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Public Research and Development Funding for Renewable Energy Technologies in Europe: A Driver of Innovation

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Abstract

The European Union has adopted ambitious targets to accelerate the energy transition. One target entails the increase of the share of renewable energy sources to at least 35% by 2030. Thereby, the EU recognizes the vital role of research and innovation in renewable energy technologies. For example, in the EU's Horizon Europe (2021-2027) funding programme, the largest ever transnational research and innovation program, 35% of the total budget of €95.5 billion are allocated to green technology research. Existing studies have analysed the relevance and effectiveness of public research and development (R&D) funding for renewable energy technologies. However, R&D expenditures of the European Commission could not be included on a country level. Through an extensive data collection effort, this piece fills that gap and includes spending of the European Commission. For 17 European countries and from 2000 to 2020, this piece provides a comprehensive picture of country-specific public R&D support for renewable energy technologies and describes the increasing importance of the European Commission's funding. Furthermore, the effectiveness of public R&D funding is analysed through a negative binomial regression model with fixed effects. The paper shows that public R&D support is an overall effective driver of green innovation while its effectiveness varies across sectors and countries. Various sensitivity analyses confirm its general effectiveness and relevance. Like in previous studies, limitations stem from restricted data availability and temporal uncertainty of innovation. These limitations are addressed, which shall incentivize future research and policymaking.

Contents

List of Abbreviations

Abbreviation	Meaning
BIC	Bayesian Information Criterion, as a measure of model-fit
CORDIS	Community Research and Development Information Service (a database for EC R&D projects)
EC	European Commission
EPS index	OECD's Environmental Policy Stringency Index
EU	European Union
FPs	EU's Framework Programmes for Research and Technological Development
IEA	International Energy Agency
KS	knowledge stock
MI Initiative	Mission Innovation Initiative
NBRM	Negative Binomial regression model
NECPs	National Energy and Climate Plans
OLS	Ordinary Least Square
PRM	Poisson regression model
RE	renewable energy
RES	renewable energy sources
R&D	research and development
SET-Plans	Strategic Energy Technology Plans

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1. Introduction

The European Union (EU) has embarked on a committed path towards decarbonisation. By 2030, it aims to reduce greenhouse gas emissions by at least 55% (compared to 1990 levels). Climate neutrality should be reached by 2050. Accelerating transformations in the energy sector towards renewable energy (RE) is crucial for achieving these targets. Currently, more than 75% of the greenhouse gas emissions in the EU stem from the energy sector. This is why the EU aims to increase the share of energy produced by renewable energy sources (RES) to at least 32% by 2030 (compared to 18% in 2018) (EU 2018a). Furthermore, in 2015, the EU and twenty-four governments committed to double public research and development support for renewable energy technologies until 2020 (Mission Innovation Initiative, in conjunction with Paris Agreement, see Cunliff 2019).

Despite the European Union's recognition of the importance of renewable energy technologies, the EU and its Member States are not yet on track. The International Energy Agency (IEA) emphasises the necessity of strengthened engagement to achieve the 32% target. One of IEA's recommendations entails accelerating innovation and technology deployment (IEA 2020b). Recently, the IEA called more explicitly for a "new wave of innovations" in the renewable energy sector (IEA 2021c, p.104).

This thesis backs up this call with current and detailed evidence. It addresses the following research question: *What was the size of European public research and development funding for renewable energy sources in 2000-2020 and its effectiveness as a driver of knowledge and innovation?*

The main contributions and findings of this piece can be summarized as follows. Regarding the first part of the research question, country-specific figures over time for the European Commission's research and development (R&D) funding for renewable energy technologies have not been available until now. This is critical, also considering the EU's pledged recognition of the importance of green innovation. The present piece fills that gap through an extensive data collection effort. The author collected data on public R&D funding for RE technologies for 17 European countries[1] and 21 years (2000-2020). In contrast to other sources,

[1] Only for these 17 countries, data were available to a sufficiently detailed extent. 16 of the 17 countries included are member states of the European Union. Norway was added to the analysis due to the significant amount of R&D funding for RE technologies the country received from the European Commission and due to its membership in the Steering Group of the Strategic Energy Technology Plans (SET-Plans) (Section 2.1).

these data also include country-specific public R&D support from the European Commission (EC) and are not limited to R&D support that stems only directly from European nation-states.

