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The Role of Central Bank Monetary Policy on Green Innovation

An empirical analysis on the impact of real policy rates on green innovation among OECD countries

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This thesis is written as a part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics, within the Financial Economics (FIE) program.

Innovation in clean energy, the transition to develop renewable energy sources, and the implementation by governments, financial institutions and legislators of environmental policies are relevant subjects of 2022. Therefore, writing our master thesis within this field provoked our interest. The thesis can contribute to the understanding of how real policy rates around the world impact the level and ratio of green innovation.

Working on the thesis has been challenging, appealing, and educational. We have developed our knowledge about green and brown innovation, the role of central banks in the energy transition, and how the central bank, through its monetary policy, impacts innovation. In addition, when classifying and structuring patent application data, we developed our skills in R-studio, which is a valuable experience for future employment.

We would like to express our deepest gratitude towards our supervisors, Assistant Professor Isabel Montero Hovdahl and Associate Professor Steffen Juranek, for their frequent guidance and feedback.

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Abstract

This thesis investigates the relationship between policy rates and green innovation among OECD countries. The study uses patent application data as a proxy for innovation and examines the impact of real policy rates on the level and ratio of green innovation. The results of the analysis show that there is a negative relationship between central bank policy rates and green innovation, indicating that higher real policy rates may hinder the development of green technologies. The study also finds that the impact of real policy rates on green innovation varies by subcategory, with some subcategories being more sensitive to changes in the real policy rates than others. Overall, the study provides evidence that central bank monetary policy can have an impact on the development of green technologies.

Keywords: green innovation, real policy rate, central bank, business cycles

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Acronyms

CB	Central Bank
CPC	Cooperative Patent Classification
CPI	Consumer Price Index
ECB	European Central Bank
EPO	European Patents Office
EPS	Environmental Policy Stringency
FFE	Fossil Fuel Energy
GHG	Greenhouse Gas
IEA	International Energy Agency
IMF	International Monetary Fund
LCE	Low-Carbon Energy
NGFS	Network for Greening the Financial System
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
PCT	Patent Cooperation Treaty
R&D	Research and Development
RE	Renewable Energy
WIPO	World Intellectual Property Organization
WACC	Weighted Average Cost of Capital

1. Introduction

The energy transition is one of the greatest challenges of our time. In recent years, discussions about central banks' (CB) role in the transition have emerged. Back in 2015, the former CB chief of the Bank of England, Mark Carney, held a speech about climate change and financial stability. During the speech, he stated that it is not for financial policymakers to lead the shift toward a low-carbon economy. Instead, it is for the governments to prioritize one climate policy over another (Carney, 2015). Likewise, the European Central Bank (ECB) expressed in its climate agenda published in 2022, that it is governments and legislators that have the primary tools to address climate change and drive the transition towards a greener economy (ECB, 2022).

Recently, the European Commission delivered a report called "Stepping up Europe`s 2030 climate ambition" to the European parliament. The report outlines the importance of turning investments towards innovative low-carbon technologies instead of traditional fossil-fuel technologies, in times of scarce liquidity (European commission, 2020).

The International Energy Agency (IEA) argues that the climate challenges are primarily an energy challenge, as around 75% of the greenhouse gas (GHG) emissions stem from the supply and use of energy (Méinère et al., 2021). Thus, the change from traditional fossil fuel energy (FFE) to low carbon energy (LCE) sources plays a major role in achieving carbon neutrality by 2050. To achieve this goal, the IEA highlights the importance of clean energy innovation and argues that the road towards net zero emissions is dependent on major acceleration in clean energy innovation. This is because innovation is the key to bringing up new technologies and developing existing ones (Sha et al., 2020).

Although the need for clean energy innovation is more acute than ever before, Ménière et al. (2021) finds that the annual growth rate in LCE supply patenting has declined in recent years. A decline in LCE supply patenting could impact the diversity of renewable energy sources and cost improvements of current ones. On the bright side, the report finds that the patenting activity in LCE supply technologies has been growing faster than fossil fuel technologies since the start of the 2000s.

To successfully reach the GHG reduction goals, effective and targeted climate policies are crucial. According to a report developed by the Organization for Economic Co-operation and

Development (OECD), climate policy measures are lagging in terms of achieving the GHG reduction goals (Dechezleprêtre et al., 2022). With current policies and actions, the global temperature is expected to increase by around 2,7°C by 2100 (CAT, 2021). Based on these findings, one can argue that there is a clear inconsistency between the climate goals and the climate policies and actions in place to achieve these goals. The inconsistency will according to Dilusio et al. (2021) lead to increased demand for environmentally friendly inventions, increased cost of implementing new policies, and macroeconomic instability, as the society have less time to adapt to new environmental policies.

Back in 2017, the Bank of England, together with other CBs, established the Network for Greening the Financial System (NGFS). Today, the network consists of more than 100 CBs (NGFS, 2022). The NGFS developed three main areas in which CBs can contribute to a greener economy. These are credit operations, collateral framework, and asset purchases. In terms of credit operations, where CBs provide liquidity to commercial banks, the NGFS suggest providing differentiated rates to commercial banks, based on the carbon intensity of the clients they are providing loans to. The second suggestion implies that CBs can adjust their requirements for assets used as collateral, based on carbon intensity. This alternative is discussed in detail by McConnell et al. (2020), where the transition risk[1] pose a threat to carbon-intensive collateral assets, suggesting a "hair-cut" valuation of these assets in CB`s collateralized lending facility. Finally, as CB`s asset purchasing program is biased toward high-carbon intensive assets (Papoutsi et al., 2022), the NGFS suggests CBs to reevaluate their purchasing program towards greener assets (Stefano et al., 2022).

Aghion et al. (2022) argue that the suggestions of greening the CBs have limited effects as they face economic and legal obstacles. They also argue that the primary mandate of the CB is to ensure price stability, and policies directed to stimulate green innovation could potentially violate the concept of "market neutrality". Consequently, to ensure price stability in times of rapid economic growth, an increase in the nominal policy rate is considered inevitable. Hence, the discussion of the CB's contribution to a greener economy has moved toward the CB's primary monetary policy tools. McConnell et al. (2020) do not consider the primary policy tools such as the CBs policy rate as an effective way of promoting investments in green

[1] Transition risk: the risk of physical or financial assets losing their value because of stringent climate policies, such as higher carbon taxes.

technologies, since a lowering of the policy rate may symmetrically increase investment in both green and brown innovations. Similarly, Aghion et al. (2022) also argue that monetary policy channels that affect the bank lending facilities have little or no material effect on green patenting, as banks are not involved in the innovation of new technologies. In contrast, Schnabel[2] (2022) held a speech where she argues that the removal of monetary stimulus to hamper inflation could harm the incentives of building a low-carbon economy. She created her statement by arguing that an increase in the CB policy rate directly increases the cost of capital, hence decreasing the willingness to invest in renewable projects.

The discussion regarding the CB`s role in the transition toward a greener economy continues. However, there have been few empirical studies of how the CB`s primary monetary policies affect the green transition. This thesis aims to contribute to the discussion by investigating whether the CB`s primary mandate of price stability compromises the increasing need for green innovation to successfully achieve a clean energy transition. To do so, we investigate whether the CB`s monetary policy, through the real policy rate, impacts the level and ratio[3] of green innovation.

We use the extensive data provided by the OECD on patent applications to classify innovation. This allows us to investigate whether green innovation and its subcategories are affected differently by changes in the real policy rate (RPR) than brown innovation. We base our findings on patent applications to the European Patent Office (EPO) by OECD countries. To conduct our analysis, we use a panel fixed effect model with country fixed effects and a linear time trend, where we also apply a weighting scheme based on each country's GDP. We start by providing evidence of an inverse relationship between the RPR and the level of green innovation. However, the relationship is strongly driven by the total weight of the US. By further separating green technologies into three subcategories, we provide strong evidence that the RPR has a negative effect on end-use technologies. The relationship between the RPR and end-use technologies is consistently significant through all robustness checks. Thereafter, we discover weak evidence that there may be a long-term effect in which innovation in LCE supply related technologies is prioritized less in favor of brown innovation during times of

[2] Isabel Schnabel has been serving as a member of the Executive Board of the ECB since 2020.

[3] Please see Equation 1 for formula of the green ratio (GR)

monetary tightening. These findings suggest that the CB’s goal of price stability may hinder the development of green innovation.

The thesis is organized as follows. In Chapter 2, we provide a theoretical foundation related to our research, by discussing key concepts and related literature. In Chapter 3, we describe the structuring and classification of patent applications data, as well as the interpretation of our dependent, independent, and control variables. The chapter also includes a presentation of some descriptive statistics for these variables. In Chapter 4, we present the empirical model that we use to test our two hypotheses. Chapter 5 presents the results of our hypothesis testing, as well as a series of robustness checks to validate our findings. In Chapter 6, we interpret and discuss our results and limitations associated with our analysis. Finally, in Chapter 7, we provide a summary of our key findings and conclusion.

2. Theoretical background and hypotheses

To provide a theoretical foundation to our study, we begin by discussing the potential pros and cons of using patent applications as a proxy for innovation. We then examine the factors that have been shown to impact the development of green innovation, which is later considered in our analysis. Finally, we review the existing literature on the relationship between the policy rate and innovation, which serves as the foundation for our hypotheses development.

2.1 Patent applications as a proxy for innovation

Because innovation in itself is hard to measure, using innovation input or output factors has become a common practice among researchers (Nagaoka et al., 2010). Research and development (R&D) expenditure is one example of an input factor used as a proxy for innovation (Hyytinen & Toivanen, 2005). However, Nagaoka et al. (2010) argue that measuring innovation through R&D expenditure could create measurement problems since it is an input factor and does not capture the end result. In contrast, patent applications are output measures of innovation.

There are both advantages and disadvantages associated with using patent applications as a proxy for innovation. First, patent applications provide researchers with detailed abstracts containing information about the applicant and the invention itself (OECD, 2009). Furthermore, patent application data are easily obtainable, discrete and can be subcategorized and classified into different technologies (Johnstone et al., 2010).

Although the use of patent application data has increased in recent years, it should be used carefully since they are not free of problems. One disadvantage related to patent application is that not all inventions are patented. Based on EPO`s "Applicant Panel Survey" report of 2008, about 50% of all inventions were not patented throughout the world (EPO, 2009c). One of the reasons for the low portion is that patents need to fulfill certain criteria. The wording in the requirements is different for different jurisdictions around the world. For instance, the patent examination at the EPO requires that the invention needs to be "new", include an inventive step, capable of industrial application and the invention needs to belong to a field of technology (EPO, 2022b). As stated by Moser (2013), the low share of patenting could also be explained by firms deliberately deciding not to patent their inventions since patenting requires full disclosure. According to Anton and Yao (2004), this may happen when property rights are limited, and the value of disclosing is offset by the fear of imitation.

In addition, due to differences in practices across patent offices in various countries, comparing patent applications can be challenging, as you cannot be sure that you are comparing “apples to apples” (Johnstone et al., 2010). Another problem of working with patent data is that the data is skewed. This happens as a small portion of all patents have high technological and economical value. Therefore, simple counts of patent applications can be misleading as it assigns the same value for all patents. Even though patent application data does not capture all inventions, it is considered the most valuable source of innovation information, assuming that the user of the data is aware of its noises and biases (Nagaoka et al., 2010).

2.2 Factors influencing the development of green innovation

There are several factors affecting the development of green innovation. Previous studies have investigated the effect of environmental policies on innovation within LCE technologies. Due to the negative externalities stemming from traditional fossil fuel energy (FFE) sources and increased awareness about the environment, governments have started favoring LCEs such as solar, wind, hydropower, and geothermal energy. As FFE has historically outperformed LCE in terms of cost, governments have in recent years increased incentives to the latter one through various environmental policies (Nesta et al., 2014). One of the most known environmental policies is carbon taxation. A report developed by the OECD finds that carbon taxation is an effective tool to mitigate carbon emissions by making LCE or renewable technologies more competitive compared to FFE technologies (OECD, 2021). Additionally, Aghion et al. (2016) explored how taxes on pollution effects the level of green and brown innovation. By using tax-inclusive fuel prices (a proxy for the carbon tax), the results found that an increase in tax-inclusive fuel prices stimulates clean innovation and depresses brown innovation.

Relatedly, Zhang et al. (2022) explored how the Environmental Policy Stringency (EPS) index impacts green innovation. By investigating 27 OECD countries and 6 developing economies, their results show that countries are likely to execute green innovation in response to a more stringent environmental policy. Interestingly, the results show an insignificant relationship between a stringent marked-based policy and green innovation but find a significant relationship between a stringent non-marked based policy and green innovation. Furthermore, Böhringer et al. (2017) investigated how the German feed-in-tariff scheme affects innovation measured by annual patent count. The paper found a significantly positive relationship between feed-in-tariffs and innovation in renewable energy technologies.

Another potential factor playing its part in the development of green innovation is the amount of renewable energy consumption. Increased consumption of renewable energy sources could act as a signal for inventors, investors, and entrepreneurs of higher future returns of green innovation, potentially increasing the willingness to take on such innovations (Herman & Xiang, 2019).

Finally, the effect of foreign direct investments (FDI) on the development of green innovation has also been studied. FDI can have a positive and negative impact on green innovation. Luo et al. (2021) finds a positive effect because of the potential knowledge spill-over effect, exchange of new technologies, and improved administration practices. On the negative side, Qiu et al. (2021) finds that FDI could potentially result in multinational corporations moving their polluting business units to countries with less stringent environmental rules and policies.

2.3 Studies on the affect of the policy rate on innovation

An increase (decrease) in the policy rate is one of the monetary policy actions the CBs take to ease (enhance) economic growth. Changes in the policy rate are one of the factors that play a part in causing cyclical fluctuations, which are referred to as business cycles. Business cycles' effect on innovation is a closely related field of study and has seen more empirical studies than the policy rates impact on innovation. Broader literature on business cycles' effect on innovation has identified two responses to business cycles.

The first approach implies that innovation responds countercyclically to business cycles. During economic contractions, the input of innovation becomes cheaper, such as materials and labor. In addition, the opportunity cost of conducting research decreases, as the potential loss of sales is lower (Hingley & Park, 2017). Looking at Spanish firms, the paper of Lopez-Garcia et al (2012), finds that R&D investments as a share of total investments increases during economical contractions, assuming no credit constraints. These results provide evidence of the countercyclical behaviors of R&D investments and innovations. On the other hand, Hingley

& Park (2017) find that patent applications at the EPO tend to increase during economic expansions, pointing evidence towards the procyclical behaviors of patent applications. They argued that for firms relying on internal cash flows to fund innovation, an economic expansion increases a firm`s ability and accessibility to obtain such funds.

Even though business cycle literature on innovation typically does not consider policy rates, business cycles remain relevant in terms of indicating the impact of policy rates on innovation. Moving over to the narrower literature which has its primary focus on investigating the relationship between the nominal policy rate and innovation, Zhang et al. (2020) find that the US nominal policy rate has a positive and significant impact on R&D and patents for Chinese enterprises. Moreover, they find that an increase in the policy rate makes firms more likely to use internal cash flows over external funds to finance innovation. Using an option pricing approach, de la Horra et al. (2022) confirm the findings for the US market. They find that the nominal policy rate has a positive and significant impact on R&D investments.

Empirical studies which investigate the relationship between inflation and innovation often include changes in the nominal policy rate as a ripple effect of inflation. Among others, the paper of Rocha et al. (2021) investigated how inflation affects innovation. In their model, firms can finance R&D investments with internal cash flows or by borrowing money from financial institutions. Their research found that, when inflation rises in an inflation-targeted regime, the CBs will increase the nominal policy rate to adjust the inflation toward the target. As a result, the opportunity cost of R&D investment will increase, lowering the willingness to invest, and reducing innovation and technological output.

Rather than investigating the relationship between the nominal policy rate and innovation, we aim to test the RPR`s relationship with innovation, as the RPR better reflects the true cost of borrowing. However, there are also few empirical papers which investigate the relationship between the RPR and innovation. A more common approach is using the real interest rate measured from i.e., bonds. Relatedly, Heger (2004) included real interest rates when investigating which factors that impact firm's innovation decisions. She found that the real interest rate had a significantly positive relationship on the decision to stop innovation.

Furthermore, we follow the likes of Evers et al. (2020) which differentiates between advanced and basic but return-dominated technologies, whereas our approach differentiates between green and brown innovation. The study of Evers et al. (2020) investigates the relationship between inflation and innovation, but also included liquidity. Given that advanced technologies are subject to idiosyncratic risk, firms may hedge this risk by holding a liquidity buffer. When inflation rises, the CBs increase the nominal policy rate to mute inflation. As a result, the opportunity cost of holding cash increases, reducing the demand for liquidity. Hence, firms tilt their innovation from advanced to basic but return-dominated technologies.

