 |
| | (10.519) | (0.258) | (0.904) | (0.196) |
| $YEAR$ | 8.957*** | 0.781** | 3.334** | 0.421 |
| | (2.300) | (0.351) | (1.324) | (0.369) |
| Constant | −337.775** | 22.325 | −47.318 | 9.149 |
| | (141.343) | (14.546) | (44.941) | (10.521) |
| Observations | 99 | 716 | 99 | 716 |
| Adjusted $R^2$ | 0.917 | 0.932 | 0.942 | 0.948 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

Models (1) and (3) are subsets where only the countries with the highest patenting activity are included. Model (1) is a regression for LCE-supply technologies, and one can see that the coefficient is positive and significant at the 1% level. The results show that a 1 dollar increase in electricity price per MWh will induce 3 more supply patents per country per year. A similar effect can be observed for enabling patents in model (3), where one can expect 0,4 patents from a 1-dollar increase per MWh. The coefficient is significant at the 5% level.

Models (2) and (4) are subsets including the remaining 23 countries. The coefficients for electricity prices have changed from positive to negative signs. The significance level is reduced for LCE-supply technologies and is not significant for enabling technologies. Additionally, the coefficients are close to zero and indicate that there is no effect on patenting activity from an increase in electricity price for the 23 countries.

However, the coefficients for *PRICE* can be difficult to interpret. This is due to the large variation in electricity prices and patenting activity between the countries in our panel. Therefore, we provide a simplified example:

Over the last 40 years, the United States had an average growth in electricity price per year of 2 dollars per MWh. This is a relatively flat rate compared to Germany, which had a yearly average growth of 8 dollars per MWh. A one-dollar increase in electricity price will have different implications for the two countries, depending on their average growth rate and price. However, for most countries, the price varies between 50 and 150 dollars over the time period. To get a deeper understanding of our results, we can think of the one-dollar increase per MWh as a 1% increase in electricity price. Using the adjusted interpretation, our results indicate that a 1% increase in electricity price in the United States will result in 3 LCE-supply patents and 0,4 enabling patents per year. Using this example can help ease the interpretation of the $PRICE_{it\text{-}1}$ coefficient. However, there are large variations between countries and this method for coefficient interpretation can not be used to draw any conclusions.

The results from the subset including the United States, Japan and Germany differ from the main model where we find no effect of electricity prices on patents within LCE-supply and enabling technologies. On the other hand, the results from our subset correspond with the results of Popp (2002). In his research, Popp (2002) finds a significant positive effect of energy prices on patenting activity within energy-efficient technologies in the United States. This amplifies the fact that electricity prices have a stronger effect in countries with higher patenting activity. Therefore, electricity prices do not seem to initiate innovation within LCE-supply and enabling technologies but rather affect countries where the innovation is already present.

## 5.3 The 2012 model

LCE-supply and enabling technologies have since 2012 shown different trends in patenting activity. As shown in the section for descriptive statistics, we found that the two technologies have been moving in separate directions. To further investigate this, we include a dummy variable and an interaction term in our models to see whether the effect of electricity prices has changed after 2012.