This piece finds that the extent of available public R&D funding (including EC contributions) for renewable energy technologies is highly heterogeneous across countries. This diversity also holds for the relative importance of EC contributions. The shares of EC funding within the public (national + EC) R&D expenditures range, for example, from 63% for Belgium to 15% for France. Most total public R&D funding for RE was available in the largest economies (Germany, France). Relative to the size of the countries' economies, Nordic countries and the Netherlands lead in available public R&D funding. Over time, public R&D funding increased in all countries until 2011. From 2012 onwards, however, national R&D expenditures decreased in most countries (except Norway, the Netherlands, Belgium and Portugal). Descriptively, this piece outlines the vital role of EC contributions. They stabilized public R&D support and compensated for decreasing national budgets. Due to the European Commission's efforts, total public R&D funding for renewable energy technologies remained stable or increased during the last decade, despite decreasing national budgets.

In response to the second part of the research question, the thesis contributes to existing findings through a detailed and recent panel dataset. The effectiveness of public R&D support as a driver of green innovation is estimated through a negative binomial regression model with fixed effects. This approach aligns with existing contributions (including Johnstone, Haščič, and Popp 2010; Costantini et al. 2015) and reduces potential endogeneity. An overall statistically significant and positive effect of public R&D funding on green innovation is confirmed for 2000-2015. Furthermore, this result is confirmed for nearly all countries and the largest sectors (biomass, solar- and wind energy), whereby the size of the estimates is heterogeneous. These main findings are in line with and contribute to existing studies that did not include EC funding or were limited to earlier periods. A full normative assessment of the ideal size of public R&D funding goes beyond the scope of this piece. Still, the results derived from a detailed and recent panel dataset strongly support the general effectiveness and relevance of public R&D support.

Furthermore, this piece contributes to existing evidence through a range of sensitivity analyses. The result of an overall positive and statistically significant effect of public R&D funding is robust: across different models (Negative Binomial regression, Poisson regression, and Ordinary Least Squares regression), for various measures of the dependent variable (measured on different quality levels and as a share of all technology patents), and for different measures of covariates (including the knowledge stock of renewable energy patents, controlling for multicollinearity, and including an alternative measure for national R&D funding). The paper also shares some limitations with previous studies. Four different limitations and their implications are addressed. These limitations include temporal uncertainty of innovation outcomes, the quantification of causal effects, the lack of data on private R&D funding, and unobserved maturity levels of technologies. This discussion shall incentivize future research and policy making.

The paper is structured as follows. Section 2 describes the political importance that European Member States attribute to public R&D support and the theoretical and empirical evidence on its effectiveness. Based on this, the contribution of the present piece is specified. Section 3 addresses the first part of the research question. It provides comprehensive descriptive analyses of public R&D support for renewable energy technologies within 17 European countries and for 2000-2020. Section 4 describes the rest of the dataset and the empirical strategy, through which part two of the research question on the effectiveness of R&D funding will be addressed. Section 5 outlines the main estimation results. The robustness of the results is evaluated in Section 6. Section 7 discusses the findings and limitations of this paper and provides recommendations for future research and policy. Section 8 concludes.

2. Literature Overview and Contribution

This section first sketches the political relevance the European Union and its Member States attribute to public R&D funding for renewable energy technologies (2.1.). Theoretical arguments (2.2.) and empirical findings (2.3.) on the effectiveness of public R&D funding follow. Based on this, the contribution of this piece is specified (2.4.).

2.1. The Pledged, Political Relevance of Public Research and Development Funding

The EU widely recognises the significance of public research and development support related to renewable energy sources (Bointner et al. 2016). It is generally regarded as crucial for successfully reaching the EU's ambitious targets of a 55% reduction in greenhouse gas emissions by 2030 (compared to 1990 levels) and of an increase of the renewable energy share to at least 32% by 2030 (EU 2018a).