When developing our hypotheses, we also consider the importance of implementing renewable energy (RE) projects, as they are considered important to produce innovative output (IEA, 2022). Looking at EU member states and the United Kingdom, Avalle (2021) investigated the financing conditions for RE projects. These projects are more capital intensive, require larger up-front payments and have lower operating costs compared to fossil fuel power plants. Therefore, the report finds the weighted average cost of capital (WACC) as an important financial variable for RE projects. Furthermore, RE projects are generally financed by debt or issuance of equity. In the initial stages it is key to leverage enough debt to successfully scale these projects. Looking at onshore wind projects, the report finds a positive correlation between CBs policy rates and the average cost of debt. These results, confirm the statement of Schnabel (2022), that an increase in the CBs policy rate directly impacts the cost of capital. For instance, the cost of debt in the energy-related sector has increased on average by 50% during 2022. Consequently, the probability of abandonment of RE projects might increase, which can result in a reduction of innovative output in the future (IEA, 2022). Therefore, it is important that renewable energy projects are not abandoned in times of rising interest rates, to keep producing innovative output.

Although RE projects are generally financed by debt or equity issuance, it is not necessarily the case for the inventions behind these projects. Hall and Lerner (2010)[4] argues that there is a considerable gap between the internal and external cost of capital on innovation. This is illustrated by Ughetto (2008), which finds that innovation by more than 1000 Italian manufacturing firms is generally never financed by debt. Therefore, the financing source is internal cash flows, as Italian firms generally do not issue equity to finance innovation. Furthermore, Nylund et al. (2019) find that internal cash flow is negatively related to innovation for a broad range of firms, including the manufacturing sector. Firms in the energy

[4] Although the study focuses primarily on R&D investments, the author states that much of the empirical evidence also applies to financing innovation.

sector are the only ones who become more innovative by using internal cash flow to finance innovation. They also find that debt financing reduces the innovation of profitable firms.

2.4 Hypotheses development

We build on the presented literature to form our two hypotheses focusing on the relationship between the RPR and the level and ratio of green innovation. Both our hypotheses represent the foundation of our analysis.

Presented literature on business cycles disagrees how innovation responds to business cycles, as they find both a procyclical and countercyclical relationship. Based on Hall and Lerner (2010) that find the internal cost of capital for R&D investments to be lower than the external cost of capital, one would expect firms to use internal cash flows to finance innovation. This reduces their exposure to an increase in the RPR, in terms of the cost of debt. However, an increase in the RPR could still increase the opportunity cost of capital. Relatedly, building upon RE project`s exposure to interest rates, and the consequence of abandonments on innovation output, we aim to explore how the CB`s monetary policy, through the RPR, impacts the level of green innovation. In times of rising policy rates to ease the inflationary pressure, as well as increased demand for green innovation, our first hypothesis is of increasing relevance:

H1: An increase in the RPR will depress the level of green innovation.

By answering this hypothesis, we can explore if the CBs primary mandate of price stability compromises the increasing need for green innovation to successfully achieve a clean energy transition.

When developing our second hypothesis, we build upon the fact that RE during the time interval of our analysis, has been less mature and outperformed in terms of cost, compared to traditional FFE (Nesta et al., 2014). The hypothesis follows the likes of Evers et al. (2020), which finds that firms tilt their innovation from advanced to basic but return-dominated technologies in times of increasing nominal policy rate. Having classified green and brown patents applications, our second hypothesis is:

H2: An increase in the RPR will depress the level of green innovation more than brown innovation.

By answering the second hypothesis, we aim to understand if green innovation is de-prioritized for brown innovation in times of increasing RPRs. However, one can argue that the prioritization choice of different technologies found by Evers et al. (2020) does not apply to our analysis, as innovation within green technologies is increasingly subsidized and incentivized, and that the demand for such technologies is higher than ever before. If the effect is sufficient, the differences outlined between green and brown technologies may be canceled out, making them equally exposed to changes in the RPRs.

3. Data description

In this section, we describe our approach in sourcing and classifying patent application as green and brown. We then discuss the interpretation of the variables included in our study. Finally, we present some descriptive statistics for these variables. This provides important information about the range and distribution of the data.

3.1 Structuring patent statistics

The two main sources of patent indicators which have been structured to make our own dataset, are gathered from "OECD, REGPAT database, August 2022"[5], and EPO's "EP full-text for data for data analytics"[6]. From OECDs REGPAT database we make use of the patent applications filed to the EPO by OECD countries. Furthermore, if we encounter any problems when structuring patent statistics, we make decisions based on the patent statistic manual released by the OECD in 2009.

Filing for a patent is both costly and time-consuming (van Pottelsberghe de la Potterie & François, 2008). At the EPO, granting a patent takes an average of 5 years and could span up to as long as 10 years. EPO is considered a regional patent office and examines applications on behalf of its member countries. If a patent is granted, the applicant can choose for which member countries they want the validation rights for. The fact that an application is granted or refused is indicative of its quality (OECD, 2009). However, to be able to make use of the latest completed dataset, we utilize patent applications as our proxy for innovation. As a regional office, EPO provides a degree of control for patent quality by only representing patent applications for which the inventor considers the value sufficient to seek protection internationally (Ménière et al., 2021).

We then continue by using the priority date as our reference date, as it is the earliest date and therefore considered as the closest date to the invention. The priority date is the first date for filing a patent application, anywhere in the world. Moreover, if the patent has inventors from

[5] Data source: https://console.cloud.google.com/storage/browser/ep-fulltext-for-text-analytics/2022week05;tab=objects?prefix=&forceOnObjectsSortingFiltering=false

[6] Data source: https://forms.office.com/pages/responsepage.aspx?id=1MdBrGEfDUaw9PySWitHHKuxmuqpz_9KusL7-G1D6wFUOEU0OVBYVk5QTzROVlBTSUtBUUREWVhHTiQlQCN0PWcu

different countries, the patent is partly attributed to each country mentioned to credit each unit of analysis with its correct proportion and avoid double counting (OECD, 2009).

Patent applications from the Patent Cooperation Treaty (PCT) entering the EPO regional phase are included in OECD's REGPAT database, which could have a time lag of up to 31 months from the priority date. After entering the regional phase, it may take an additional 6 months before this step is published by the EPO (OECD, 2009). Thus, the most recent complete patent data is from 2018.

The inventor's dataset is used instead of the applicants, as it better measures the inventive performance of countries (OECD, 2009). This is mainly because the inventor dataset includes the country of the R&D unit that created the patented invention, meanwhile, the patent applicant shows the country for which the legal owner is subject to taxation (Bohm et al., 2015). However, every patent application does not contain the information of the inventors. Therefore, the applicant database is made use of to check for any missing observations in the inventor dataset. Leading to an additional 12,243 observations in our dataset. The full dataset contains 10,445,128 rows.

23 observations of the inventor's country of residence are missing from the full dataset. All these patents contained the professional address of the inventor and were thus checked manually. Only two of the addresses are located in the OECD countries and were assigned to their legitimate country.

To identify green patents, we made use of IEA's cartography of LCE technologies (Ménière et al., 2021). Please see Appendix 7.1.1 to see which technologies that have been classified as green and their respective Cooperative Patent Classification (CPC) classes. IEA's cartography of LCE technologies is based on a rigorous selection and re-organization of different sections of EPO's dedicated classification scheme for climate change mitigation (EPO, 2022d). The dedicated classification scheme for climate change mitigation relies on the CPC classes. A patent may have multiple CPC codes allocated across different technical fields. If the patent contained a singular CPC class from the IEA's cartography of LCE technologies, it has been classified as a green patent, unless it shares a CPC code with a brown patent application. After this procedure, we end up with a total of 269,662 green patents since 1977.

Furthermore, classifying green innovation according to IEAs classification cartography has allowed us to further subdivide green patent applications into three different categories. These are LCE supply technologies, enabling technologies and end-use technologies. The patent has been allocated to the technological field in which it had the highest count of CPC codes. If a patent had an equal number of CPC codes across the different technical fields, it has been randomly allocated to one of the three subcategories. Following this procedure, we have observed 53,163 LCE supply patents, 51,689 enabling patents and 164,810 end-use patents, since 1977.

EPO's EP full-text data for text analytics dataset was needed to identify brown patents. The dataset contains all the full-text data for patents published by the EPO since 1977. However, it does not contain European patent applications filed via the PCT route which is published by the World Intellectual Property Organization (WIPO) (EPO, 2022a). The dataset comprises approximately 6.5 million EP publications and is about 261 GB in size (EPO, 2022b).

Brown patents are identified according to the IEA`s methodology for identifying fossil fuel supply-related technologies in patent data (IEA, 2021). Besides classifying brown patents solely on their CPC classification, some CPC classes required additional filtering according to IEAs methodology. The additional filtering, which required the inclusion and/or exclusion of search queries, is shown in Appendix 7.1.2, together with the brown technologies. All accessible text has been made use of to perform the full-text analysis. The EPO has three official filing languages (OECD, 2009), so to be able to extract all the relevant full-texts, search queries were applied in English, German, and French using regular expressions. After the full-text search queries were carried out, we were left with 50,714 unique observations. 10,086 of these patents contain CPC classes from both green- and brown patents, so these have been excluded from the final sample. This leaves us with 40,628 unique observations of brown patents since 1977.

3.2 Interpretation of variables

3.2.1 Dependent variable

We run regression analyses on green patent applications, brown patent applications, and the green ratio (GR) to test our two hypotheses. As explained in Chapter 2.1, we utilize patent applications as a proxy for innovation. The green and brown patent application enables us to investigate how changes in the RPR impact the level of green- and brown innovation. The third variable enables us to investigate how changes in the RPR impact the ratio of green innovation.

The dependent variables are expressed by total patent applications per country. Since the regression model includes country fixed effect, we do not consider it necessary to adjust our three dependent variables by per capita, as the population remains stable over time within the countries in our sample.

The last dependent variable, the GR, expresses the ratio of energy-supply related technologies classified as green and brown. As one can see from Equation 1, we only include LCE supply-related patent applications in the GR. This is because brown patents are only fossil fuel supply-related technologies. Meanwhile, green patents include a broader spectrum of related technologies. For instance, in addition to LCE supply technologies, green patents include enabling and end-use technologies, which could be energy efficiency in buildings or electric vehicles. Therefore, it is more natural to compare only the energy supply-related patent applications.

Equation 1: Green Ratio

$$Green\ ratio\ (GR) = \frac{LCE\ supply\ patent\ applications + 1}{Brown\ patent\ applications + 1}$$

Equation 1: The GR presents the formula applied to estimate the ratio of LCE supply patent applications to brown patent applications.

As we have given fractional counts to countries to credit each unit of the patent development process, there are a few observations where countries have less than an entire patent application, which leads to an inflated ratio. To account for this problem, 1 is added to the numerator and denominator of the equation. The overall effect of the ratio will remain unchanged. However, there will be a small inaccuracy in the GR, as the data will be slightly different from its original values.

The dependent variables in our analysis have been transformed by the natural logarithm. Besides simplifying the interpretation of the model, the transformation follows common practice when making use of patent applications as dependent variables. In addition, the transformation benefits the skewness of the residual.

3.2.2 Independent variable

As this thesis aims at understanding how the CB`s monetary policy impacts the level and ratio of green innovation, we make use of the RPR as our main variable of interest. We have made use of the RPR instead of the nominal policy rate because it better reflects the true cost of borrowing. Hence, it allows for a more accurate comparison of interest rates across time. To obtain RPRs, the nominal policy rate was controlled for the consumer price index (CPI), according to the concept of the Fisher equation[7] (Cooray, 2002). The CPI is extensively used as a measure of inflation by economic policymakers (Kotzeva et al., 2020). Both the nominal policy[8] rate and CPI index[9]. was sourced from the International Monetary Fund (IMF) database.

3.2.3 Control variables

Environmental policy index

To validate the results and ensure the robustness of our regression analysis, we will include several control variables in addition to our main variable of interest. To consider the impact of climate policies on the development of green innovation as described in Chapter 2.2, we include the three subcategories of the EPS index as control variables. The data on the EPS index was sourced from the OECD database[10].

Investigating the effect of environmental policies on economic outcomes can be challenging on a cross-country basis. This is because the mix of environmental policies can vary widely across countries. To fill this gap, the OECD developed the EPS index, which allows for the evaluation of environmental policies across countries. To ensure good quality, only environmental policies on climate change and air pollution are included. This means that

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[7] Fisher equation: $(1 + the\ real\ interest\ rate) = \frac{(1+the\ nominal\ interest\ rate)}{(1+the\ inflation\ rate)}$

[8] Data source: https://data.imf.org/regular.aspx?key=61545855

[9] Data source: https://data.imf.org/?sk=4FFB52B2-3653-409A-B471-D47B46D904B5&sId=1485878855236

[10] Data source: https://stats.oecd.org/index.aspx?lang=en

policies that are set on a regional or municipal level, such as waste and water management, are left out because these are challenging to scale up to a national level (Kruse et al., 2022).

The first subcategory of the EPS index, the market-based policies (MBP), consists of CO2 trading schemes, renewable energy trading schemes, CO2 taxes, nitrogen oxides taxes, sulfur oxides taxes, and fuel taxes. Common for all these MBPs is that they create a price on pollution through taxes or tradable permits on emissions. The non-market based policies (NMBP) include emission limits value for nitrogen oxides, sulfur oxides, coal-power plants, and sulfur content within fuel such as diesel. Common for all NMBPs is that they all set certain standards and emission limit values. Finally, the technology support policies (TS) contain public research and development (R&D) expenditure for LCE relative to the size of each country's nominal gross domestic product (GDP). It also contains price support for solar and wind technologies through feed-in tariff schemes and renewable energy auctions. The categories are constructed by scoring the stringency from zero (no policies) to six (most stringent) (Kruse et al., 2022).

Renewable energy consumption over total consumption

To control for the effect of expected future profits and market size within the renewable energy market, the renewable energy consumption on total energy consumption per country is controlled for. The data was sourced from the "Our World in Data" website[11]. The variable is denominated as a percentage of total energy consumption.

Foreign direct investments

Finally, we add foreign direct investments (FDI) as a control variable. FDI can have a positive and negative impact on green innovation, as explained in Chapter 2.2. The FDI[12] was sourced from the World Bank database. The FDI is denominated as a percentage of GDP. When the FDI variable is above zero, it means that the respective country had more foreign investments than divestment in the respective year, vice versa.

[11] Data source: https://ourworldindata.org/renewable-energy

[12] Data source: https://databank.worldbank.org/source/world-development-indicators

Gross domestic product & unemployment rate

As elaborated in the literature review, we will control for the effect of business cycles on innovation. Therefore, we include GDP and the unemployment rate which are major indicators of business cycles. The two variables often move in opposite directions, whereas GDP tend to rise during times of economic expansion, the unemployment rate tend to decrease during economic expansions.

The GDP is transformed by its natural logarithm to simplify its interpretation. In this way, one can interpret it in which a marginal change in GDP is explained in terms of percentage changes in the dependent variables, which is considered a log-log interpretation. The unemployment rate is denominated as a percentage of the total labour force in each country.

3.3 Descriptive statistics

3.3.1 Dependent variable

Having sourced, classified, and structured the patent application data, various figures are utilized to get an overview of the data. Figure 1 illustrates the development of the green and

Figure 1: Development of Green Patent Applications and its Three Subcategories, and Brown Patent Applications

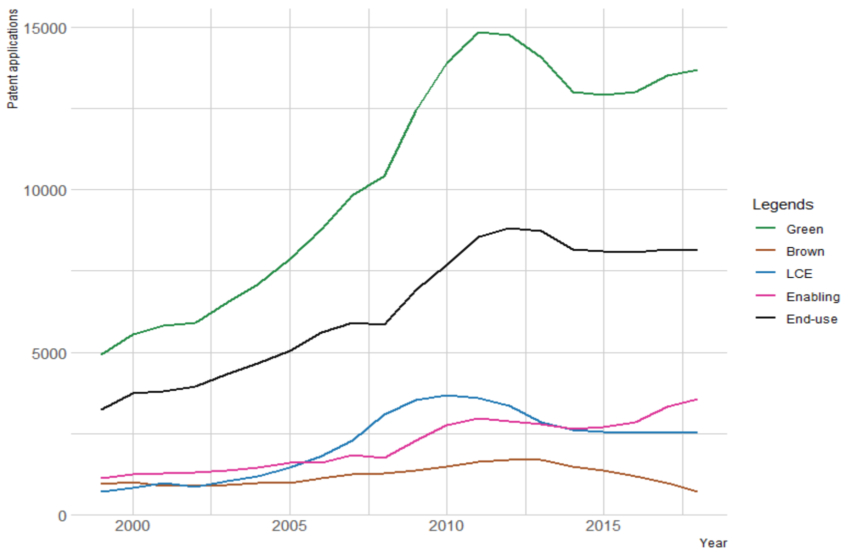


Figure 1 presents the development of Green, Brown, LCE supply, enabling and end-use patent applications from 1999 until 2018. The y-axis illustrates the count of patent applications, while the x-axis illustrates the years included in our data sample.

brown patent applications, as well as the development of the three subcategories of green innovation. As shown in Figure 1, green patent applications have seen a remarkable growth since 1999, while brown patent applications have remained stable until recently, before they began to decline. Looking at the three types of green technology innovation, end-use and enabling technologies has increased steadily, whereas the LCE supply technologies has decreased in recent years. Common for LCE supply and brown, is that they are both energy-supply related technologies, whereas both have seen a drop of patent application in past few years.