**Table 5.3:** Regression Results - Included dummy variable for 2012

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | | Supply | | | Enabling | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All countries | US, JP, DE | 23 countries | All countries | US, JP, DE | 23 countries |
| $PRICE_{it-1}$ | 0.057 | 2.809*** | −0.065 | −0.129 | −0.020 | −0.127 |
| | (0.248) | (0.979) | (0.048) | (0.180) | (0.432) | (0.092) |
| $K_{(supply)it-1}$ | 0.817*** | 0.742*** | 0.858*** | 0.038*** | 0.013 | 0.017 |
| | (0.022) | (0.022) | (0.021) | (0.011) | (0.012) | (0.020) |
| $K_{(enabling)it-1}$ | −0.027 | −0.222*** | −0.012 | 0.830*** | 0.846*** | 0.978*** |
| | (0.031) | (0.064) | (0.010) | (0.012) | (0.050) | (0.028) |
| $RENEW_{it-1}$ | −0.229 | −18.637*** | 0.063 | 1.173* | 4.705 | 0.027 |
| | (0.926) | (6.401) | (0.213) | (0.644) | (4.287) | (0.193) |
| $YEAR$ | 4.996*** | 9.349*** | 1.209*** | 2.846*** | 4.044*** | 0.656 |
| | (1.499) | (1.363) | (0.328) | (0.823) | (1.534) | (0.399) |
| $D_1$ | −159.289** | −74.727** | −36.013*** | −68.726*** | −77.348*** | −20.770** |
| | (68.137) | (33.655) | (12.877) | (24.855) | (15.985) | (10.348) |
| $D_1 * PRICE_{it-1}$ | 0.157 | −0.610*** | 0.059 | 0.043 | −0.258*** | 0.070** |
| | (0.295) | (0.212) | (0.043) | (0.141) | (0.033) | (0.031) |
| Constant | −100.546** | −440.747*** | −18.505 | −118.823** | −91.091 | 4.154 |
| | (46.778) | (131.491) | (13.802) | (54.939) | (65.712) | (11.676) |
| Observations | 815 | 99 | 716 | 815 | 99 | 716 |
| $R^2$ | 0.949 | 0.944 | 0.945 | 0.975 | 0.958 | 0.950 |
| Adjusted $R^2$ | 0.947 | 0.939 | 0.942 | 0.974 | 0.954 | 0.948 |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

The three first models in Table 5.3 are for LCE-supply technologies. Models (4), (5) and (6) are for enabling technologies.

The variable of interest in this model is the interaction term where we observe the change in effect from electricity price after 2012. For supply technologies, the interaction term is only significant for the subset including the United States, Japan and Germany, presented in model (2). The coefficient indicates that for years after 2012, the effect of electricity price is reduced by 0.610 patents. Therefore, the total effect of electricity prices on patenting activity for years after 2012 is 2.199. For all countries in our panel, presented in model (1), the effect of electricity prices before and after 2012 is not significant.

For enabling technologies, the coefficients for the interaction term in models (5) and (6) are significant. We observe that the effect of electricity prices is reduced by 0.258 patents for the United States, Japan and Germany, while the effect is increased by 0.07 patents for the remaining 23 countries.

Both the coefficients in the models for high patenting activity are significant at the 1% level. This indicates that the effect of electricity prices after 2012 is slightly reduced for the United States, Japan and Germany. However, all of the coefficient values are around 0,5 patents, indicating that even though there is a significant change for the subsets, this change is very small.

The estimated coefficient for the interaction term, representing the change in electricity prices for years after 2012, has a much shorter time period. Therefore, one should be careful when comparing the effect of electricity prices before and after 2012.

## 5.4 Model without weights

All our models are weighted by GDP in order to give more weight to countries with higher patenting activity. In this section, we further investigate our models without weights.

Model (1) and model (3) are the weighted models for all countries in the panel. Models (2) and (4) show regressions for LCE-supply and enabling patent counts when we remove the weights.

**Table 5.4:** Regression Results - Weights robustness test

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Supply | | Enabling | |
| | (1) | (2) | (3) | (4) |
| | with weights | without weights | with weights | without weights |
| $PRICE_{it\text{-}1}$ | 0.097 | −0.111** | −0.143 | −0.116* |
| | (0.293) | (0.052) | (0.116) | (0.069) |
| $K_{(supply)it\text{-}1}$ | 0.865*** | 0.903*** | 0.061*** | 0.062 |
| | (0.020) | (0.029) | (0.015) | (0.042) |
| $K_{(enabling)it\text{-}1}$ | −0.095*** | −0.053*** | 0.798*** | 0.858*** |
| | (0.018) | (0.021) | (0.018) | (0.033) |
| $RENEW_{it\text{-}1}$ | −3.840 | −0.069 | −0.507 | −0.091 |
| | (3.200) | (0.290) | (0.478) | (0.128) |
| $YEAR$ | 1.786*** | 0.798*** | 1.443** | 0.716* |
| | (0.545) | (0.306) | (0.624) | (0.371) |
| Constant | 196.457 | 5.890 | 22.303 | 9.130 |
| | (163.860) | (18.407) | (27.835) | (8.330) |
| Observations | 815 | 815 | 815 | 815 |
| Adjusted $R^2$ | 0.930 | 0.949 | 0.971 | 0.973 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 | |