One international acknowledgement that quantifies R&D investment targets is countries' joint commitment to the Mission Innovation (MI) initiative. The MI initiative was created in December 2015 in conjunction with the Paris Agreement. The European Union and twenty-four governments committed to double public R&D support for clean energy technologies. (Cunliff 2019)

Other relevant publications and acknowledgements include the EU's strategy for an Energy Union, launched in 2015. Therein, R&D is described as an essential pillar for the energy transition and for securing competitiveness in providing clean energy (European Commission 2015b). The Strategic Energy Technology Plans (SET-Plans) also endorse the concern for collaborative R&D engagement. The SET-Plans are led by a Steering Group consisting of representatives from the EU Member States and Norway (included in the analysis), Turkey, Island and Switzerland (European Commission 2018). (De Negri et al. 2020)

The National Energy and Climate Plans (NECPs) shape the EU's energy sector governance and ensure that the EU meets its climate and energy targets. All Member States were obliged to submit a national energy and climate plan to the European Commission (by December 31st 2019, nearly all NECPs have been submitted by the end of May 2020). While the implementation of the NECPs has only just started in 2020, the plans also address the necessity to align states' research and development activities, particularly those that target RES (IEA

2020; EU 2018b). Finally, in support of the more recently published European Green Deal (European Commission 2019b), the European Commission's (EC) research and innovation programme "Horizon Europe" (2021-2027) forms a powerful instrument. With a total budget of €95.5 billion, it is the largest ever transnational research and innovation program. More than 35% of the funding will be allocated to research on green technologies. The need to mobilise research related to RE sources is explicitly recognised (see point 2.2.3 in European Commission 2019a).

Be it through the MI initiative, the European Union's strategy for an Energy Union or the SET-Plans, the NECPs or the European Green Deal: The EU pledged recognition of the importance of research and development for renewable energy technologies. This highlights the political relevance of a thorough analysis of public (including the EC's) R&D funding available in European countries and over time, as done in this piece.

2.2. The Theoretical Relevance of Public Research and Development Funding as Driver of Innovation

By addressing the second part of the research question, this thesis contributes to the literature on public R&D support's effectiveness. The policy measure is mainly categorised as a 'technology-push policy'[2]. Public R&D support is understood as 'pushing' technological change. It directly targets progress in scientific understanding and thereby drives technological progress. (Jaffe and Trajtenberg 2002; Nemet 2009)

Arguments that aim to justify technology-push policies emphasize, for example, their fostering of availability and exploitability of 'technological opportunities'. Only if scientific understanding in a relevant industry was sufficiently strong or enhanced through public R&D support, opportunities are available and exploitable and, thus, innovation can be achieved (Rosenberg 1974; Nelson and Winter 1977; Klevorick et al. 1995). Others emphasise the positive impact of public R&D on firms' capacities to absorb knowledge (Cohen and Levinthal 1990; Mowery 1983; Rosenberg 1990). These arguments concern the justifiability of public

[2] Tax credits for companies that incentivize investment in R&D or taxes on competing technologies form other examples of technology-push policies. (Jaffe and Trajtenberg 2002; Nemet 2009)
Pitelis (2018, p.6) mentions an alternative category of policy instruments: "systemic" ones. These act on the level of the innovation system as a whole, rather than targeting specific parts of innovative processes. They can provide a platform or support the alignment of other policy instruments, collaboration and knowledge transfer. Clearly, they can also include public R&D support which is of main interest in this piece, such as in the form of public infrastructure provisions or cooperative R&D grants. (Pitelis 2018)

R&D support in general. For the case of renewable energy technologies, public R&D support is justifiable for at least the following additional reasons.

First, the future benefits of investments in environmental R&D are typically highly uncertain. Public support can de-risk R&D investments, while otherwise, private firms would have to bear these risks exclusively (Jaffe and Trajtenberg 2002). The second reason relates to time. Renewable energy technologies require significant time and R&D investments until they reach competitiveness. In addition, if innovation processes take a long time, future returns are particularly threatened by knowledge spillovers and competitors who could catch up. Public R&D support can tackle underinvestment and accelerate the process of reaching commercialisation and competitiveness (Rennings 2000; Peters et al. 2012). For example, public R&D support can support affiliations between institutions or the creation of innovation networks in which knowledge spillovers are mutually beneficial (Groba and Breitschopf 2013)