Moving more specifically into green innovation, the development of the share of the three subcategories are expressed in Figure 2. The figure shows that the green innovation on average consists of around 60% in end-use technologies, 25% in enabling technologies, and the remaining 15% within LCE supply technologies. Looking at the development of the shares, one can see that innovation within enabling technologies is the fastest growing. Since 2008, the share of innovation within LCE supply technologies has on average decreased.

Figure 2: Share of the Subcategories within Green Innovation

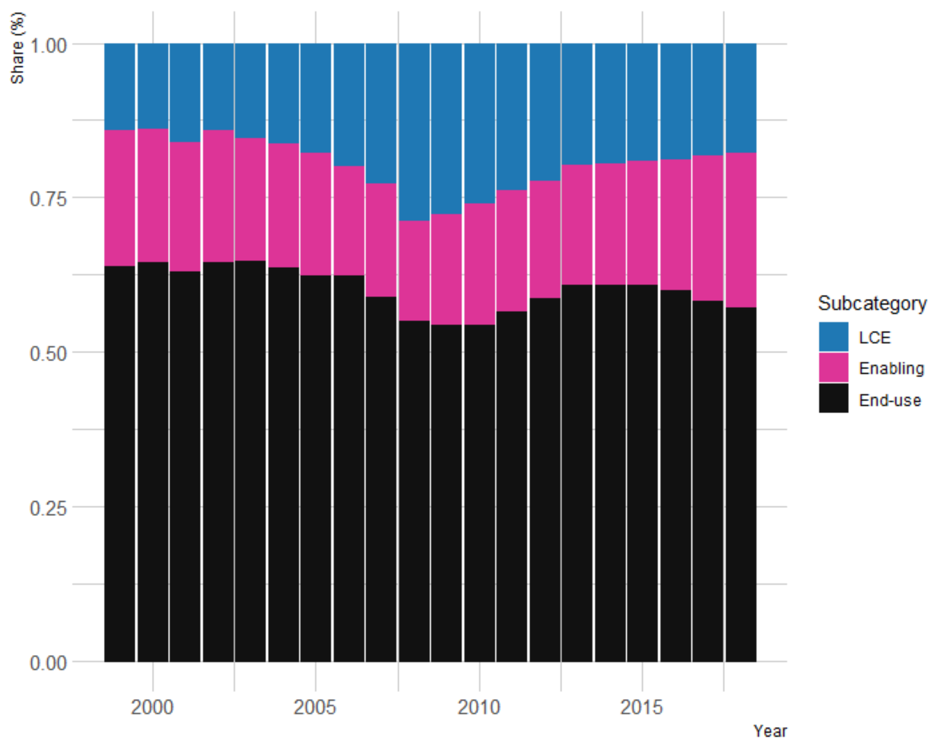


Figure 2 presents the development of LCE supply, Enabling and End-use patent applications from 1999 until 2018. The y-axis shows the share of patent application on total green patent application, while the x-axis illustrates the years included in our data sample.

Furthermore, Table 1 displays the ranking for each country[13] based on the sum of green patent applications since 1999[14]. The US is the highest-ranking country in terms of green patent

Table 1: Overview of Dependent Variable per Country

Rank	Country	Green	LCE supply	Enabling	End-use	Brown	GR
1	US	50444	10224	9143	31725	9904	1.03
2	JP	46077	6584	12721	26902	1121	5.72
3	DE	37716	9200	6517	22272	2273	4.01
4	FR	14323	2566	2510	9319	2281	1.07
5	KR	13158	2043	5040	6067	282	6.13
6	GB	8750	1907	1484	5467	2332	0.95
7	IT	5295	1324	671	3507	568	2.28
8	NL	4454	1064	458	2985	1190	1.05
9	SE	4411	808	476	3254	312	2.69
10	DK	4088	2644	359	1106	454	6.40
11	CA	3676	597	971	2089	573	1.09
12	CH	3530	994	733	1947	176	5.96
13	AT	2708	582	436	1752	192	3.11
14	ES	2485	1180	260	1093	157	7.53
15	BE	2049	476	285	1212	227	2.24
16	FI	1978	398	230	1400	276	1.46
17	AU	1379	352	258	805	210	1.92
18	NO	768	300	163	327	1033	0.33
19	PL	446	109	72	275	54	1.86
20	IE	354	142	36	184	34	3.09
21	CZ	234	55	31	158	12	2.52
22	HU	211	45	20	154	17	2.26
23	PT	186	76	27	90	17	2.96
24	GR	122	41	12	70	8	2.53
25	SI	99	22	20	58	2	1.91
26	SK	68	30	10	31	8	2.11
Total		209,006	43,794	41,465	123,747	23,713	2,85

Table 1 presents the descriptive statistics for the level of green share for the 26 OECD countries. The period spans from 1999 to 2018. The GR presents the ratio of LCE patent applications to brown patent applications. Be aware that the 2,85 is an average of all GRs.

[13] Please see Appendix 7.2 for an overview of country codes.

[14] Please see Appendix 7.3 for an overview of the average patent applications and GR per country during our sample period.

applications, followed by JP and DE. The US is also the top applicant for brown patents. The green ratio is also reported, where KR (6.13) and JP (5.72) are substantially ahead of the rest of the sample. The total number of LCE supply patent applications (43,794) is significantly higher than that of brown patent applications (23,713), resulting in a green ratio of (2.85) on average amongst the countries in our sample.

3.3.2 Independent variable

Figure 3 represents the development of our main variable of interest, the RPR. The upper panels contain the RPR development for non-ECB member countries, while the lower panels contain the ECB member countries. Overall, the RPRs in our sample have on average declined since 1999. This trend is largely due to a decrease in nominal policy rates, combined with the inflation which has been fluctuating around the 2% inflation target set by CBs. In recent years, we have observed negative RPRs in some countries, reflecting low nominal policy rates, sometimes even negative.

Figure 3: Development of RPRs

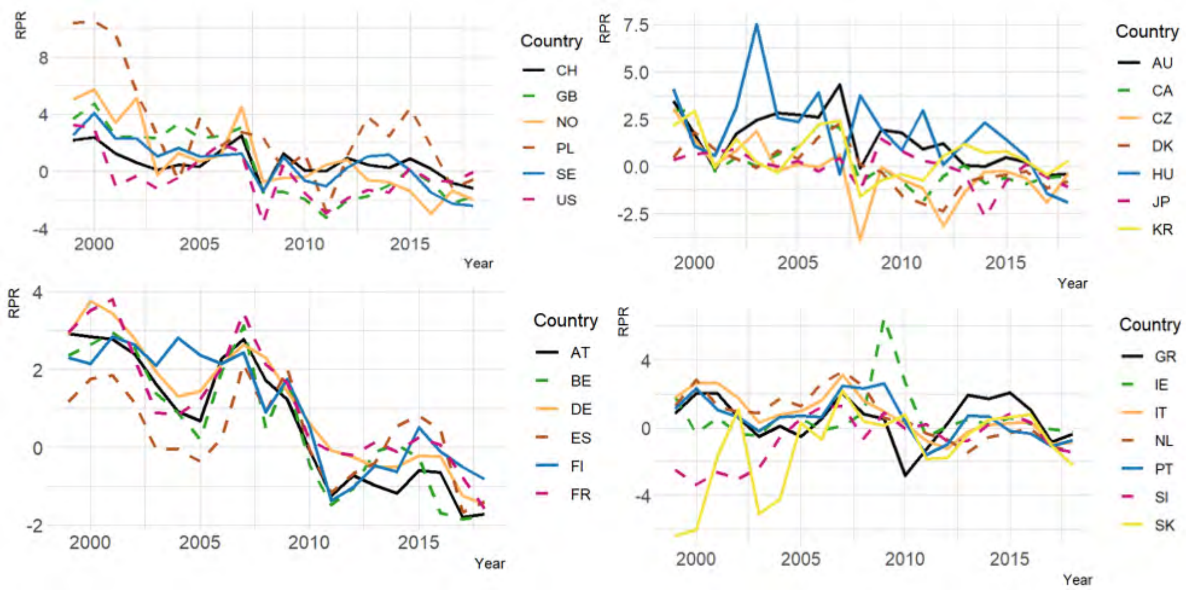


Figure 3 presents the development of the RPR for all countries in our sample. The period spans from 1999 to 2018.

3.3.3 Control variables

Building upon the Porter hypothesis that applicable and stringent environmental policies can promote green innovation (van Leeuwen & Mohnen, 2017), we start by including the subcategories of the EPS Index named “market-based policies”, “non-market based policies” and “technology support policies”. The index is constructed by scoring the stringency of environmental policies from zero (no policies) to six (most stringent).

Figure 4 illustrates the stringency development for each of the three subcategories. The stringency of the environmental policies included in the EPS index has been increasing over time, as illustrated by the bars. The NMBP is on average the most stringent policy, followed by TS and MBP. When comparing the average EPS score and the green share, they seem to have a positive relationship. The main reason why the data sample is limited to 26 out of 38 OECD member states, is due to the OECD not reporting the EPS index for several of its member countries.

Figure 4: Development EPS Stringency Score

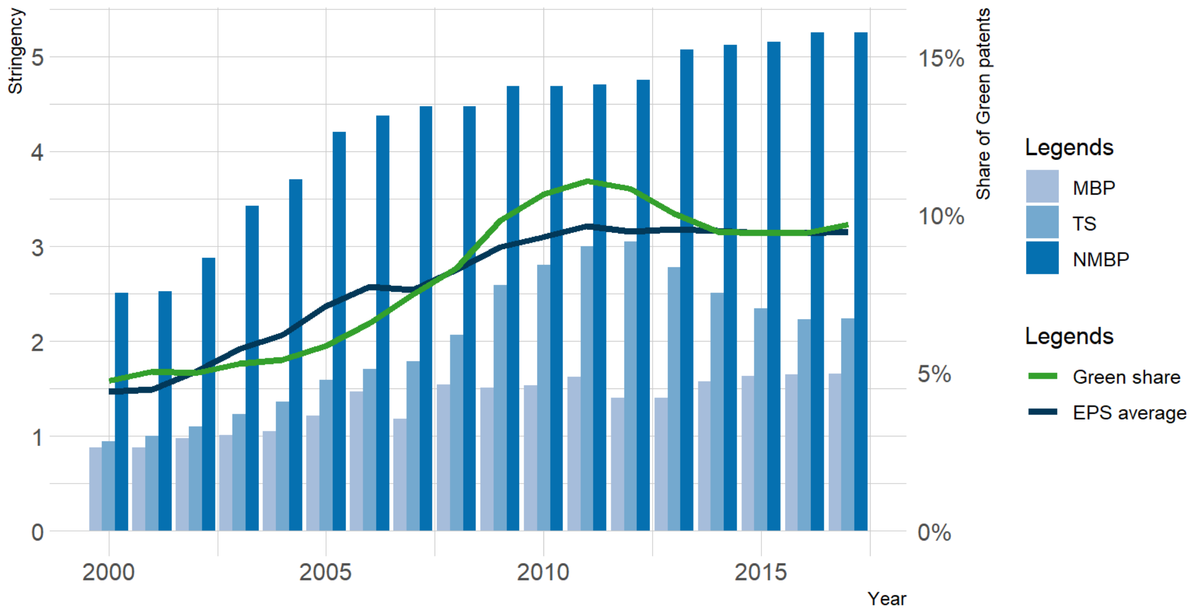


Figure 4 illustrates the development of the stringency by the three subcategories of the EPS Index. The three subcategories are equally weighted in the average EPS. The Green share is the share of green patent applications on all categories of patent applications. Each subcategory is scored on a scale from zero (no policies) to six (most stringent).

Table 2 presents an overview of descriptive statistics for the variables used in our regression for the 26 OECD countries. The sample period spans from 1999 to 2018, structured by annual frequency, totaling 520 observations. Our main variable of interest, the RPR, has a mean value of 0.6%. This means that on average, the nominal interest rate is set 0.6% higher than the rate of inflation. Additionally, the standard deviation (1.9%) of the RPR indicates that there is a wide range of values within the sample. The GDP variable is denominated in billions of USD. The standard deviation indicates that there is a large spread in GDP across countries, also illustrated by looking at the min and max values. In comparison, the unemployment is closer spread around its mean, but has some minor outliers. The renewable energy consumption on total energy consumption and foreign direct investments is denominated as percentages. The negative minimum value of the FDI variable arises when some countries in our sample have observation of more foreign divestments than investments during a year.

Table 2: Total Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Green	520	401.9	739.9	0.0	3,685.0
Brown	520	45.6	100.9	0.0	782.3
GR	520	2.9	2.8	0.1	19.9
LCE supply	520	82.8	153.9	0.0	939.5
Enabling	520	80.3	170.0	0.0	989.9
End-use	520	238.8	462.3	0.0	2,541.6
RPR	520	0.6	1.9	-6.4	10.5
MBP	520	1.4	0.8	0.0	4.0
NMBP	520	4.4	1.3	0.0	6.0
TS	520	2.1	1.2	0.0	6.0
GDP	520	1,497.4	2,956.3	20.3	20,527.2
Unem	520	7.6	4.2	2.1	27.5
REC	520	14.1	15.2	0.2	72.4
FDI	520	5.1	10.2	-40.1	86.5

Table 2 presents the descriptive statistics for all dependent, independent, and control variables included in our regression analysis. The table contains data from 1999 to 2018, from 26 OECD countries, amounting to 520 observations in total. The table reports the number of observations, mean, standard deviation, minimum and maximum values. Variables in absolute values.

4. Econometric methodology

Our data sample consists of 20 years of observations of patent applications in 26 countries and is labeled as panel data. To decide whether fixed- or random effect is the best fitted estimator, we run a Hausman test. The results are presented in Appendix 7.4 and show that the fixed effects is our preferred estimator.

To examine the impact of the RPR on green patent applications, we use the panel fixed effect model with country fixed effects and a linear time trend. The linear time trend is added due to our observations spanning over a short period of time. Additionally, when the ECB increases the policy rate, they do it simultaneously for 12 of the countries in our data sample. Including a year fixed effect would simply kill most of the effect from the change in the ECB nominal policy rate, as it is naturally trending over the years across countries. Thus, a linear time trend is added as compensation for time fixed effects. Our main empirical model is:

Equation 2: Empirical Model

$$ln(Y_{it+1}) = \beta_1 \boldsymbol{RPR_{it}} + \beta_2 MBP_{it} + \beta_3 NMBP_{it} + \beta_4 TS_{it} + \beta_5 \ln(GDP)_{it} + \beta_6 Unem_{it} + \beta_7 REC_{it} + \beta_8 FDI_{it} + time_t + a_i + \varepsilon_{it}$$

where the dependent variable Y_{it+1} represents the number of green patent applications, brown patent applications, or GR for any country i in year t_{+1}. The dependent variables have been transformed with the natural logarithm (ln). The variable is leaded by one year instead of lagging all the independent variables as the R&D process tends to lead to a first patent application within the year (De Rassenfosse & Guellec, 2009). We include the variables as presented in Chapter 3.2, whereas the $\mathbf{RPR}_{it}$ represents our independent variable of interest, the real policy rate. The Market Based Policy (MBP_{it}), Non-Market Based Policy ($NMBP_{it}$), and Technology Support (TS_{it}) represent the three subcategories of the EPS index. Furthermore, $\ln(GDP)_{it}$ denotes the natural logarithm of the Gross Domestic Product, and $Unem_{it}$ designates the unemployment rate as a % of the total labour force in each country. REC_{it} represents renewable energy consumption as a % of total energy consumption. The final control variable FDI_{it} denotes the net inflow (% of GDP) of Foreign Direct Investment. Furthermore, $time_t$ is the linear time trend. a_i represents the time-invariant unobserved individual-specific effect, and ε_{it} is the error term.

In a fixed effects model, Abadie et al. (2017) show that it is only necessary to cluster the standard errors if there is heterogeneity in treatment effects, and there is clustering in the sample or the assignment. Our sample of OECD countries is not randomly selected, which is why we apply clustered standard errors by country in our model. The clustered standard errors allow for unrestricted forms of serial correlation and heteroskedasticity in the error terms within the OECD countries (Wooldridge, 2019).

Moreover, we weight our model according to each country's GDP, to ensure that the data from the larger economies has a greater influence on the overall results. The main reason behind this decision is that it is the larger economies in our sample who are the main contributors to green innovation. By weighting the model according to the scale of the economy, we reduce the impact of random fluctuations from low inventive countries. Low inventive countries could be considered as countries which consistently file for patents in the proximity of zero. An increase or decrease by a few patents for these countries could thus make a huge impact as there is a drastic change in percentage for each observation. This could potentially cause bias in our coefficients. Hence, weighting according to a country's GDP allows us to get a more representative result of the underlying trends in the data, and helps us smooth out the short-term fluctuations. To ensure the validity of our weighting scheme, we conduct two robustness checks. First, we apply equal weight to each country. Secondly, we exclude the US to control for the country's large GDP. These controls allow us to assess the sensitivity of our results to the choice of weighting scheme.