The results coincide with previous findings, which indicate that the positive effect of electricity prices on patenting activity is mainly driven by the US, Japan and Germany. We observe that the coefficients for LCE-supply technologies change from positive to negative when removing the weights. The countries with the highest patenting activity are also the ones with the highest GDP, giving the results from the United States, Germany and Japan more weight in the model. As we already know, the effect of electricity prices is strongly positive for these countries and slightly negative for all other countries. When giving more weight to the larger countries, we see that the coefficient adjusts for the strong positive effect in these countries.

## 5.5 Lags on electricity price

To test the robustness of the price effects, we test for 2-year and 3-year lags in electricity prices. This is done for the reason that the delay from the change in electricity price before a patent is applied for could be longer than one year.

**Table 5.5:** Lags on electricity price

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Supply | | | Enabling | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | 1 year | 2 years | 3 years | 1 year | 2 years | 3 years |
| $PRICE_{it\text{-}1}$ | 0.097 | | | −0.143 | | |
| | (0.293) | | | (0.116) | | |
| $PRICE_{it\text{-}2}$ | | −0.043 | | | −0.096 | |
| | | (0.220) | | | (0.086) | |
| $PRICE_{it\text{-}3}$ | | | −0.159 | | | −0.013 |
| | | | (0.148) | | | (0.084) |
| $K_{(supply)it\text{-}1}$ | 0.865*** | 0.866*** | 0.865*** | 0.061*** | 0.060*** | 0.060*** |
| | (0.020) | (0.020) | (0.019) | (0.015) | (0.014) | (0.014) |
| $K_{(enabling)it\text{-}1}$ | −0.095*** | −0.097*** | −0.099*** | 0.798*** | 0.799*** | 0.800*** |
| | (0.018) | (0.017) | (0.017) | (0.018) | (0.018) | (0.018) |
| $RENEW_{it\text{-}1}$ | −3.840 | −3.240 | −2.754 | −0.507 | −0.717 | −1.072 |
| | (3.200) | (2.836) | (2.453) | (0.478) | (0.548) | (0.756) |
| $YEAR$ | 1.786*** | 2.224*** | 2.552*** | 1.443** | 1.285** | 1.041*** |
| | (0.545) | (0.520) | (0.603) | (0.624) | (0.518) | (0.399) |
| Constant | 196.457 | 169.401 | 147.921 | 22.303 | 31.679 | 47.451 |
| | (163.860) | (149.336) | (133.383) | (27.835) | (29.863) | (36.496) |
| Observations | 815 | 812 | 809 | 815 | 812 | 809 |
| Adjusted $R^2$ | 0.930 | 0.930 | 0.930 | 0.971 | 0.971 | 0.970 |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

As shown in table 5.5, the coefficient for electricity price slightly changes between the three lags for both categories. However, the effect is not significant for any of the three lags when including all countries in our panel. The other coefficients in the model barely change for the different time lags. The model does not seem to be significantly affected by the adjustments for different time lags. Following Kruse and Wetzel (2016), we conclude that a one-year lag is sufficient in the model.

# 6 Conclusion

This analysis aims to come closer to understanding what drives innovation within green technologies. However, this is a highly discussed and complex question where the scientific community has not reached a final conclusion.

The uncertain global situation in 2022 has led to changes in the energy supply and abnormally high electricity prices. Therefore, the motivation for this analysis was to investigate whether we can expect the increased electricity prices to affect innovation within LCE technologies. The fundament of the analysis was the following research question:

*How do electricity prices affect innovation within LCE-Supply and Enabling technologies?*

To answer this question, patents are used as a proxy for innovation. A linear regression model is applied to a panel including 26 OECD countries from 1978 to 2018.