Third, public R&D funding is justified by conceiving innovation in renewable energy technologies as a positive externality. For example, firms lack incentives to invest in RES innovation at a socially optimal level. Knowledge spillovers, from which society profits, are not reflected in the firms' prices. In other words, the private return on R&D investments is smaller than its social return. A fourth reason for which public R&D is justifiable relates to these externalities. Namely, the relative competitiveness of renewable energy technologies is at a disadvantage: positive externalities of renewable energy are not only not reflected in its price. The negative externalities of environmentally harmful energy sources are also not fully reflected in the prices of these energy sources (Horbach 2008). For example, backing up the theory with numbers, the net-negative effective carbon price is estimated to amount to -$3.44/tCO2 for 2018 and after taking fossil fuel subsidies into account (Cunliff 2019)[3]. According to the World Bank, an effective carbon price of + $40–80/tCO2 would be necessary to meet the targets of the Paris Agreement (World Bank Group 2019). Due to these externalities and competitive disadvantages, innovation in RE is undersupplied in the absence of public interventions. Public R&D support can effectively address this market failure. It can compensate for competitive disadvantages that stem from externalities or fossil fuel subsidies. (Oltra 2008; Peters et al. 2012; Rennings 2000)

Several authors support the view that a complementary mix of policies (including public R&D funding, mixed, e.g., with effective pricing of CO2 emissions) is needed to achieve the transition to renewable energy (e.g., Arnold et al. 2014; Mazzucato 2013; Rennings 2000). So-

[3] For members of the Mission Innovation initiative (22 countries and the EU) (see Section 2.1.).

called ‘demand-pull policies’ represent an alternative to public R&D support and can form a part of such a mix. This piece will focus on the effectiveness of public R&D support. The estimation equation, though, will also include alternative demand-pull measures. Demand-pull measures aim to affect innovation through market demand. For example, changes in demand create investment opportunities and possibilities for firms to tackle unmet needs (Rosenberg 1969). In particular, changes in the prices of conventional energy sources through, for example, effective taxes on carbon can affect the demand for alternative sources (such as RES) and incentivise innovation activities in RE technologies (Lichtenberg 1986; Popp 2002). Feed-in-tariffs that favour renewable energy technologies form an example of a ‘price-based’ demand-pull instrument. Firms are guaranteed a price above the market price. Tradable green certificates whose quantity is decreased over time form an example of a “quantity-based” demand-pull instrument. They make RE substitutes more attractive. Other examples for demand-pull policies are environmental taxes or regulative standards, in so far as they again aim to affect demand directly. (Nemet 2009)

2.3. Empirical Evidence

Existing contributions assess the impact of public R&D support on green innovation on a firm-level (micro impacts, such as effects on innovation rents, productivity or competitiveness) or a country level (macro impacts, such as effects on social welfare, efficiency or knowledge stock) (Groba and Breitschopf 2013). The present piece aims to contribute to the assessment on a country level.

Johnstone, Haščič, and Popp (2010) provided a frequently cited contribution that took such an aggregated perspective. Their data covered 25 countries and the period 1978-2003. The dependent variable deployed was renewable energy patent counts as a measure for innovation. They found that (a) RE policies (including national R&D support and measured as indices) drive innovation in RES and that (b) different policy measures will be effective for different technologies. A series of other empirical studies have confirmed these two findings (Ek and Söderholm 2010; Popp 2015; the following).

Marques and Fuinhas (2012) confirmed (a) and (b) when analysing the impact of RE policies on RES adoption, a measure for RES development. Thus, as their dependent variable, the authors employed the share of RES in the total energy supply. Lee and Lee (2013) could again confirm (a) and (b). Adding to Johnstone et al. (2010), they emphasised that not only different types but specifically customised policies were required to foster innovation in specific RE technologies. Subsequently, the effectiveness of domestic versus foreign public policies for RE innovation has been examined by Peters et al. (2012) for the case of solar photovoltaic modules and by Dechezleprêtre and Glachant (2014) for wind energy. Their analyses specify the validity of finding (a): public R&D support (as a technology-push policy) has been found to only foster domestic innovation, while demand-pull policies also affect foreign innovation outcomes.