To further ensure the validity of the model and variables, we perform multiple tests and checks to examine the assumptions underlying the OLS (ordinary least squared), which is included in Appendix 7.5. To summarize, we start by validating the need to cluster the standard errors by performing a Breusch-Godfrey test for serial correlations, and a Breusch-Pagan test for heteroskedasticity in the error term. Thereafter, we remove Turkey from our sample to avoid bias in our regression analysis, due to the RPR's deviation from the rest of the sample. We also consider whether there exists multicollinearity between our explanatory variables. However, we find no evidence of a strong or perfect correlation. Finally, we include a minor discussion regarding the satisfaction of the zero conditional mean assumption. The model is considered satisfactory, although we warn that one should be careful with causal interpretations.

5. Empirical results

In this section, we present the results of our regression analysis. We begin by presenting the results from our simple OLS regression. Furthermore, we also include several control variables that are known to impact the development of green innovation, as discussed in Chapter 2.2. To assess the validity of our results, we conduct a series of robustness checks.

In advance of investigating the relationship between the level- and ratio of green patent applications, we do a follow-up test of the simple model of Zhang et al. (2020). As the study of the impact of policy rates on patent applications is a relatively new field, this provides a starting point for further investigation of our hypotheses. The simple model in Appendix 7.6 indicates that there are differences between the datasets, and that there is an inverse relationship between the policy rate and innovation in general.

5.1 Hypothesis 1

Total Green Innovation

We will now examine our first hypothesis and explore if there exists a significant relationship between the RPR and the level of green innovation. To examine the relationship, we start by running a simple OLS regression model. We continue by performing several panel fixed effect regressions with country fixed effects and a linear time trend. To remind you, our first hypothesis is:

H1: An increase in the RPR will depress the level of green innovation.

The results from the regression analysis of the green innovation are presented in Table 3. The simple OLS regression suggests that a one percent increase in the RPR is associated with a 28% decrease in the level of green innovation, at a 1% significance level, in the following year. The reason for the effect happening in the following year is because the dependent variable includes a one-year time lead. However, as the result is based on a simple OLS, it expresses a correlation between the RPR and the level of green innovation. To check the validity of the relationship, we introduce several control variables, together with country fixed effect, as visible in columns (2) to (8) of Table 3. The slope of the RPR suggests a negative relationship to the level of green patent applications. Looking at column (8), the coefficient is negatively statistically significant when introducing all control variables, at a 5% significance

Table 3: Regression Analysis Hypothesis 1

	Dependent variable:							
	$\ln(\text{Green}_{t+1})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RPR	-0.280***	-0.030***	-0.034***	-0.031***	-0.027***	-0.023**	-0.023**	-0.021**
	(0.066)	(0.010)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
MBP		0.142	0.139	0.138	0.114	0.117	0.117	0.116
		(0.107)	(0.101)	(0.102)	(0.080)	(0.074)	(0.074)	(0.074)
NMBP			0.067	0.067	-0.028	-0.030	-0.030	-0.031
			(0.052)	(0.050)	(0.042)	(0.036)	(0.036)	(0.036)
TS				0.037	0.005	-0.001	-0.001	-0.002
				(0.040)	(0.035)	(0.029)	(0.029)	(0.029)
ln(GDP)					0.856***	0.894***	0.895***	0.898***
					(0.275)	(0.270)	(0.267)	(0.266)
Unem						0.021**	0.021**	0.021**
						(0.010)	(0.010)	(0.010)
REC							0.0005	0.0003
							(0.008)	(0.008)
FDI								-0.002
								(0.002)
time	0.011	0.048***	0.035***	0.031***	0.022***	0.021***	0.021***	0.021***
	(0.011)	(0.005)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	6.699***							
	(0.417)							
Control(GDP)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
Observations	494	494	494	494	494	494	494	494
R^2	0.121	0.594	0.611	0.614	0.655	0.650	0.650	0.651
Adjusted R^2	0.118	0.569	0.586	0.589	0.632	0.625	0.625	0.625

Note: Table 3 presents the output of our OLS regression model with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. All regressions are weighted by each country's average GDP. The dependent variable represents the natural logarithmic of green patent applications, with one year time lead in all columns. The underlying data spans from 1999 to 2018, for 26 countries. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

level. This means that a 1% increase in the RPR is associated with a 2,1% decrease in the level of green innovation. Looking at column (5) to (8), we observe a positively significant relationship between the GDP and the level of green innovation. Looking at column (8), the slope suggests that a one percent increase in GDP is related to a 0,898% increase in the level of green innovation, at a 1% significance level. In comparison, we observe that the unemployment rate coefficient is also associated with a positive impact on green innovation, which is surprising as the GDP and the unemployment rate tend to have an inverse relationship. Interestingly, we do not observe a significant relationship between the stringency of climate policies and the level of green innovation, which contradicts the findings of Zhang et al. (2022). Nor do we observe that the renewable energy consumption and foreign direct investment have a significant relationship with our dependent variable.

Subcategories of Green Innovation

In addition of running regression analysis on green innovation in general, we make use of the classification system in Appendix 7.1.1, to differentiate between innovation within LCE supply technologies, enabling technologies and end-use technologies. This enables us to investigate whether the RPR affects the subcategories differently, as well as if one of the subcategories are stronger contributors to the significance level found in Table 4. For further analysis, all regressions will include the same control variables as those in Table 3, column (8).

As illustrated in Table 4, our data sample consists of 15% LCE supply technologies, 25% enabling technologies, and 60% end-use technologies. In column (1) and (2), we observe a negative relationship between the RPR and the level of innovation within LCE supply technologies and enabling technologies. However, the coefficient is not statistically significant, which means that the relationship cannot be inferred. We observe that a 1% increase in GDP is associated with a 1,4% and 0,628% in column (1) and (2) respectively. Seen together with the negative coefficient on the RPR, this gives an indication that innovation within these two technologies reacts procyclical to business cycles.

Moving to column (3), we observe a negative relationship between the RPR and the level of end-use technologies, at a 1% significance level. The slope of the RPR coefficient suggests that a 1% increase is related to a 3,5% decrease of innovation within end-use technologies by 3,5%. Hence, the significance level found on green innovation seems to be stemming from end-use technologies. In this model, as with the previous ones, we observe what might be a procyclical response of innovation to business cycles, as a 1% increase in GDP is related to a 0.72% increase in the level of end-use technologies.

Table 4: Regression Subcategories of Green Innovation

	Dependent variable:		
	$\ln(\text{LCE supply}_{t+1})$	$\ln(\text{Enabling}_{t+1})$	$\ln(\text{End-use}_{t+1})$
	(1)	(2)	(3)
RPR	-0.015	-0.015	-0.035***
	(0.009)	(0.012)	(0.009)
MBP	-0.020	0.148	0.122*
	(0.151)	(0.087)	(0.070)
NMBP	-0.060	-0.076**	0.009
	(0.115)	(0.033)	(0.018)
TS	0.073	0.005	-0.044
	(0.069)	(0.037)	(0.031)
ln(GDP)	1.400**	0.628***	0.720***
	(0.524)	(0.177)	(0.258)
Unem	0.031**	0.014	0.024**
	(0.014)	(0.012)	(0.011)
REC	-0.041**	0.011	0.001
	(0.016)	(0.016)	(0.007)
FDI	-0.003	-0.002	-0.003**
	(0.004)	(0.006)	(0.001)
time	0.022	0.029*	0.028***
	(0.015)	(0.016)	(0.008)
Control(GDP)	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	No	No	No
Observations	494	494	494
R^2	0.506	0.452	0.592
Adjusted R^2	0.470	0.411	0.562

Note: Table 4 presents the output of our OLS regression model with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. All regressions are weighted by each country's average GDP. The dependent variables represent the natural logarithmic of LCE supply, Enabling, and End-use patent applications, with one year time lead. The underlying data spans from 1999 to 2018, for 26 countries. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

5.2 Hypothesis 2

We will now examine our second hypothesis to investigate if there is a relationship between the RPR and the ratio of green innovation. To investigate the relationship, we run panel fixed effect regressions with country fixed effects and a linear time trend. To remind you, our second hypothesis is as follows:

H2: An increase in the RPR will depress the level of green innovation more than brown innovation.

Before investigating the ratio between green and brown patent applications, we individually explore the relationship between the RPR and level of brown innovation. We thus start by making use of brown patent applications as the dependent variable, before continuing with the GR. Besides weighting our model for each country's GDP, we run an additional regression where we weight the model by each country's last ten-year production and refinery capacity of oil, gas, and coal[15]. This allows us to examine whether economies with a greater reliance on fossil fuel resources are more affected by a change in the RPR, as countries with a greater share of natural resources tend to be the primary drivers of innovation in fossil fuel related technologies.

The results from the regression analysis performed to explore hypothesis 2 are reported in Table 5. In column (1), the coefficient of the RPR suggests a negative relationship to the level of brown innovation, but this relationship is not statistically significant. However, when weighting each country by its respective last ten-year production and refinery capacity, we obtain a negatively significant relationship, as illustrated in column (2). The negative relationship implies that brown innovation within countries which have a larger share of natural resources are negatively affected by an increase in the RPR. In comparison to green innovation, we observe that brown innovation also might react procyclical to business cycles, as RPR is negatively related brown innovation, whereas GDP has a positive relationship.

Furthermore, we find no evidence in column (3) and (4) to support our hypothesis that an increase in the RPRs depresses the ratio of green innovation. Nor do we observe that any of

[15] Data source: https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2022-full-report.pdf

the control variables have an impact on the ratio of green innovation. However, it might be that countries with large natural resources get simultaneously affected by an increase in the RPR, which may be why we do not observe any effect on the GR in column (4).

Table 5: Regression Analysis Hypothesis 2

	Dependent variable:			
	$\ln(Brown_{t+1})$		$\ln(GR_{t+1})$	
	(1)	(2)	(3)	(4)
RPR	-0.006	-0.021**	-0.009	-0.002
	(0.014)	(0.010)	(0.016)	(0.019)
MBP	0.018	-0.040	-0.038	-0.251
	(0.092)	(0.110)	(0.129)	(0.229)
NMBP	-0.121**	-0.054	0.061	0.068
	(0.054)	(0.066)	(0.072)	(0.111)
TS	0.131***	0.169***	-0.058	-0.069
	(0.038)	(0.025)	(0.051)	(0.055)
ln(GDP)	0.853***	1.018***	0.547	-0.517
	(0.214)	(0.276)	(0.486)	(0.697)
Unem	0.039**	0.044*	-0.008	-0.013
	(0.014)	(0.022)	(0.009)	(0.012)
REC	-0.012	-0.010	-0.028	-0.048
	(0.021)	(0.019)	(0.020)	(0.044)
FDI	-0.001	-0.001	-0.002	0.0002
	(0.003)	(0.003)	(0.005)	(0.007)
time	-0.007	-0.042***	0.028	0.077*
	(0.018)	(0.013)	(0.017)	(0.039)
Control(GDP)	Yes	No	Yes	No
Control(OGC)	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
Observations	494	494	494	494
R^2	0.177	0.136	0.250	0.099
Adjusted R^2	0.117	0.072	0.194	0.032

Note: Table 5 presents the output of our OLS regression with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. Columns (1) and (3) are weighted by each country's average GDP, meanwhile columns (2) and (4) are weighted by each country's last ten-year production and refinery capacity of oil, gas, and coal. The dependent variables in column (1) and (2) represent the natural logarithmic of brown patent applications, while the dependent variables in columns (3) to (4) represent the natural logarithmic of the GR. The underlying data spans from 1999 to 2018, for 26 countries. *p<0.1; **p<0.05; ***p<0.01.

5.3 Robustness analysis

To check the validity of our results thus far, we run a series of robustness checks. These include utilizing a different measure of the RPR, substituting the RPR for the nominal policy rate and inflation, running different time leads, splitting our sample in two sub-periods, using equal weights, and omitting the US. All regression models are included in Appendix 7.7.

5.3.1 Alternative RPR

Because firms cannot lend at the exact same rate as the CB policy rate, we utilize the RPR obtained from the World Bank[16]. This RPR represents the lending rate adjusted for each country`s respective GDP deflator. The lending rate might be a more accurate measure because it takes into account the interest margin that firms pay to borrow from financial institutions, on top of the nominal CB policy rate, as the lending rate consist of the nominal CB policy rate plus an interest margin.

When substituting the original RPR, we observe that the significant effect of the RPR on green innovation vanishes in Table 19 column (1). The main reason for the drop in significance is mainly because the significance level of the RPR on innovation within end-use technologies drops from 1% to 10%, as observed in column (4). Remember, the end-use technologies represent approximately 60% of green innovation. Since the effect of the RPR within this technology decrease, the significance level is not strong enough to impact the total level of green innovation. Moreover, the substitution of RPR has no influence of the results when investigating the ratio of green innovation. These findings align with the same effect observed when using the original RPR.

5.3.2 Nominal policy rate and inflation

Our second robustness test, consist of replacing the original RPR by the nominal CB policy rate and inflation. This enables us to individually investigate the relationship between the two factors that the original RPR consists of. It is important to note that there might be difficulties interpreting the relationship between the nominal policy rate and inflation. For instance, there is often an inverse relationship between the two variables. However, the relationship is not

[16] Data source: https://data.worldbank.org/indicator/FR.INR.RINR

always consistent, as there may be other external factors influencing the relationship, such as economic growth and the unemployment rate. In addition, a change in the nominal policy rate might affect the inflation rate, and vice versa. Thus, one need to carefully consider the potential confounding effects of one another.

In Table 20, we observe that the inflation is the driver behind the RPR, as we see that the inflation coefficient is positively statistically significant for all types of technological innovation, except for innovation within enabling technologies. One way to interpret this result, is as inflation increases, it indicates that the economy is growing, which positively impact the level of green innovation. However, if the CBs increase the nominal policy rate to mute inflation, the action will indirectly make a negative impact on green innovation, as the action may simultaneously decrease the inflation in the economy. Nonetheless, one should be careful when interpreting this relationship.

5.3.3 Time leads

Our third robustness check includes applying different time leads on our dependent variables when investigating the effect of the RPR on the level and ratio of green innovation. In this way, we can explore if the changes in our main variable of interest have short, intermediate, or long-term effects on our dependent variables. According to De Rassenfosse and Guellec (2009), the R&D process can last as many as five years. Thus, we conduct a sensitivity analysis applying different time leads reaching from 2 to 5 years.

Table 21 reports the time leads for green innovation, its subcategories, and the GR, ranging from 2 to 5 years. For green innovation, we observe a short to intermediate-term effect from the RPR. However, when looking at the long-term effect with a 5-year lead, we do not observe a significant relationship. This indicates that the RPR effect on the invention process of green technologies seems to take on average 1 to 4 years.

For innovation within LCE supply technologies, we observe an intermediate to long-term effect from the RPR. Furthermore, we do not observe any significant relationship between our main variable of interest and innovation within enabling technologies, for any time leads performed. This observation is in line with the result obtained with our main model in Table 4, column (2).

In contrast to innovation within LCE supply technologies, the relationship between the RPR and the level of innovation within end-use technologies is associated with a short to intermediate-term effect. There seems to be different time horizons from the effect of the RPR and innovation observed between the two technologies. The difference in time horizon might arise because end-use technologies are less mature than LCE supply technologies. Therefore, further developing LCE supply technologies might be more time consuming, and the impact from the RPR on innovation output might take a longer period.

Finally, from column (19) to (20), we observe an inverse long-term relationship between the RPR and the ratio of green innovation, which indicates that the GR might eventually be negatively affected by an increase in the RPR. The main reason for this is because the GR only includes green innovation within LCE supply technologies, which we observed had an intermediate to long term relationship with the RPR. However, the adjusted r-squared is relatively low for these regressions, so one should be careful to interpret the relationship casually. Furthermore, when we apply weights to the GR by natural resources we observe the same long-term effect on the GR, however, this is not reported in Table 21 as it provides us with an almost identical result.

5.3.4 Split sample

As our period consist of 20 years, this robustness test involves splitting the sample in two periods. We do this to control for the potential effects only impacting a certain period. The first periods span from 1999 to 2008, and the second period from 2009 to 2018.

The main takeaways from Table 22 and Table 23, is that we observe the relationship between the RPR and the level of green innovation to be insignificant during the first period, while the relationship in the second period becomes statistically negatively significant at a 5% level. On the other hand, the RPR had significant effect on innovation within enabling technologies in the first period, but the significant effect disappears during the second period. Finally, the financing conditions for innovation within end-use technology seems to be more important during the second period since the coefficient decreases substantially. This indicates that an increase in the RPR will have a stronger negative impact on the level of end-use technologies innovation in the second period compared to the first.

5.3.5 Equal weights per country

Rather than weighting our model by GDP, we conduct a robustness check where the countries are equally weighted. By comparing the results of the main model with those of the equal-weighted robustness check, we can observe whether the main model was influenced or biased by the decision to weight the countries by their GDP. This provides us with valuable insights and help to ensure the robustness and validity of our analysis.

When we include equal weights across countries in Table 24, column (1), the significance level of the RPR coefficient on green innovation vanishes. One factor that contributes to this is that the significance of the RPR on innovation within end-use technologies drops from 1% in our main model to 5% in Table 24, column (4). As a result, the RPR`s impact on innovation within end-use technologies is not significant enough to drive the overall significance of its effect on total green innovation. This indicates that the result from our main model is impacted by the choice of weights.