For our main results, we do not find any significant effect of electricity prices for either LCE-supply or enabling technologies. The results correspond with the paper from Johnstone et al. (2010), which finds no significant effect of electricity price on patent activities within green energy technology. This indicates that other factors mainly drive innovation within green technologies. Assuming that there are no omitted variables in the model, our results suggest that the primary determinant for innovation within LCE-supply and enabling technologies is the availability of knowledge. This corresponds well with the conclusion reached by Kruse and Wetzel (2016). Furthermore, this is supported by Popp's theory that "the supply of ideas, as well as the demand for new ideas, plays an important role in shaping the direction of innovation" (Popp, 2002).

However, when extracting a subset for the United States, Japan and Germany, we discover a positive significant effect of electricity prices. As these countries account for about 68% of total innovation within our data, this result indicates that electricity price affects countries with high patenting activity. To test the robustness of our analysis, we included an environmental policy stringency index in our model. However, we do not find any significant effect of policies for our 26 OECD countries. The results stay close to the main model, where knowledge seems to be the main driver.

Next, we look at the shift in trends for patenting activity since 2012. We found that the effect of electricity prices on innovation did not significantly change before and after 2012. However, for the United States, Japan and Germany, the effect of electricity prices is slightly reduced after 2012.

To conclude, the results of our analysis signal that different countries will have different drivers for green innovation. However, there are some limitations to our models. Due to the complexity of the question of what drives innovation, our model could have problems related to endogeneity. One reason for this is the simultaneity problem related to our knowledge stocks. The additional lag reduces this, yet there is no guarantee that all simultaneity-related issues are removed from the model. Another potential reason for endogeneity in the model is caused by omitted variable bias. Even though we have included and tested for different variables, other explanations for innovation within green technologies might still exist. Therefore, looking for other potential drivers for innovation could be interesting for future research.

Further, using patent data to compare innovation trends across countries has some limitations. This is due to the difference in patent regulations for countries, which makes it hard to compare counts of patents. Therefore, one should keep this in mind when reading the results for different country subsets. On the other hand, it would be interesting for future research to understand the difference in the effect of electricity prices for countries with higher patenting activity. Understanding how innovation is induced in these countries could potentially help to increase innovation in other countries.

The time period of the analysis is limited due to a lack of data. This is primarily because of the data for the share of renewables which only dates back to 1985. Further, some countries also have missing data for certain variables, meaning that the time period for these countries is shorter in the analysis. Including a longer time period and a more balanced panel would be beneficial for future research.

At last, we are in the midst of a global energy and climate crisis. For future research, it will be particularly interesting to observe whether the current shocks and the extreme electricity prices we are experiencing today will affect innovation within low-carbon energy technologies in the future.

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# Appendix

## A1 Cooperative Patent Classification (CPC)

EPO uses two classification schemes for patents, which is beneficial in order to analyse innovation within specific categories. The first one is the International Patent Classification (IPC), where there are approximately 70 000 different classification codes for various technical areas (EPO, 2017a). The second one, the Cooperative Patent Classification (CPC) is an extension of the IPC.

CPC is divided into nine sections, A-H and Y with their respective subclasses and groups. This adds up to a total of approximately 250 000 classification entries (EPO, 2017b). The difference between CPC and IPC is the additional section Y that is included in CPC, which is related to the general tagging of new technological developments (EPO, 2017b). All the CPC classifications used in our analysis are categorized within this section Y. The categories are based on the cartography of LCE technologies from the article "Patents and the Energy Transition" (IEA, 2021c).