5.3.6 Omitting the US

The US have a four times larger GDP than the next largest economy in our sample, as expressed in Figure 6 in Appendix 7.7. Since we weight our countries by GDP in our main regression, the US are given a higher percentage of emphasis than the other countries in our sample. To ensure that our results are not driven by the US, we conduct a robustness check where we exclude them.

When the US is omitted from our sample, we obtain results similar to those obtained with equal weighting, as seen in Table 25. This suggests that the weighting of the US by its GDP is the primary driver influencing our results on green innovation in our main model.

6. Discussion

This section presents our interpretation of the regression results. We encounter funding channels and business cycles when discussing the results. Furthermore, limitations to our analysis are presented and discussed.

6.1 Interpretation of results

The regression analysis performed in the previous chapter showed that the level of green innovation is negatively associated with an increase in the RPR. However, our robustness checks revealed multiple weaknesses in the relationship between the RPR and green innovation, suggesting that the relationship might not be as reliable as initially indicated. In addition, by further investigating the three subcategories of green innovation, we also observed that the negative relationship was highly influenced by innovation within end-use technologies, which had a negatively statistically significant relationship with the RPR in all our robustness checks. Finally, we observed that an increase in the RPR is associated with a negatively long-term effect on the GR, although the evidence we presented was weak.

To interpret the results from the level of green innovation, we start out by looking into the funding channels of innovation. As stated by Hall and Lerner (2010), the cost of financing innovation with external funds is higher than with internal funds. Therefore, firms might prefer internal cash flows over debt and equity issuance, in line with the pecking order theory (Myers, 1984). The American firm Intel Corporation is one example of a firm preferring internal cash flow, as their capital structure policy states that the company should maintain an abundance of internal cash to fund multiple years of R&D activities, to avoid being subject to fluctuations in the capital markets (Berk & DeMarzo, 2016). However, even though firms prefer internal cash flows over external funds to finance innovation, they are still exposed to an increase in the RPR. When the RPR increases, the real cost of other obligations within the company increasesR. This can reduce the amount of funds the company has available to invest in the R&D activities, which increases the opportunity cost of capital. The increased opportunity cost could ultimately result in firms prioritizing investments in other parts of the business areas, reducing innovation and technological output. Such evidence was found by Heger (2004), which argued that an increase in the real interest rate increased the probability to cease ongoing innovation activities. Our results suggest that an increasing RPR will lead to fewer green patent applications. However, the effect might be different depending on factors such as size and industry of firms. Thus, further research is needed in order to fully understand whether an increase in the RPR will increase the probability of abandoning green innovation activities and projects.

In the case where firms finance innovation by debt, an increase in the RPR will in general increase both the WACC and the cost of debt for most firms. An increase in the RPR makes the true cost of financing innovation by debt more expensive, as well as the existing debt the company is serving. The increased costs might result in firms reducing their willingness and ability to invest in R&D projects.

Based on the described effect of increased RPR on internal and external funds, both suggest a negative relationship between the RPR and the level of green innovation. The results obtained from our main model suggest weak evidence that as the true cost of borrowing increases, the level of green innovation decreases, lending support to the effects described above. We find strong evidence on the same mechanism for end-use technologies. Moreover, we performed different time leads on the subcategories of green innovation. Then we find weak evidence that all subcategories and the GR eventually are associated with a negative impact by an increase in the RPR.

Our findings on the effect of RPR on green innovation contradict Aghion et al. (2022), which argues that the monetary policy channels that affect the bank lending facilities have little or no material effect on green patenting, as banks are not involved in the innovation of new technologies. Relatedly, further research could use firm level data to investigate whether firms financing green innovation activities with internal cash flows over external funds are less exposed to an increase in the RPR. Understanding how firms responds to changes in the RPR with regard to their funding channel could provide valuable insight for policymakers.

However, there exists arguments for R&D investments being different from traditional investments in tangible assets. For example, because R&D investments are considered as long-term investments, and once a large investment in human capital is done, the cost is characterized as sunk cost. In fact, 50% or more of R&D expenditures consist of wages and salaries of R&D employees (Hall & Lerner, 2010). As a result of such high adjustment costs, and the long-term characteristics, firms might be reluctant to cease innovation midway through the process. During one of the most famous economic contractions, the financial crisis of 2008, Intel Corporation Group deliberately sustained R&D investments to maintain the company`s long-term viability (Berk & DeMarzo, 2016). Nonetheless, such evidence was not found in our analysis.

To further interpret our results, we encounter the effect of business cycles on innovation, which might also play a significant role in the level and ratio of green innovation. Our regression results suggest that green innovation responds procyclical to business cycles, as a decrease in the RPR enhances the level and ratio of green innovation. During economic expansions, inventors may be more likely to increase innovation as they have easier access to capital and favourable markets for the adoption of green technologies. For firms relying on internal funds such as retained earnings to finance innovation, economic expansions might increase their ability and accessibility to obtain these funds. Our findings provide evidence in the similar direction as Hingley and Park (2017) which finds that patent filings of the EPO respond procyclical to business cycles.

On the other hand, our findings reject that innovation within green technologies react countercyclical to business cycles. The countercyclical behaviour of innovation could be explained by firms smoothing their R&D expenditure to continuously produce innovation output, even during economic contractions. For example, during the financial crisis, Intel Corporation Group smoothed their R&D expenditure by reducing investments in other business departments, a strategy referred to as "the opportunity cost effect" by Hingley and Park (2017), which argues that the opportunity cost of conducting research is lower during economic contractions. Furthermore, a reduction of investments in the R&D department might lead to potential risk for firms. If the knowledge obtained through R&D projects are embedded in the employee and not codified, they might run the risk of losing important intangible assets for firms to profit from in the future. Therefore, smoothing their R&D expenditure over time may reduce the risk of losing human capital and to sustain enough capital to fund these R&D projects during all stages, from idea creation to commercialization. Nevertheless, evidence of countercyclical behavior was not found in our regression analysis. To gain a deeper understanding of how green innovations respond to business cycles, it is necessary with further research which examines the impact of business cycles on green innovation in greater detail.

6.2 Limitations of our study

There are several limitations to our thesis. The main limitations are associated with the final dataset used to perform regression analysis. First, the dataset is structured with annual observations. This is because the standard EPO patent filing reporting is conducted on an annual basis. It would have been beneficial to work with shorter frequency, for example matching the frequency of CB policy meetings, to capture every movement in the policy rate.

Other limitations arise from the fact that we have few years of observations. This limitation is mainly because of the ECB, which was not established until 1999. We were unsuccessful in our attempt to gather the policy rates of our sample before the establishment of the ECB. Hence, we were unable to use the full dataset of patent applications, which is available since 1977. In addition, the combination of few years of observations and the inclusion of multiple members of the ECB, made it ineffective to include year fixed effect in our model. Thus, we added a linear time trend as compensation.

Furthermore, it might be considered naïve of us to count every patent application with equal value. This thesis aimed at understanding whether an increase in the RPR compromised the increasing need for green innovation. Thus, we made use of patent applications as it is primarily a measure of innovation activity or efforts (Klementsen, 2015). This gave us an indication whether the intensity of green innovation remained stable in times of monetary tightening. Even though there is significant effect on the number of patent applications, there still might be a situation where more frequently cited patents are not impacted by changes in the policy rates. If this is the case, an increase in the policy rate may not influence the transition to a greener economy.

7. Conclusion

This thesis aims to investigate whether the real policy rate (RPR) impacts the level and ratio of green innovation. To do this, we analyze green innovation within 26 OECD countries using patent application data from 1999 to 2018. Our study is based on two hypotheses, which we test using a panel fixed effect model with country fixed effects and a linear time trend. We include several control variables that are associated to the development of green innovation, such as environmental policies, business cycles indicators, foreign direct investments, and renewable energy consumption. We also conduct several robustness analyses to validate our results.

Our findings lend stronger support to our first hypothesis than the second, which indicates that the RPR is associated with a negative effect on both the level and ratio of green innovation. However, we observe that our weighting scheme by GDP highly favors the US, which is a strong contributor to the relationship between the level of green innovation and the RPR. Additionally, we provide strong evidence that this relationship is highly influenced by end-use technologies. The relationship between the RPR and end-use technologies remained statistically significant through all robustness checks. The findings suggest that the CB's mandate of price stability may be a threat to the development of green innovation. Furthermore, we provide weak evidence of a long-term effect, in which innovation within LCE supply related technologies is de-prioritized in favor of brown innovation during times of monetary tightening. Our findings contribute to the limited literature and growing discussion about the role of CBs in the energy transition, and how their monetary policy, through the RPR, impact the level and ratio of green innovation.

The mechanism behind the negative relationship between the RPR and the level and ratio of green innovation could potentially be explained through the RPR impact on the opportunity cost of capital and WACC. This impacts firm's willingness and ability to invest in R&D related projects, potentially decreasing innovation, and technological output. Relatedly, we observe that the level and ratio of green innovation responds procyclical to business cycles.

Our thesis adds to the current discussion about CB role in the energy transition, as we provide evidence that CB monetary policy can have an impact on the level and ratio of green innovation. However, we are aware of the CBs mandate of market neutrality. Despite that, policymakers should be aware of this relationship when formulating monetary policy.

References

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. (2017). *When Should You Adjust Standard Errors for Clustering?* (Working Paper No. 24003). National Bureau of Economic Research. https://doi.org/10.3386/w24003

Aghion, P., Boneva, L., Breckenfelder, J., Laeven, L., Olovsson, C., Popov, A. A., & Rancoita, E. (2022). *Financial Markets and Green Innovation* (SSRN Scholarly Paper No. 4173682). https://doi.org/10.2139/ssrn.4173682

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & Van Reenen, J. (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. *Journal of Political Economy*, *124*(1), 1–51. https://doi.org/10.1086/684581

Anton, J. J., & Yao, D. A. (2004). Little Patents and Big Secrets: Managing Intellectual Property. *The RAND Journal of Economics*, *35*(1), 1–22. https://doi.org/10.2307/1593727

Avalle, M. (2021, June 29). Renewable energy financing conditions in Europe: Survey and impact analysis. *AURES II*. http://aures2project.eu/2021/06/29/renewable-energy-financing-conditions-in-europe-survey-and-impact-analysis/

Berk, J., & DeMarzo, P. (2016). *Corporate Finance* (Fourth Edition). Pearson Education Limited.

Bohm, T., Karkinsky, T., Knoll, B., & Riedel, N. (2015). *The Impact of Corporate Taxes on R&D and Patent Holdings*. 43.

Böhringer, C., Cuntz, A., Harhoff, D., & Asane-Otoo, E. (2017). The impact of the German feed-in tariff scheme on innovation: Evidence based on patent filings in renewable energy technologies. *Energy Economics*, *67*, 545–553. https://doi.org/10.1016/j.eneco.2017.09.001

Carney, M. (2015). *Breaking the tragedy of the horizon—Climate change and financial stability*. 12. https://www.bankofengland.co.uk/-/media/boe/files/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability.pdf?la=en&hash=7C67E785651862457D99511147C7424FF5EA0C1A

CAT. (2021). *The CAT Thermometer*. https://climateactiontracker.org/global/cat-thermometer/

Cooray, A. (2002). *The Fisher Effect: A Review of the Literature*. https://www.researchgate.net/publication/5165768_The_Fisher_Effect_A_Review_of_the_Literature

de la Horra, L. P., Perote, J., & de la Fuente, G. (2022). The impact of economic policy uncertainty and monetary policy on R&D investment: An option pricing approach. *Economics Letters*, *214*, 110413. https://doi.org/10.1016/j.econlet.2022.110413

De Rassenfosse, G., & Guellec, D. (2009). *Quality versus quantity: Strategic interactions and the patent inflation*.

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S., & Stantcheva, S. (2022). *Fighting climate change: International attitudes toward climate policies*. OECD. https://doi.org/10.1787/3406f29a-en

Diluiso, F., Annicchiarico, B., Kalkuhl, M., & Minx, J. C. (2021). Climate actions and macro-financial stability: The role of central banks. *Journal of Environmental Economics and Management*, *110*, 102548. https://doi.org/10.1016/j.jeem.2021.102548

ECB. (2022). *ECB climate agenda 2022*. European Central Bank. https://www.ecb.europa.eu/press/pr/date/2022/html/ecb.pr220704_annex~cb39c2dcbb.en.pdf?e1cc4f3420e8e9f906855410f40e73b5

EPO. (2009). *APPLICANT PANEL SURVEY 2008* (p. 105). European Patents Office. https://documents.epo.org/projects/babylon/eponet.nsf/0/FDCBCEAFC08805B3C12575A5004005F5/$File/aps_2008_report_en.pdf

EPO. (2022a). *EP full-text data for text analytics*. https://www.epo.org/searching-for-patents/data/bulk-data-sets/text-analytics.html

EPO. (2022b). *Ep-fulltex…analytics – Bucket details – Cloud Storage – Google Cloud console*. https://console.cloud.google.com/storage/browser/ep-fulltext-for-text-analytics/2022week05?pageState=(%22StorageObjectListTable%22:(%22f%22:%22%255B%255D%22))&prefix=&forceOnObjectsSortingFiltering=false

EPO. (2022c). *The European Patent Convention*. https://www.epo.org/law-practice/legal-texts/html/epc/2020/e/ar52.html

EPO. (2022d). *Updates on Y02 and Y04S*. https://www.epo.org/news-events/in-focus/classification/classification/updatesYO2andY04S.html

European Commission. (2020). *Stepping up Europe's 2030 climate ambition*. European Comission. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020DC0562&from=en

Evers, M., Niemann, S., & Schiffbauer, M. (2020). Inflation, liquidity and innovation. *European Economic Review*, *128*, 103506. https://doi.org/10.1016/j.euroecorev.2020.103506

Hall, B. H., & Lerner, J. (2010). Chapter 14—The Financing of R&D and Innovation. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the Economics of Innovation* (Vol. 1, pp. 609–639). North-Holland. https://doi.org/10.1016/S0169-7218(10)01014-2

Heger, D. (2004). *The Link between Firms' Innovation Decision and the Business Cycle: An Empirical Analysis* (SSRN Scholarly Paper No. 686712). https://doi.org/10.2139/ssrn.686712

Herman, K. S., & Xiang, J. (2019). Induced innovation in clean energy technologies from foreign environmental policy stringency? *Technological Forecasting and Social Change*, *147*, 198–207. https://doi.org/10.1016/j.techfore.2019.07.006

Hingley, P., & Park, W. G. (2017). Do business cycles affect patenting? Evidence from European Patent Office filings. *Technological Forecasting and Social Change*, *116*, 76–86. https://doi.org/10.1016/j.techfore.2016.11.003

Hyytinen, A., & Toivanen, O. (2005). Do financial constraints hold back innovation and growth?: Evidence on the role of public policy. *Research Policy*, *34*(9), 1385–1403. https://doi.org/10.1016/j.respol.2005.06.004

IEA. (2021). *Patents and the Energy Transition – Analysis*. IEA. https://www.iea.org/reports/patents-and-the-energy-transition

IEA. (2022). *World Energy Investment 2022 – Analysis*. IEA. https://www.iea.org/reports/world-energy-investment-2022

Johnstone, N., Haščič, I., & Popp, D. (2010). Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts. *Environmental and Resource Economics*, *45*(1), 133–155. https://doi.org/10.1007/s10640-009-9309-1

Klemetsen, M. E. (2015). *The effects of innovation policies on firm level patenting* (Working Paper No. 830). Discussion Papers. https://www.econstor.eu/handle/10419/192812

Kotzeva, M., Diez de Medina, R., Marc Ducharme, L., Schreyer, P., Bratanova, L., & Fu, H. (2020). *Consumer Price Index Manual*. International Monetary Fund. https://www.imf.org/en/Data/Statistics/cpi-manual

Kruse, T., Dechezleprêtre, A., Saffar, R., & Robert, L. (2022). *Measuring environmental policy stringency in OECD countries: An update of the OECD composite EPS indicator*. OECD. https://doi.org/10.1787/90ab82e8-en

Lopez-Garcia, P., Montero, J. M., & Moral-Benito, E. (2012). *Business Cycles and Investment in Intangibles: Evidence from Spanish Firms* (SSRN Scholarly Paper No. 2064535). https://doi.org/10.2139/ssrn.2064535

Luo, Y., Salman, M., & Lu, Z. (2021). Heterogeneous impacts of environmental regulations and foreign direct investment on green innovation across different regions in China. *Science of The Total Environment*, *759*, 143744. https://doi.org/10.1016/j.scitotenv.2020.143744

McConnell, A., Yanovski, B., & Lessmann, K. (2020). *Central Bank Collateral as an Instrument for Climate Mitigation* (SSRN Scholarly Paper No. 3630662). https://doi.org/10.2139/ssrn.3630662

Ménière, Y., Rossatto, C., Rudyk, I., Rodríguez, J. P., & Ortega, M. B. (2021). *Patents and the energy transition*. 72.