**Table A1.1:** Cartography of LCE-supply and enabling technologies

| Cartography of LCE supply and enabling technologies | | | |
|---|---|---|---|
| Low-carbon energy supply | Wind | | Y02E10/70/LOW |
| | Solar | Solar PV | Y02E10/50/LOW |
| | | Solar thermal | Y02E10/40/LOW |
| | | Other Solar | Y02E10/60 |
| | Other renewables | Geothermal energy | Y02E10/10/LOW |
| | | Hydro | Y02E10/20/LOW |
| | | Marine | Y02E10/30/LOW |
| | | Other | Y02E10/00 |
| | Technologies for the production of fuel of non-fossil origin | Biofuels | Y02E50/10 |
| | | Fuel from waste | Y02E50/30 |
| | | Other | Y02E50/00 |
| | Combustion technologies with mitigation potential | | Y02E20/00/LOW |
| | Energy generation of nuclear origin (electricity) | | Y02E30/00/LOW |
| Enabling and cross-cutting energy systems (enabling technologies) | CCUS | | Y02C20/00/LOW |
| | Batteries | | Y02E60/10 |
| | Hydro and fuel cells | | Y02E60/30/LOW |
| | Other | | Y02E60/00 OR Y02E60/13 OR Y02E60/14 ”R Y02E60/16 OR Y02E70/00/LOW OR Y02E60/60 OR Y02E40/00 OR Y02E40/10,20,30,40,50,60 |
| | Smart Grids | | Y04S |

*Table is retrieved from IEA (2021c)*

# A2 Total LCE-supply and enabling patents

**Table A2.1:** Number of LCE technology patents for 36 OECD countries

| Countries | 1978-1986 | 1986-1994 | 1994-2002 | 2002-2010 | 2010-2018 | Total |
|---|---|---|---|---|---|---|
| AT | 75 | 82 | 115 | 331 | 582 | 1187 |
| AU | 46 | 32 | 119 | 280 | 325 | 803 |
| BE | 58 | 33 | 104 | 268 | 595 | 1059 |
| CA | 29 | 129 | 309 | 666 | 694 | 1829 |
| CH | 163 | 174 | 388 | 1112 | 1799 | 3638 |
| CL | 0 | 0 | 1 | 3 | 16 | 20 |
| CZ | 0 | 2 | 5 | 30 | 48 | 85 |
| DE | 1039 | 1211 | 2558 | 6312 | 9852 | 20974 |
| DK | 21 | 49 | 182 | 909 | 1983 | 3144 |
| EE | 0 | 0 | 0 | 9 | 17 | 26 |
| ES | 14 | 25 | 69 | 518 | 799 | 1426 |
| FI | 11 | 55 | 85 | 250 | 486 | 888 |
| FR | 721 | 615 | 738 | 2025 | 3893 | 7994 |
| GB | 302 | 301 | 458 | 1136 | 1842 | 4041 |
| GR | 1 | 9 | 8 | 33 | 21 | 72 |
| HU | 16 | 10 | 6 | 25 | 51 | 111 |
| IE | 4 | 5 | 19 | 124 | 162 | 316 |
| IL | 18 | 27 | 76 | 221 | 328 | 671 |
| IS | 0 | 0 | 1 | 3 | 5 | 9 |
| IT | 66 | 150 | 251 | 785 | 1022 | 2276 |
| JP | 476 | 1254 | 3924 | 7740 | 12441 | 25837 |
| KR | 0 | 3 | 158 | 2071 | 6001 | 8235 |
| LT | 0 | 0 | 0 | 2 | 6 | 8 |
| LU | 20 | 21 | 38 | 61 | 108 | 248 |
| LV | 0 | 0 | 1 | 4 | 14 | 19 |
| MX | 0 | 0 | 3 | 14 | 21 | 38 |
| NL | 94 | 115 | 271 | 749 | 1142 | 2372 |
| NO | 11 | 15 | 78 | 233 | 239 | 576 |
| NZ | 0 | 10 | 14 | 41 | 90 | 156 |
| PL | 1 | 2 | 3 | 44 | 156 | 207 |
| PT | 1 | 3 | 9 | 36 | 58 | 108 |
| SE | 149 | 122 | 291 | 395 | 652 | 1610 |
| SI | 0 | 1 | 1 | 11 | 26 | 39 |
| SK | 0 | 0 | 4 | 10 | 17 | 31 |
| TR | 0 | 0 | 4 | 35 | 75 | 115 |
| US | 1509 | 2079 | 3461 | 8964 | 10617 | 26633 |

AT = Austria, AU = Australia, CA = Canada, CH = Czech Republic, DE = Germany, DK = Denmark, ES = Spain, FI = Finland, FR = France, GB = Great Britain, HU = Hungary, IE = Ireland, IL = Israel, IT = Italy, JP = Japan, KR = South Korea, LU = Luxembourg, NO = Norway, NL = New Zealand, PL = Poland, SE = Sweden, TR = Turkey, US = The United States, MX = Mexico, CZ = Czech Republic, SI = Slovenia, CL = Chile, EE = Estonia, IS = Iceland, LV = Latvia, LT = Lithuania, GR = Greece, SK = Slovakia

Table A2.1 provides information on LCE-supply and enabling patents for 36 OECD countries. Countries with less than 100 patents in total are excluded from our analysis. These are: Latvia, Mexico, Czech Republic, Greece, Slovenia, Chile, Estonia, Iceland, Slovakia and Lithuania.

# A3 Distribution of dependent variable

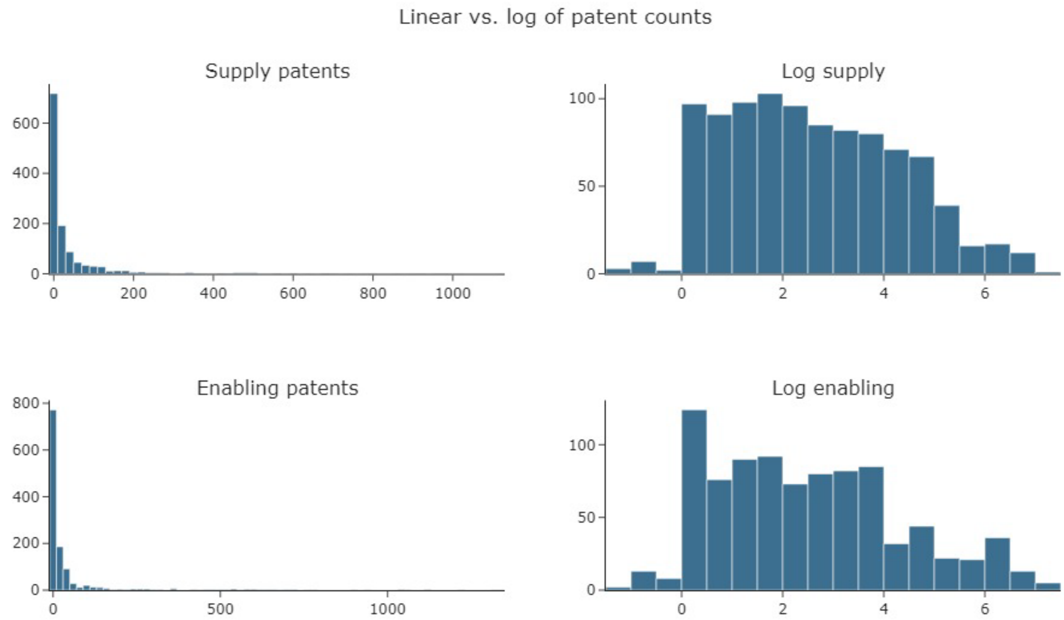


**Figure A3.1:** Distribution of dependent variables

Figure A3.1 shows the distribution of LCE-supply and enabling patents for 26 OECD countries. The right hand-side of the figure presents the log-transformed distribution, while the left side is a regular count. The figure indicates that the distribution is very skewed, and the log-transformed counts are slightly more normally distributed.