Moser, P. (2013). Patents and Innovation: Evidence from Economic History. *Journal of Economic Perspectives*, *27*(1), 23–44. https://doi.org/10.1257/jep.27.1.23

Myers, S. C. (1984). *Capital Structure Puzzle* (No. w1393). National Bureau of Economic Research. https://doi.org/10.3386/w1393

Nagaoka, S., Motohashi, K., & Goto, A. (2010). Chapter 25—Patent Statistics as an Innovation Indicator. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the Economics of Innovation* (Vol. 2, pp. 1083–1127). North-Holland. https://doi.org/10.1016/S0169-7218(10)02009-5

Nesta, L., Vona, F., & Nicolli, F. (2014). Environmental policies, competition and innovation in renewable energy. *Journal of Environmental Economics and Management*, *67*(3), 396–411. https://doi.org/10.1016/j.jeem.2014.01.001

NGFS. (2022, April 10). *Membership*. Banque de France. https://www.ngfs.net/en/about-us/membership

Nylund, P. A., Arimany-Serrat, N., Ferras-Hernandez, X., Viardot, E., Boateng, H., & Brem, A. (2019). Internal and external financing of innovation: Sectoral differences in a longitudinal study of European firms. *European Journal of Innovation Management*, *23*(2), 200–213. https://doi.org/10.1108/EJIM-09-2018-0207

OECD. (2009). *OECD Patent Statistics Manual*. Organisation for Economic Co-operation and Development. https://www.oecd-ilibrary.org/science-and-technology/oecd-patent-statistics-manual_9789264056442-en

OECD. (2021). *Effective Carbon Rates 2021: Pricing Carbon Emissions through Taxes and Emissions Trading | en | OECD*. https://www.oecd.org/tax/tax-policy/effective-carbon-rates-2021-0e8e24f5-en.htm

Papoutsi, M., Piazzesi, M., & Schneider, M. (2022). *How unconventional is green monetary policy?* https://web.stanford.edu/~piazzesi/How_unconventional_is_green_monetary_policy.pdf

Qiu, S., Wang, Z., & Geng, S. (2021). How do environmental regulation and foreign investment behavior affect green productivity growth in the industrial sector? An empirical test based on Chinese provincial panel data. *Journal of Environmental Management*, *287*, 112282. https://doi.org/10.1016/j.jenvman.2021.112282

Rocha, L. A., Cardenas, L. Q., Reis, F. A., Silva, N. G. A., & Almeida, C. A. S. D. (2021). INFLATION AND INNOVATION VALUE: HOW INFLATION AFFECTS INNOVATION AND THE VALUE STRATEGY ACROSS FIRMS. *ESTUDIOS ECONÓMICOS*, *XXXVIII*(76), 147–195.

Schnabel, I. (2022, April 17). A new age of energy inflation: Climateflation, fossilflation and greenflation. *A New Age of Energy Inflation: Climateflation, Fossilflation and Greenflation*. https://www.ecb.europa.eu/press/key/date/2022/html/ecb.sp220317_2_annex~3b7ce81994.en.pdf?285c4eae28cc46f64ac7e25f31168df7

Sha, F., Gallagher, K. S., Gandiglio, M., García, M., Gatellier, B., Gogan, K., Gutzwiller, L., Stignor, C. H., Handelsman, J., Hauer, A., Henriot, S., Herzog, A., Herzog, H., Hongo, T., Hosker, E., Jayne, K., Jeffrey, H., Kavlak, G., Kittner, N., … Nishimura, M. (2020). Energy Technology Perspectives 2020—Special Report on Clean Energy Innovation. *Energy Technology Perspectives*, 185.

Stefano, S., Martin, H., & Lukas, H. (2022). *Green central banking*. European Parliamentary Research Service. https://www.europarl.europa.eu/RegData/etudes/BRIE/2022/733614/EPRS_BRI(2022)733614_EN.pdf

Ughetto, E. (2008). Does Internal Finance Matter for R&D? New Evidence from a Panel of Italian Firms. *Cambridge Journal of Economics*, *32*, 907–925. https://doi.org/10.1093/cje/ben015

van Leeuwen, G., & Mohnen, P. (2017). Revisiting the Porter hypothesis: An empirical analysis of Green innovation for the Netherlands. *Economics of Innovation and New Technology*, *26*(1–2), 63–77. https://doi.org/10.1080/10438599.2016.1202521

van Pottelsberghe de la Potterie, B., & François, D. (2008). The Cost Factor in Patent Systems. *Journal of Industry, Competition and Trade*, *9*(4), 329. https://doi.org/10.1007/s10842-008-0033-2

Wang, T., & Thornhill, S. (2010). R&D investment and financing choices: A comprehensive perspective. *Research Policy*, *39*(9), 1148–1159. https://doi.org/10.1016/j.respol.2010.07.004

Wooldridge, J. M. (2019). *Introductory Econometrics: A Modern Approach—Jeffrey M. Wooldridge—Google Bøker*. https://books.google.no/books?hl=no&lr=&id=wUF4BwAAQBAJ&oi=fnd&pg=PR3&dq=Introductory+Econometrics+Modern+Approach&ots=cAWFZDmpji&sig=-z8sqQUDUuZMxga2VDZOTT6wvNU&redir_esc=y#v=onepage&q=Introductory%20Econometrics%20Modern%20Approach&f=false

Zhang, D., Guo, Y., Wang, Z., & Chen, Y. (2020). The impact of US monetary policy on Chinese enterprises' R&D investment. *Finance Research Letters*, *35*, 101301. https://doi.org/10.1016/j.frl.2019.09.016

Zhang, D., Zheng, M., Feng, G.-F., & Chang, C.-P. (2022). Does an environmental policy bring to green innovation in renewable energy? *Renewable Energy*, *195*, 1113–1124. https://doi.org/10.1016/j.renene.2022.06.074

Appendix

7.1 Classifications

7.1.1 Classifying green patent applications

To classify green patents, we have made use of IEA's cartography of LCE technologies (Ménière et al., 2021). Table 6 presents the category of the technology from the left. We have utilized the three main technologies as patent count for our dependent variables LCE supply, Enabling and End-use. The next two columns display the subclasses of each technology. The last column shows the CPC code used to classify the green patent application. After following this procedure, we are left with 279,748 patents. Finally, we count all patents as green patents, unless the patent application shares a CPC class with brown patents. We are then left with our final count of 269,662 green patent applications since 1977.

Table 6: The IEA Classification System – Green Patent Applications

Technology	Sub class	Sub-class 2	CPC code
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
	Hydrogen and fuel cells		Y02E60/30/Low
	Other		Y02E60/00 OR Y02E60/13 OR Y02E60/14 OR Y02E60/16 OR Y02E70/00/Low OR Y02E60/60 OR Y02E40/00 OR Y02E40/10, 20, 30, 40, 50, 60

	Smart grids		Y04S
Energy substitution and efficiency in end use (end-use technologies)	Buildings		Y02B
	Production/chemical and oil refining		Y02P20/00/Low OR Y02P30/00/Low
	Production/metal and minerals processing		Y02P10/00/Low OR Y02P40/00/Low
	Production/other	Agriculture	Y02P60/00/Low
		Consumer products	Y02P70/00/Low
		Other production	Y02P80/00/Low OR Y02P90/00/Low
	Transportation/ electric vehicles and EV infrastructure	EV and infrastructure	Y02T90/40/Low
		Fuel cells for road vehicles	Y02T90/40/Low
	Transportation/other road technologies		Y02T10/00 OR Y02T10/10/Low OR Y02T10/80, 82, 84, 86, 88, 90 OR Y02T90/00
	Other transportation/ aeronautics, maritime and railways	Aeronautics	Y02T50/00/Low
		Maritime and waterways	Y02T70/00/Low
		Railways	Y02T30/00
	Computing and communication		Y02D10/00 OR Y02D30/00/Low

Note: The patent classification follows IEA's Cartography of LCE technologies. *Low* indicates that not only the class itself, but also its respective classification should be taken into account for the corresponding cartography level (Ménière et al., 2021). The patents have first been classified in each subclass. Thereafter, all the patents counted have been classified as green patents, unless the patent application shares a CPC class with brown patents.

7.1.2 Classifying brown patent applications

To classify brown patents, we have made use of IEA's methodology for identifying fossil fuel supply-related technologies (IEA, 2021). Table 7 presents the fossil fuel supply categories to the left, followed by the technological subcategory, and the CPC codes used to classify the patent applications. The last two columns show the short label of the full-text search and/or CPC codes used to include and/or exclude patents. After following this process, we are left with 50,714 patents. Finally, we count all patents as brown patents, unless the patent application shares a CPC class with green patents. We are then left with our final count of 40,628 brown patent applications since 1977.

Table 7: The IEA Classification System – Brown Patent Applications

Fossil fuel supply category	**Technology**	**CPC code**	**Filtering including queries**	**Filtering excluding queries**
Upstream	Conventional oil and gas exploration and extraction	B03B9/02		
		B03D2203/006		
		B63B35/4413	[1],[2],[4]	
		B63B2035/442	[1],[2],[4]	
		B63B2035/448	[1],[2],[4]	
		B63B75/00	[1],[2],[4]	
		C09K8/Low		
		C10L5/04		
		E02B17/00	[1], [8]	[10]
		E02B17/0004 to E02B2017/0039/ Low	[1], [8]	[10]
		E02B2017/0056/Low to E02B2201/00/Low	[1], [8]	[10]
		E21B1/00/ Low to E21B41/00/Low	[1], [2], [4], [8]	[12]
		E21B43/00	[1], [2], [4], [8]	[12]
		E21B43/003	[1], [2], [4], [8]	[12]
		E21B43/006	[1], [2], [4], [8]	[12]
		E21B43/01/Low	[1], [2], [4], [8]	[12]
		E21B43/02/ Low to E21B43/12/ Low	[1], [2], [4], [8]	[12]
		E21B43/14	[1], [2], [4], [8]	[12]
		E21B43/16/ Low	[1], [2], [4], [8]	[12]
		E21B43/25/ Low	[1], [2], [4], [8]	[12]
		E21B43/28/ Low to E21B43/34/ Low	[1], [2], [4], [8]	[12]
		E21B44/00/ Low to E21B49/00/ Low	[1], [2], [4], [8]	[12]
Upstream	Unconventional oil and gas exploration and extraction	E21B43/26/Low	[1], [2], [4], [8]	
		E21B7/04/Low	[1], [2], [4], [8]	
		E21B43/16/Low	[1], [2], [4], [8]	
		E21B43/006	[1], [2], [4], [8]	
		E21B41/0099	[1], [2], [4], [8]	
	Coal and solid fuels exploration and mining	B03B9/005		
		B03B1/00/Low	[1], [3]	
		B03D2203/08		
		B61D11/00/Low	[1], [3]	
		E21C25/00/Low to E21C51/00/Low	[1], [3]	
Processing and downstream	Oil refining	C10G2/00/ Low to C10G99/00/Low		
		C10G1/00, C10G1/002 to C10G1/042, C10G1/047 to C10G1/10		

		C10L1/00/Low	[1], [2], [5]	[9], [13]
	Gas conditioning	C10K1/00/Low		
		C10K3/00/Low		
		C10L3/06/Low	[4], [6]	[9], [13]
		F25J3/0209/Low		
		F25J3/061 Low		
	Solid fuel conditioning	C10F5/00/Low to C10F7/00/Low		
		C10L5/06/Low	[3], [7]	[9], [13]
		C10L5/24	[3], [7]	[9], [13]
		C10L5/26/Low	[3], [7]	[9], [13]
		C10L5/34/Low	[3], [7]	[9], [13]
	Coal-to-gas	C10B1/00/Low to C10B51/00/Low		
		C10B53/04 to C10B53/08		
		C10B55/00/Low to C10B57/00/Low		
		C10J1/00/ Low to C10J3/00/Low		
	Coal-to-liquids and gas-to-liquids	C01B3/22/Low	[14]	
		C01B3/32/Low	[14]	
		C10J3/00/Low	[15]	
	Hydrogen fuel production	C01B3/22/Low		
		C01B3/32/Low		
Transmission and distribution	Liquid fuel pipelines	B63B27/34	[2], [5]	
		B63B27/24/Low	[2], [5]	
		F17D1/00/Low to F17D5/00/Low	[2], [5]	
	Gas fuel pipelines	B63B27/24/Low	[4], [6]	
		F17D1/04/Low	[4], [6]	
		F17D1/065/Low	[4], [6]	
	Liquid fuel tanker shipping	B63B25/08/Low	[2], [5]	
		B67D9/00/Low	[2], [5]	
	Liquefied gaseous fuel shipping	F25J1/0022/Low		
	Compressed gaseous fuel shipping	B63B2025/087	[4], [6]	
		B63B25/14	[4], [6]	
		B63B25/16	[4], [6]	
	Solid fuel shipping	B63B25/04	[3]	
	Road tanker liquid fuels transport	B60P3/22/Low	[11], [5]	
	Road tanker gaseous fuels transport	B60P3/22/Low	[11],[6]	
		B61D5/00/Low	[2], [5]	

Rail tanker liquid fuels transport	B61D3/00/Low	[2], [5]
	B61D15/00/Low	[2], [5]
	B61D49/00/Low	[2], [5]
Rail tanker gaseous fuels transport	B61D3/00/Low	[4], [6]
	B61D15/00/Low	[4], [6]
	B61D49/00/Low	[4], [6]
Rail solid fuel transport	B61D7/00/Low	[3], [7]
	B61D9/00/Low	[3], [7]
	B61D3/00/Low	[3], [7]
	B61D15/00/Low	[3], [7]
	B61D49/00/Low	[3], [7]
Underground liquid fuels storage	B65G5/00/Low	[1], [2], [5]
Underground gaseous fuels storage	F17C2270/0142/Low	[4], [6]
Stationary tank storage for liquids	E02D27/38	[2], [5]
Stationary tank storage for gases	F17B1/26	[4], [6]
	F17C1/00/Low to F17C13/00/Low F17C2221/032/Low	[4], [6]
Solid fuel storage	B65G3/00/Low	[3], [7]
Liquid fuel distribution (gas stations)	G01M3/2892 G01M3/32/Low	[5]
Gaseous fuel distribution	F17C2265/06/Low	[4], [6]

Note: The patent classification follows IEA's methodology for identifying fossil fuel supply related technologies. *Low* indicates that not only the class itself, but also its respective classification should be taken into account for the corresponding cartography level (IEA, 2021).

The search queries have here been reproduced in English. However, they have been applied in English, French, and German. The search queries also follow IEA's methodology for identifying fossil fuel supply related technologies in patent data. The search for queries has been performed through the full text of the relevant patent.

Table 8: Search Queries

Queries in English	Corresponding short label
fossil OR (non w renewable) OR hydrocarbon? OR petrol+	[1]
petroleum OR (crude w oil) OR oil	[2]
coal OR mineral? OR coke OR peat OR BKB OR briquette OR asphaltite OR ortholignite OR metaanthracite OR lignite OR hardcoal OR browncoal OR (brown w coal) OR (oil 2w deposit) OR (oil w bear+) OR bitumen OR bituminous OR (tar w sand) OR (oil w sand)	[3]
methane OR (natural w gas) OR hydrate? OR (petroleum w gas+) OR hydrogen OR (boil 2w gas+) OR BOG OR LNG OR LPG OR (liqui+ 2w (fuel? OR petroleum)) OR (liqui+ 2w gas+) OR (gaseous w fuel?)	[4]
LNG OR LPG OR (liquid w fuel?) OR diesel OR gasoline OR (jet w fuel?) OR (fuel w oil) OR (bunker w fuel?) OR kerosene OR (oil w product?) OR octane OR cetane OR propane OR butane	[5]
methane OR (natural w gas+) OR CNG OR LNG OR PLNG OR propane OR butane OR LPG OR Hydrate? OR (petroleum w gas+) OR hydrogen OR liquefied OR (compressed w gas+)	[6]
coal OR BKB OR briquette OR asphaltite OR ortholignite OR metaanthracite OR lignite OR hardcoal OR browncoal	[7]
drilling OR offshore OR onshore OR oil OR hydrocarbon? OR gas+ OR subsea OR seabed OR reservoir OR petroleum OR methane OR formation OR riser? OR (well w head) OR bop OR (blowout w prevent+) OR fracturing OR frack+ OR ((bottom OR down) w hole)	[8]
biomass OR biofuel OR bioethanol OR biodiesel	[9]
(wind w turbine) OR tower OR mast OR ((power OR electric) 3w generat+)	[10]
+tank+ OR reservoir OR citerne	[11]

Note: The search queries are to be applied to the corresponding CPC field.

A singular patent has multiple CPC classes. In addition to filtering based on full-text queries, some of the patents are only included and/or excluded as brown patents, if they contain a certain CPC class.