# A4 Histograms of electricity price

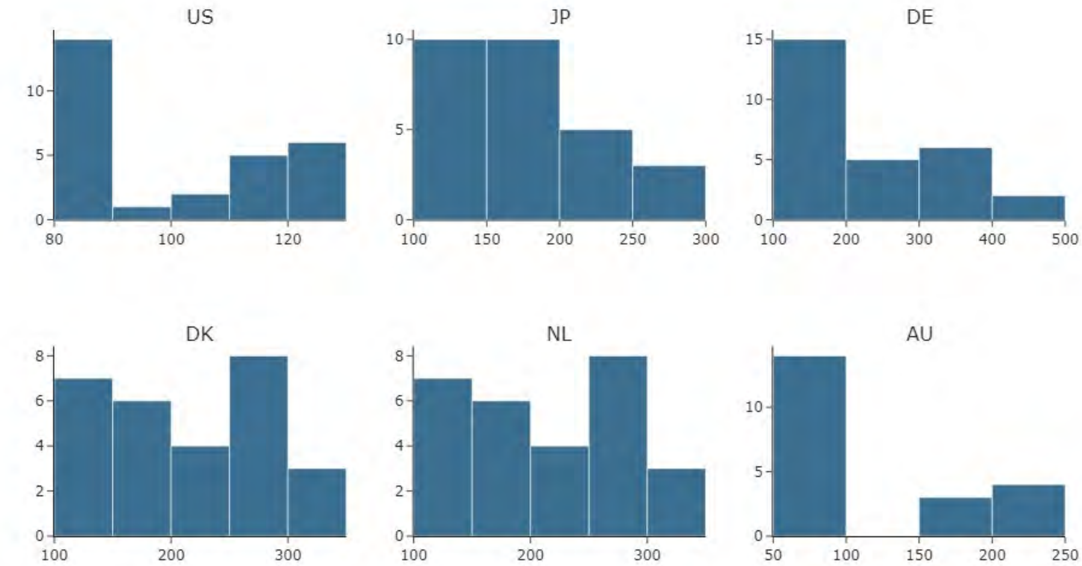


**Figure A4.1:** Electricity price for countries

Figure A4.1 presents histograms of electricity prices for the three countries with the highest patenting activity, and countries with more average patenting activity from 1978 to 2018.