Table 9: Additional CPC Filtering

CPC classes	Corresponding short label
E21B43/26/Low OR E21B7/04/Low OR E21B7/06/Low OR E21B43/16/Low OR E21B43/24/Low OR E21B43/006 OR E21B41/0099	[12]
C10L2200/0469/Low	[13]
C01B2203/062	[14]
C10G2/30/Low	[15]

Note: The CPC classes are to be applied to the corresponding CPC field

7.2 Country codes

Table 10: Country Codes

Country code	Country
AU	Australia
AT	Austria
BE	Belgium
CA	Canada
CH	Switzerland
CZ	Czech Republic
DE	Germany
DK	Denmark
ES	Spain
FI	Finland
FR	France
GB	United Kingdom
GR	Greece
HU	Hungary
IE	Ireland
IT	Italy
JP	Japan
KR	South Korea
NL	Netherland
NO	Norway
PL	Poland
PT	Portugal
SE	Sweden
SI	Slovenia
SK	Slovak Republic
US	United States of America

7.3 Descriptive statistics per country

Table 11: Per Country Green Patents

Green patents summary

Statistic	AT	AU	BE	CA	CH	CZ	DE	DK	ES	FI	FR	GB	GR	HU	IE	IT	JP	KR	NL	NO	PL	PT	SE	SI	SK	US
N	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
Mean	135	69	102	184	176	12	1,886	204	124	99	716	438	6	11	18	265	2,304	658	223	38	22	9	221	5	3	2,522
St. Dev.	57	9	42	44	65	6	574	121	66	41	289	184	3	6	10	86	664	444	79	16	19	6	103	3	2	810
Min	54	48	43	84	82	1	1,039	51	25	42	285	189	1	1	3	112	1,395	47	108	11	0	1	82	0	0	1,165
Max	216	86	156	232	288	21	2,719	436	192	172	1,054	711	14	22	33	389	3,619	1,363	318	65	63	24	350	12	9	3,685

Table 11 presents the per-country descriptive statistics for green patents application ranging from 1999 to 2018.

Table 12: Per Country Brown Patents

Brown patents summary

Statistic	AT	AU	BE	CA	CH	CZ	DE	DK	ES	FI	FR	GB	GR	HU	IE	IT	JP	KR	NL	NO	PL	PT	SE	SI	SK	US
N	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
Mean	10	10	11	29	9	1	114	23	8	14	114	117	0	1	2	28	56	14	60	52	3	1	16	0	0	495
St. Dev.	5	5	4	14	4	1	30	18	4	7	30	37	1	1	1	8	16	8	15	24	2	1	6	0	1	130
Min	2	4	5	14	1	0	60	4	1	6	72	32	0	0	0	13	35	2	18	22	0	0	5	0	0	240
Max	24	22	19	59	15	2	166	71	15	32	174	166	2	4	4	43	93	27	85	93	7	3	26	1	2	782

Table 12 presents the per-country descriptive statistics for brown patents application ranging from 1999 to 2018.

Table 13: Per Country Green Ratio

Green Ratio summary

Statistic	AT	AU	BE	CA	CH	CZ	DE	DK	ES	FI	FR	GB	GR	HU	IE	IT	JP	KR	NL	NO	PL	PT	SE	SI	SK	US
N	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
Mean	3.1	1.9	2.2	1.1	6.0	2.5	4.0	6.4	7.5	1.5	1.1	0.9	2.5	2.3	3.1	2.3	5.7	6.1	1.1	0.3	1.9	3.0	2.7	1.9	2.1	1.0
St. Dev.	1.1	1.1	1.3	0.5	4.3	1.4	1.2	3.5	5.3	0.7	0.4	0.8	1.5	1.8	2.4	1.0	1.8	3.8	0.8	0.2	1.4	2.5	1.4	0.8	1.6	0.4
Min	1.1	0.6	0.5	0.1	1.5	0.4	1.9	1.6	0.5	0.6	0.5	0.2	0.3	0.2	1.0	0.3	3.6	1.0	0.2	0.1	0.2	0.6	0.9	1.0	0.7	0.4
Max	5.4	4.3	4.3	2.3	19.3	5.2	6.3	15.6	19.9	3.4	1.8	4.1	6.0	7.0	11.4	4.0	10.6	15.3	3.2	0.8	5.7	10.8	5.3	3.4	7.7	2.0

Table 13 presents the per-country descriptive statistics for the GR, building upon green and brown patent applications from 1999 to 2018.

7.4 Hausman test

The table shows the results after performing a Hausman test to check whether fixed- or random effects are the preferred estimators in our analysis. The null hypothesis is that there is no correlation between the time-invariant unobserved individual-specific effect and the regressors. If there is no correlation, we do not reject the null hypothesis, and the random effects are our preferred estimator. However, the test results from the Hausman test show a p-value well below 5%, which means we reject the null hypothesis. Therefore, our preferred estimator is the fixed effects.

Table 14: Hausman Test

Dependent	Chisq	p-value
$lnGreen_{t+1}$	**66.365**	**2.59e-11**

7.5 Model specifications

7.5.1 Model testing

Breusch-Pagan test

We perform two tests to confirm the need to cluster our standard errors in the regression models. As the clustered standard errors allow for unrestricted forms of serial correlation and heteroskedasticity (Wooldridge, 2019), the presence of either will confirm our need to cluster the standard errors.

First, the Breusch-Pagan test checks whether there is heteroskedasticity present in our main regression models. The null hypothesis is that the error variances are all equal. The p-values in the tables are under 5%, which means we reject the null hypothesis, and that there is heteroskedasticity present in all our models.

Table 15: Breusch-Pagan Test – (Heteroskedasticity Test)

Dependent	BP	df	p-value
$lnGreen_{t+1}$	190.46	33	2.2e-16
$lnBrown_{t+1}$	103.86	33	2.949e-9
$lnGR_{t+1}$	118.53	33	1.805e-11

Breusch-Godfrey test

Secondly, The Breusch-Godfrey test checks for serial correlations in the error term. The null hypothesis is that there is no presence of serial correlations. In comparison to the Breusch-Pagan test, the results show a p-value under 5%. We reject the null hypothesis and prove that there is a serial correlation in our model. The result from both tests confirms our need to cluster our standard errors for all models, as we confirm the presence of both serial correlation and heteroskedasticity in all of them.

Table 16: Breusch-Godfrey/Wooldridge Test – (Serial Correlation Test)

Dependent	**Chisq.**	**df**	**p-value**
$Green_{t+1}$	139.59	19	2.2e-16
$Brown_{t+1}$	100.1	19	5.136e-13
GR_{t+1}	153	19	2.2e-16

Multicollinearity

The correlation matrix displays the correlation coefficient between multiple variables. Our variable of interest has a moderate negative correlation with NMBP (-0.257) and TS (-0.260). Otherwise, there is no evidence of strong or perfect intercorrelation between the policy rate

Table 17: Correlation Matrix

	RPR	ln(GDP)	Unem	MBP	NMBP	TS	REC	FDI
RPR	1							
ln(GDP)	-0.046	1						
Unem	0.013	-0.186	1					
MBP	-0.121	0.031	-0.139	1				
NMBP	-0.257	0.183	-0.018	0.325	1			
TS	-0.260	0.337	-0.103	0.194	0.448	1		
REC	-0.085	-0.110	-0.152	0.376	0.165	0.132	1	
FDI	0.157	-0.124	-0.019	-0.123	-0.022	-0.096	-0.135	1

and any other variable. Furthermore, the three subcategories MBP, NMBP, and TS of the EPS, are expected to have a positive correlation with each other, as they all measure the stringency of different environmental policies. There is no evidence of a strong correlation between them, and we can include them individually. Nonetheless, the correlation between the subcategories is of less concern, as the policy rates are our variable of interest. The correlation matrix does not imply that there is a violation of the multicollinearity assumption.

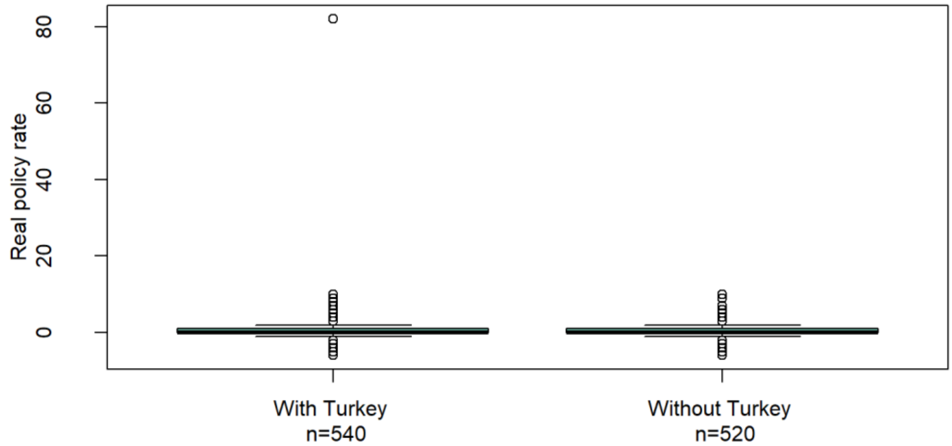
Zero Conditional Mean

For the zero conditional mean assumption to hold, all explanatory variables must be uncorrelated with the error term. There are no statistical tests to perform to check whether the assumption is violated, which makes it hard to conclude whether one can interpret the coefficients in our model in a casual way. However, we add multiple control variables which are likely to correlate with both the RPR and patent applications. It could be argued that the zero conditional mean assumption is violated as some of our explanatory variables are systematically related to other factors that affect the level of patent applications. Thus, one should be careful to interpret our models casually (Wooldridge, 2019).

7.5.2 Removing outliers

The CB of Turkey follows an ideology where they lower the policy rate to bring down inflation, which is the opposite of all other CBs in our sample. This has led to an extreme policy rate value, as can be seen in Figure 5. To avoid bias caused by outliers in our regression, Turkey is omitted from the data sample used in the regression analysis.

Figure 5: Boxplot Turkey



Note: Figure 5 displays two boxplots, before and after omitting Turkey.

7.6 Preliminary analysis

In advance of investigating the relationship between the level- and ratio of green patent applications, we do a follow-up test of the simple model of Zhang et al. (2020). Alongside de la Horra. (2022), the studies find that an increase in the US nominal policy rate will lead to an increase in R&D investment for both Chinese and US companies, as well as an increase in patent applications for Chinese enterprises.

The simple model in Table 18 will give an indication whether our datasets have any differences. As dependent variables in the regression, we make use of the total number of patent applications across every category to the EPO, denoted as All. We also do additional control checks where we use BR&D as a dependent variable. In column (1) we run a simple OLS regression without country fixed effect, and we observe that the PR has a significant and negative impact on all patent applications. However, when we include country fixed effects in column (2), the significance of the PR disappears.

Moreover, we add different time leads to the dependent variable from column (3) to (4). The policy rate becomes significant at a 5% level and indicates that there might be an intermediate effect from a change in the policy rate on all patent applications. What is not shown in the columns, is that we also tried to add BR&D as a control variable, however, the PR coefficient and standard errors remained stable. Following a similar vein, making use of BR&D as a dependent variable in columns (5) to (7), there is no initial sign of a significant effect from the PR on BR&D. However, when we add different time leads, there eventually comes a slight indication of a long-run effect.

To summarize, the preliminary analysis fails to reproduce the results of Zhang et al. (2020). Where their simple model found that the nominal interest rate had a positive effect on patent applications, we find the opposite. However, this does not come as a surprise. Hingley and Park (2017) use a similar cross-country sample as ours when studying business cycles' impact on patents. They found that patent applications to the EPO increase during an economic expansion, which could be considered a similar finding to our simple preliminary analysis.

Table 18: Preliminary Regression Model

	Dependent variable:						
	$\ln(All_{t+1})$		$\ln(All_{t+2})$	$\ln(All_{t+3})$	ln(BR&D)	$\ln(BR\&D_{t+1})$	$\ln(BR\&D_{t+2})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PR	-0.308***	-0.044	-0.048**	-0.042**	-0.010	-0.013	-0.027*
	(0.034)	(0.029)	(0.022)	(0.019)	(0.016)	(0.015)	(0.016)
time	-0.055***	0.021***	0.017***	0.016***	0.039***	0.038***	0.034***
	(0.018)	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.005)
Constant	8.485***						
	(0.256)						
Control (GDP)	No	No	No	No	No	No	No
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No
Observations	494	494	468	442	520	494	468
R^2	0.105	0.423	0.432	0.415	0.585	0.569	0.564
Adjusted R^2	0.101	0.390	0.397	0.377	0.563	0.544	0.537

Note: Table 18 presents the output of our OLS regression model with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. The dependent variable represents the natural logarithmic of all patent applications, with one year time lead in columns (1) and (2). Columns (3) and (4) are leaded with 2 and 3 years respectively. The last 3 columns use the natural logarithm of BR&D as the dependent variable with different time leads. The underlying data spans from 1999 to 2018, for 26 countries. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

7.7 Robustness analysis

Table 19: Different RPR:

	Dependent variable:				
	$\ln(Green_{t+1})$	$\ln(LCE\ supply_{t+1})$	$\ln(Enabling_{t+1})$	$\ln(End\text{-}use_{t+1})$	$\ln(GR_{t+1})$
	(1)	(2)	(3)	(4)	(5)
RPR2	-0.018	-0.017	-0.021	-0.026*	-0.002
	(0.013)	(0.021)	(0.015)	(0.013)	(0.018)
MBP	0.118	-0.018	0.150*	0.125*	-0.038
	(0.074)	(0.153)	(0.084)	(0.069)	(0.131)
NMBP	-0.031	-0.059	-0.073**	0.007	0.058
	(0.036)	(0.119)	(0.033)	(0.017)	(0.075)
TS	0.002	0.076	0.008	-0.038	-0.056
	(0.030)	(0.070)	(0.039)	(0.033)	(0.051)
ln(GDP)	0.929***	1.425***	0.656***	0.768***	0.555
	(0.259)	(0.505)	(0.174)	(0.256)	(0.471)
Unem	0.023**	0.032**	0.015	0.027**	-0.007
	(0.010)	(0.014)	(0.013)	(0.010)	(0.008)
REC	0.0002	-0.041**	0.011	0.001	-0.028
	(0.008)	(0.016)	(0.016)	(0.006)	(0.020)
FDI	-0.003	-0.003	-0.002	-0.004**	-0.003
	(0.002)	(0.004)	(0.006)	(0.002)	(0.005)
Time	0.020**	0.019	0.026	0.027***	0.029
	(0.008)	(0.016)	(0.016)	(0.009)	(0.017)
Control(GDP)	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Observations	494	494	494	494	494
R^2	0.651	0.510	0.461	0.583	0.251
Adjusted R^2	0.625	0.474	0.421	0.552	0.196

Note: Table 19 *presents the output of our OLS regression with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. All regressions are weighted by each country's average GDP. The dependent variables represent the natural logarithmic of Green, LCE supply, Enabling, End-use, and GR, with one year time lead . The underlying data spans from 1999 to 2018, for 26 countries. *p<0.1; **p<0.05; ***p<0.01.*

Table 20: Nominal Policy Rate and Inflation

	Dependent variable:				
	$\ln(Green_{t+1})$	$\ln(LCE\ supply_{t+1})$	$\ln(Enabling_{t+1})$	$\ln(End\text{-}use_{t+1})$	$\ln(GR_{t+1})$
	(1)	(2)	(3)	(4)	(5)
PR	-0.014	0.011	-0.010	-0.034**	0.009
	(0.011)	(0.012)	(0.012)	(0.012)	(0.018)
Inflation	0.037**	0.070***	0.027	0.034**	0.048***
	(0.013)	(0.022)	(0.016)	(0.012)	(0.012)
MBP	0.123*	0.002	0.153	0.122*	-0.022
	(0.070)	(0.129)	(0.090)	(0.069)	(0.112)
NMBP	-0.029	-0.053	-0.074**	0.009	0.066
	(0.035)	(0.112)	(0.033)	(0.018)	(0.070)
TS	-0.004	0.063	0.003	-0.044	-0.064
	(0.029)	(0.073)	(0.037)	(0.030)	(0.053)
ln(GDP)	0.908***	1.438***	0.635***	0.719***	0.573
	(0.267)	(0.510)	(0.175)	(0.257)	(0.483)
Unem	0.025*	0.046*	0.017	0.024*	0.002
	(0.014)	(0.022)	(0.013)	(0.013)	(0.012)
REC	0.002	-0.034**	0.013	0.001	-0.024
	(0.008)	(0.015)	(0.016)	(0.006)	(0.020)
FDI	-0.003	-0.004	-0.003	-0.003**	-0.003
	(0.002)	(0.004)	(0.006)	(0.001)	(0.006)
Time	0.022***	0.025*	0.030*	0.028***	0.031*
	(0.007)	(0.013)	(0.015)	(0.009)	(0.018)
Control(GDP)	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Observations	494	494	494	494	494
R^2	0.641	0.491	0.452	0.591	0.245
Adjusted R^2	0.614	0.452	0.410	0.560	0.187

*Note: Table 20 presents the output of our OLS regression with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. All regressions are weighted by each country's average GDP. The dependent variables represent the natural logarithmic of Green, LCE supply, Enabling, End-use, and GR, with one year time lead . The underlying data spans from 1999 to 2018, for 26 countries. *p<0.1; **p<0.05; ***p<0.01.*