# A5 Overview environmental policy stringency index

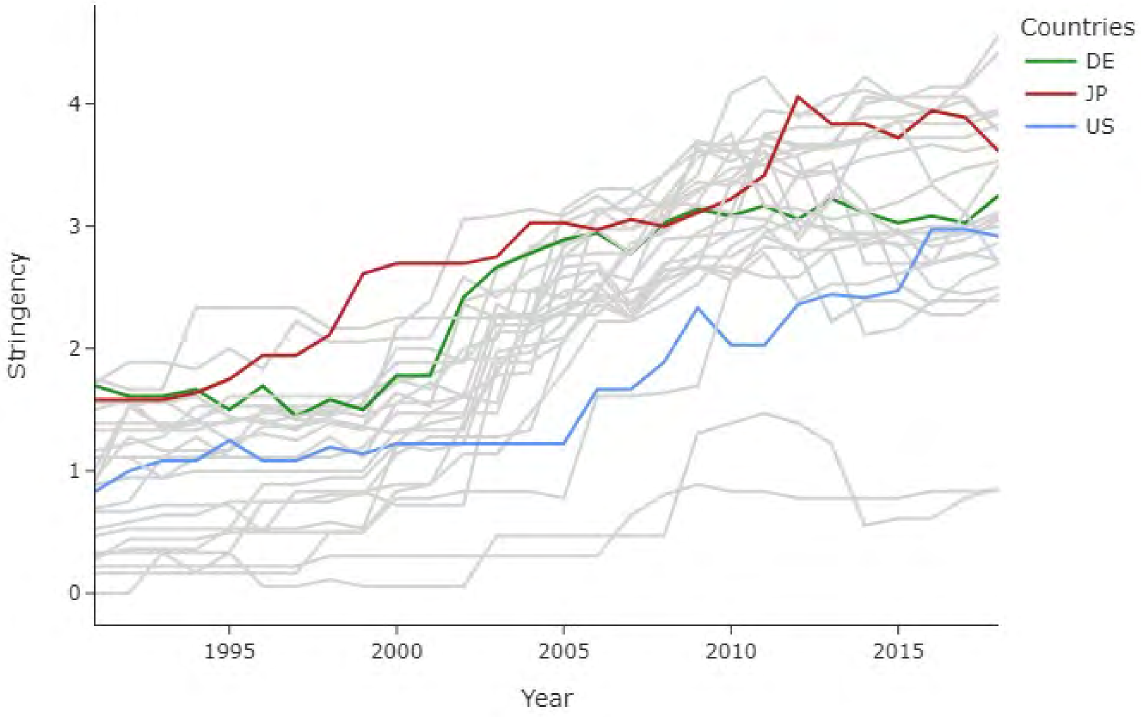


**Figure A5.1:** Environmental Policy Stringency for 26 OECD countries

Figure A5.1 presents the environmental policy stringency for 26 OECD countries from 1990 to 2018. Germany and Japan are considered more average on the level of stringency, while the United States is more on the lower limit. Overall, the majority of countries have followed the same trends over the time period, including a jump in stringency around 2000.

# A6 Statistical tests

## A6.1 The VIF test for Multicollinearity

The variance inflation factor (VIF) is used in order to test for multicollinearity. As none of the variables has a VIF above 5, we conclude with moderate multicollinearity.

**Table A6.1:** VIF test

| $PRICE_{it\text{-}1}$ | $K_{(supply)it\text{-}1}$ | $K_{(enabling)it\text{-}1}$ | $RENEW_{it\text{-}1}$ |
|---|---|---|---|
| 1.069 | 2.883 | 2.852 | 1.053 |

## A6.2 The Hausman test for fixed or random effects

For panel data estimation there are two main methods for estimating unobserved effects (Wooldridge, 2018, p. 462). The Hausmann test is commonly used to decide whether the fixed or random effects model should be used (Wooldridge, 2018, p. 473).

The null hypothesis is that the random effects model is preferred. If the p-value is less than 0.05, we reject the null hypothesis. In our case, the P-value indicates rejection of the null hypothesis, meaning the fixed effects model is preferred.

**Table A6.2:** Hausman test

data:PAT$_{\text{(supply)it}}\sim PRICE_{\text{it-1}} + K_{\text{(supply)it-1}} + K_{\text{(enabling)it-1}} + RENEW_{\text{it-1}} + YEAR$

chisq = 83.418, df = 5, p-value < 2.2e-16

alternative hypothesis: one model is inconsistent

## A6.3 Breusch-Pagan test

The Breusch - Pagan test is used to determine the presence of heteroscedasticity. The null hypothesis is that homoscedasticity is present. Our p-value is less than 0.05 and we reject the null hypothesis, meaning that heteroskedasticity is present in the model.

**Table A6.3:** Breusch-Pagan test

| |
|---|
| data: $\mathrm{PAT}_{\mathrm{ijt}} \sim PRICE_{\mathrm{it\text{-}1}} + K_{\mathrm{(supply)it\text{-}1}} + K_{\mathrm{(enabling)it\text{-}1}} + RENEW_{\mathrm{it\text{-}1}} + YEAR)$ |
| $BP = 4994.7, df = 30, p - value < 2.2e - 16$ |

## A6.4 Durbin-Watson test

The results of the Durbin-Watson test indicate that there is positive autocorrelation in our model, as the Durbin-Watson statistic is below 2.

**Table A6.4:** Durbin-Watson test

| |
|---|
| data: $\mathrm{lm}(\mathrm{PAT}_{\mathrm{ijt}} \sim PRICE_{\mathrm{it\text{-}1}} + K_{\mathrm{(supply)it\text{-}1}} + K_{\mathrm{(enabling)it\text{-}1}} + RENEW_{\mathrm{it\text{-}1}} + YEAR)$ |
| $DW = 0.84826, p - value < 2.2e - 16$ |
| alternative hypothesis: true autocorrelation is greater than 0 |
| Test for autocorrelation |