Table 21: Time Leads

	Dependent variable:									
	$\ln(Green_{t+2})$	$\ln(Green_{t+3})$	$\ln(Green_{t+4})$	$\ln(Green_{t+5})$	ln(LCE supply$_{t+2}$)	ln(LCE supply$_{t+3}$)	ln(LCE supply$_{t+4}$)	ln(LCE supply$_{t+5}$)	$\ln(Enabling_{t+2})$	$\ln(Enabling_{t+3})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RPR	-0.020*	-0.025***	-0.023**	-0.015	-0.012	-0.019***	-0.028***	-0.020***	-0.010	-0.012
	(0.010)	(0.009)	(0.009)	(0.009)	(0.015)	(0.007)	(0.008)	(0.006)	(0.010)	(0.011)
MBP	0.135*	0.142*	0.112	0.088	0.027	0.067	0.080	0.136	0.175*	0.155*
	(0.074)	(0.070)	(0.071)	(0.084)	(0.181)	(0.197)	(0.194)	(0.159)	(0.085)	(0.078)
NMBP	-0.025	0.021	0.025	0.044	-0.026	0.025	-0.008	0.043	-0.063*	-0.022
	(0.047)	(0.039)	(0.045)	(0.043)	(0.116)	(0.101)	(0.110)	(0.091)	(0.035)	(0.043)
TS	-0.025	-0.040	-0.061	-0.087***	0.013	-0.035	-0.099	-0.127**	0.007	0.001
	(0.036)	(0.045)	(0.041)	(0.028)	(0.072)	(0.068)	(0.058)	(0.058)	(0.046)	(0.049)
ln(GDP)	0.843***	0.661**	0.534*	0.344	1.257**	0.983	0.865	0.487	0.626***	0.536*
	(0.277)	(0.270)	(0.275)	(0.220)	(0.574)	(0.588)	(0.628)	(0.487)	(0.223)	(0.261)
Unem	0.018	0.010	0.003	-0.006	0.011	-0.008	-0.016	-0.022**	0.015	0.005
	(0.012)	(0.012)	(0.010)	(0.007)	(0.015)	(0.014)	(0.011)	(0.009)	(0.011)	(0.010)
time	0.022**	0.018	0.021*	0.029***	0.016	0.014	0.018	0.012	0.025	0.022
	(0.008)	(0.011)	(0.010)	(0.008)	(0.019)	(0.023)	(0.022)	(0.017)	(0.019)	(0.024)
Control(GDP)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	468	442	416	390	468	442	416	390	468	442
R^2	0.623	0.582	0.520	0.438	0.466	0.432	0.348	0.231	0.449	0.415
Adjusted R^2	0.593	0.547	0.477	0.384	0.424	0.385	0.290	0.158	0.405	0.366

	Dependent variable:									
	$\ln(\text{Enabling}_{t+4})$	$\ln(\text{Enabling}_{t+5})$	$\ln(\text{End-use}_{t+2})$	$\ln(\text{End-use}_{t+3})$	$\ln(\text{End-use}_{t+4})$	$\ln(\text{End-use}_{t+5})$	$\ln(\text{GR}_{t+2})$	$\ln(\text{GR}_{t+3})$	$\ln(\text{GR}_{t+4})$	$\ln(\text{GR}_{t+5})$
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
RPR	0.002	0.009	-0.031***	-0.035***	-0.029***	-0.017	-0.001	-0.005	-0.029***	-0.039***
	(0.012)	(0.007)	(0.011)	(0.010)	(0.008)	(0.014)	(0.020)	(0.014)	(0.010)	(0.009)
MBP	0.098	0.109	0.143**	0.159***	0.122**	0.057	0.019	0.033	0.013	0.070
	(0.095)	(0.087)	(0.060)	(0.050)	(0.049)	(0.076)	(0.140)	(0.137)	(0.122)	(0.108)
NMBP	0.011	0.025	-0.004	0.048	0.049	0.053	0.094	0.036	0.020	0.038
	(0.048)	(0.041)	(0.030)	(0.032)	(0.035)	(0.037)	(0.061)	(0.071)	(0.059)	(0.040)
TS	-0.023	-0.048	-0.056	-0.049	-0.049	-0.071*	-0.099**	-0.122**	-0.127*	-0.079
	(0.048)	(0.036)	(0.035)	(0.047)	(0.050)	(0.041)	(0.044)	(0.054)	(0.071)	(0.058)
ln(GDP)	0.378	0.248	0.674***	0.467**	0.385**	0.323**	0.243	0.201	0.017	-0.184
	(0.261)	(0.233)	(0.226)	(0.192)	(0.181)	(0.149)	(0.460)	(0.378)	(0.278)	(0.208)
Unem	-0.004	-0.007	0.029**	0.028*	0.024*	0.015*	-0.032***	-0.044**	-0.037**	-0.017
	(0.010)	(0.014)	(0.014)	(0.016)	(0.013)	(0.008)	(0.010)	(0.016)	(0.017)	(0.018)
time	0.030	0.039**	0.031***	0.024***	0.022***	0.031**	0.034*	0.044**	0.045**	0.028*
	(0.023)	(0.018)	(0.008)	(0.007)	(0.007)	(0.012)	(0.017)	(0.018)	(0.020)	(0.016)
Control(GDP)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	416	390	468	442	416	390	468	442	416	390
R^2	0.374	0.336	0.548	0.521	0.467	0.394	0.225	0.190	0.119	0.097
Adjusted R^2	0.318	0.272	0.513	0.481	0.419	0.336	0.164	0.122	0.041	0.004

*Note: Table 21 presents the output of our OLS regression with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. All regressions are weighted by each country's average GDP. The control variables FDI and REC are included in the regression but are not reported due to lack of space. The dependent variables represent the natural logarithmic of Green, LCE supply, Enabling, End-use, and GR, with two to five-year time lead. The underlying data spans from 1999 to 2018, for 26 countries. *p<0.1; **p<0.05; ***p<0.01.*

Table 22: Sample Split (1999 – 2008)

	Dependent variable:				
	$\ln(\text{Green}_{t+1})$	$\ln(\text{LCE supply}_{t+1})$	$\ln(\text{Enabling}_{t+1})$	$\ln(\text{End-use}_{t+1})$	$\ln(\text{GR}_{t+1})$
	(1)	(2)	(3)	(4)	(5)
RPR	-0.011	0.020	-0.021**	-0.023**	0.009
	(0.008)	(0.012)	(0.008)	(0.011)	(0.016)
MBP	0.108	-0.114	0.190	0.167	-0.328**
	(0.100)	(0.125)	(0.117)	(0.103)	(0.133)
NMBP	-0.025	-0.028	-0.022	-0.013	-0.004
	(0.021)	(0.038)	(0.044)	(0.021)	(0.034)
TS	0.095	0.185	0.109	0.073	-0.007
	(0.101)	(0.119)	(0.121)	(0.103)	(0.106)
ln(GDP)	0.534**	0.412	0.584**	0.498*	0.533
	(0.237)	(0.468)	(0.226)	(0.242)	(0.667)
Unem	-0.024*	-0.013	-0.026	-0.012	-0.007
	(0.014)	(0.020)	(0.021)	(0.018)	(0.030)
REC	0.006	-0.023	0.015	-0.008	-0.018
	(0.013)	(0.024)	(0.016)	(0.015)	(0.025)
FDI	0.002	0.003	0.004	-0.0003	0.005
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
time	0.049***	0.140***	-0.002	0.037***	0.107***
	(0.012)	(0.026)	(0.012)	(0.011)	(0.034)
Control(GDP)	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Observations	260	260	260	260	260
R^2	0.613	0.609	0.278	0.467	0.339
Adjusted R^2	0.554	0.549	0.169	0.386	0.239

*Note: Table 22 presents the output of our OLS regression with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. All regressions are weighted by each country's average GDP. The dependent variables represent the natural logarithmic of Green, LCE supply, Enabling, End-use, and GR, with a one year time lead . The underlying data spans from 1999 to 2008, for 26 countries. *p<0.1; **p<0.05; ***p<0.01.*

Table 23: Sample Split (2009 – 2018)

	Dependent variable:				
	$\ln(Green_{t+1})$	$\ln(LCE\ supply_{t+1})$	$\ln(Enabling_{t+1})$	$\ln(End\text{-}use_{t+1})$	$\ln(GR_{t+1})$
	(1)	(2)	(3)	(4)	(5)
RPR	-0.030**	-0.015	-0.018	-0.045***	0.033
	(0.011)	(0.010)	(0.011)	(0.012)	(0.024)
MBP	-0.002	0.030	0.020	-0.065	0.099
	(0.034)	(0.070)	(0.054)	(0.039)	(0.144)
NMBP	0.008	-0.062*	-0.027	0.049	0.046
	(0.015)	(0.032)	(0.021)	(0.033)	(0.041)
TS	-0.082***	-0.052	-0.071***	-0.109***	-0.081
	(0.023)	(0.038)	(0.018)	(0.034)	(0.061)
ln(GDP)	0.335**	-0.180	0.033	0.600*	-0.830***
	(0.140)	(0.163)	(0.167)	(0.298)	(0.287)
Unem	0.013*	-0.002	0.021**	0.020**	-0.066***
	(0.006)	(0.016)	(0.010)	(0.010)	(0.022)
REC	-0.002	-0.006	-0.031***	0.010	0.010
	(0.007)	(0.015)	(0.010)	(0.011)	(0.036)
FDI	-0.003	-0.003	-0.002	-0.003	-0.010***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
time	-0.012	-0.056***	0.036***	-0.002	-0.018
	(0.008)	(0.016)	(0.010)	(0.015)	(0.031)
Control(GDP)	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Observations	234	234	234	234	234
R^2	0.450	0.431	0.268	0.387	0.271
Adjusted R^2	0.423	0.402	0.159	0.327	0.211

Note: Table 23 *presents the output of our OLS regression with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. All regressions are weighted by each country's average GDP. The dependent variables represent the natural logarithmic of Green, LCE supply, Enabling, End-use, and GR, with a one year time lead . The underlying data spans from 2009 to 2018, for 26 countries. *p<0.1; **p<0.05; ***p<0.01.*

Table 24: Equal Weights

	Dependent variable:				
	$\ln(Green_{t+1})$	$\ln(LCE\ supply_{t+1})$	$\ln(Enabling_{t+1})$	$\ln(End\text{-}use_{t+1})$	$\ln(GR_{t+1})$
	(1)	(2)	(3)	(4)	(5)
RPR	-0.013	-0.009	-0.030	-0.030**	0.002
	(0.012)	(0.019)	(0.020)	(0.012)	(0.020)
MBP	0.093	0.109	0.027	0.095	0.059
	(0.070)	(0.090)	(0.102)	(0.060)	(0.110)
NMBP	0.023	0.089**	-0.027	0.023	0.126***
	(0.028)	(0.042)	(0.047)	(0.024)	(0.043)
TS	-0.004	0.046	-0.046	-0.007	-0.043
	(0.025)	(0.039)	(0.028)	(0.027)	(0.042)
lnGDP	0.759***	0.959***	0.461***	0.438***	0.471
	(0.174)	(0.272)	(0.136)	(0.148)	(0.342)
Unem	-0.003	-0.007	0.010	-0.006	-0.014
	(0.013)	(0.016)	(0.013)	(0.013)	(0.011)
REC	0.017	0.016	0.011	0.008	0.006
	(0.010)	(0.016)	(0.012)	(0.009)	(0.011)
FDI	-0.002	-0.002	-0.002	-0.001	-0.003
	(0.001)	(0.003)	(0.004)	(0.001)	(0.004)
time	0.020**	-0.006	0.046***	0.030***	0.001
	(0.009)	(0.016)	(0.012)	(0.008)	(0.016)
Control(GDP)	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Observations	494	494	494	494	494
R^2	0.671	0.553	0.474	0.610	0.263
Adjusted R^2	0.647	0.519	0.435	0.581	0.208

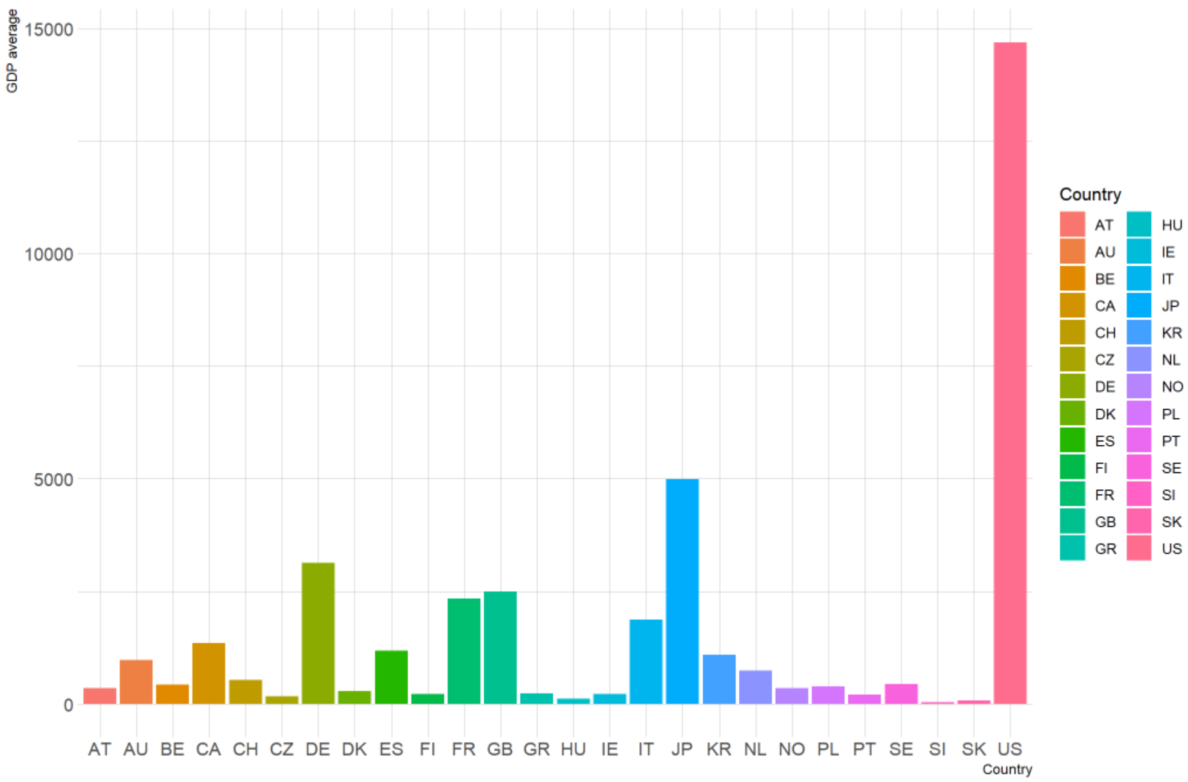
Note: Table 24 *presents the output of our OLS regression with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. The dependent variables represent the natural logarithmic of Green, LCE supply, Enabling, End-use, and GR, with a one year time lead . The underlying data spans from 1999 to 2018, for 26 countries. *p<0.1; **p<0.05; ***p<0.01.*

Table 25: Omitting the US

	Dependent variable:				
	$\ln(Green_{t+1})$	$\ln(LCE\ supply_{t+1})$	$\ln(Enabling_{t+1})$	$\ln(End\text{-}use_{t+1})$	$\ln(GR_{t+1})$
	(1)	(2)	(3)	(4)	(5)
RPR	-0.015	0.006	-0.015	-0.031**	-0.017
	(0.017)	(0.021)	(0.019)	(0.013)	(0.021)
MBP	0.152*	0.170*	0.076	0.136*	0.138
	(0.079)	(0.094)	(0.094)	(0.069)	(0.094)
NMBP	0.023	0.112***	-0.045	0.026	0.150***
	(0.026)	(0.040)	(0.049)	(0.019)	(0.031)
TS	-0.019	0.023	-0.029	-0.028	-0.072
	(0.027)	(0.051)	(0.026)	(0.029)	(0.044)
lnGDP	0.743***	0.919**	0.571***	0.568**	0.272
	(0.250)	(0.399)	(0.165)	(0.226)	(0.434)
Unem	0.011	0.005	0.022*	0.010	-0.017
	(0.012)	(0.019)	(0.012)	(0.011)	(0.011)
REC	0.002	-0.010	-0.005	0.002	0.005
	(0.011)	(0.018)	(0.016)	(0.007)	(0.015)
FDI	-0.002	-0.001	-0.002	-0.002	0.001
	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)
time	0.022***	0.016	0.053***	0.020***	0.010
	(0.007)	(0.016)	(0.008)	(0.005)	(0.012)
Control(GDP)	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Observations	475	475	475	475	475
R^2	0.661	0.547	0.467	0.593	0.250
Adjusted R^2	0.636	0.513	0.427	0.563	0.194

Note: Table 25 *presents the output of our OLS regression with country fixed effects and linear time trend. All standard errors in the regression are clustered on country-level in parentheses. All regressions are weighted by each country's average GDP. The dependent variables represent the natural logarithmic of Green, LCE supply, Enabling, End-use, and GR, with a one year time lead . The underlying data spans from 1999 to 2018, for 25 countries. *p<0.1; **p<0.05; ***p<0.01.*

Figure 6: GDP Average for Each Country



Note: Figure 6 *displays the average GDP for each country in our sample. The scale of the y-axis is expressed as billion USD, whereas the x-axis displays the 20 year average, ranging from 1999 to 2018.*