Restricting their analysis to the biofuels sector, Costantini et al. (2015) again confirmed findings (a) and (b). The authors conclude that both technology push and demand-pull policies positively affect innovation in the biofuels sector, although heterogeneously. Technology push policies only affect more advanced technologies (next to price-based demand-pull policies). Nesta, Vona, and Nicolli (2014) combined an examination of the effect of different RE policies on innovation with varying levels of competition. Overall, the authors confirmed finding (a) but concluded that RE policies are more likely effective in deregulated energy markets. Pitelis (2018) and Pitelis et al. (2020) again confirmed findings (a) and (b). In addition, Pitelis (2018) emphasised that lag structures employed in estimations matter. Pitelis et al. (2020) highlight that RE technologies differ in whether a mix of RE policies can effectively drive innovation or only demand-pull instruments.

2.4. Contribution

To these empirical findings and the stated political relevance of public R&D support for renewable energy technologies, this piece will contribute as follows:

(A) The present piece will provide a comprehensive picture of the extent of R&D contributions for RE technologies. It will describe R&D funding issued not only by national governments but also by the European Commission, over time and on a sector- and country-level. To the author's knowledge, such a detailed descriptive analysis on a country level over time has not been carried out so far. This evidence will be particularly relevant given the importance EU Member States pledged to attribute to public R&D support for renewable energy technologies.

(B) Detailed data is required to adequately capture investments and innovations that are environmentally friendly (Pless, Hepburn, and Farrell 2020). The piece will examine the validity of findings (a) and (b) based on a uniquely detailed panel dataset of environmentally friendly public (national + EC’s) R&D support on country-levels.

(C) The data employed in the estimation of this piece cover the period 2000-2015. This allows the author to contribute to the literature by evaluating the validity of existing findings based on data for very recent public R&D funding.

(D) Various sensitivity analyses scrutinise the empirical results on the relevance of public R&D funding.

3. Public Research and Development Funding

This section addresses the first part of the research question. It provides a thorough analysis of the extent of public R&D funding for renewable energy technologies in Europe. Private data has not been available (3.1.). Though, data on total public R&D funding could be collected as accumulated expenditures from two sources: the national budget of individual countries (3.2.) and the European Commission's budget (3.3.)[4].

3.1. Private Funding

Private R&D funding from businesses and other private sources, such as philanthropic organizations, plays an essential role in the total share of R&D funding for renewable energy technologies. For solar energy, private R&D funding estimates range from 60% to 70% of total R&D funding (De Negri et al. 2020). For 2011, the European Commission (2015a) provides comparable sector-specific figures and estimates that in 2011, 55% of total R&D funding for solar energy technologies stemmed from the private sector (European Commission 2015a, p.74). For Italy, survey data on renewable energy R&D funding from the private sector has been exceptionally available for 2013-2018: approximately 20%-40% of total R&D funding for RE technologies are estimated to stem from the private sector (IEA 2021a). A recent IEA report (IEA 2020a, p.43f) highlights how companies active in renewable energy technologies intensified their R&D efforts more strongly than other firms in the energy technology sector. Between 2010 and 2019, global private R&D expenditures for RE technologies have risen by approximately 74%.

Collecting private R&D data for the present analysis proved to be an impossible task. Not only is the availability of private data restricted to a few specific RE technologies. Even if technology-specific data were fully available, the complex structure and distribution of companies across various legal entities that reside in different countries would still make a precise attribution of private R&D investments to countries challenging to impossible (Bointner et al. 2016). The implications of this restriction for the estimation results of this piece are discussed in Section 7.3.

[4] The risk of double counting is very limited. According to the IEA (2021a), in its data on national budgets, only funding that is provided by federal government institutions is considered. Thus, the sources of origin are very unlikely to being mixed up with EC funding.

3.2. National Funding

National R&D budgets are accessible through the International Energy Agency's (IEA) data browser. The "Detailed country RD&D budgets" report contains the required country- and sector-specific data (IEA 2021b). It is expressed in Million Euro and real values (2020 prices and exchange rates), which is why an inflationary adjustment was not necessary. Thereby, only funding within "Group 3: Renewable Energy Sources" was considered (IEA 2021a).

Over time and across countries, national R&D expenditures in the RE sector increased from 2000 until 2011 and decreased after that (Figure 1).[5] Norway, the Netherlands and Belgium (and Portugal, where public R&D funding for RE was very low) were the only countries whose national R&D budgets for renewable energy technologies did not decrease between 2011 and 2020.

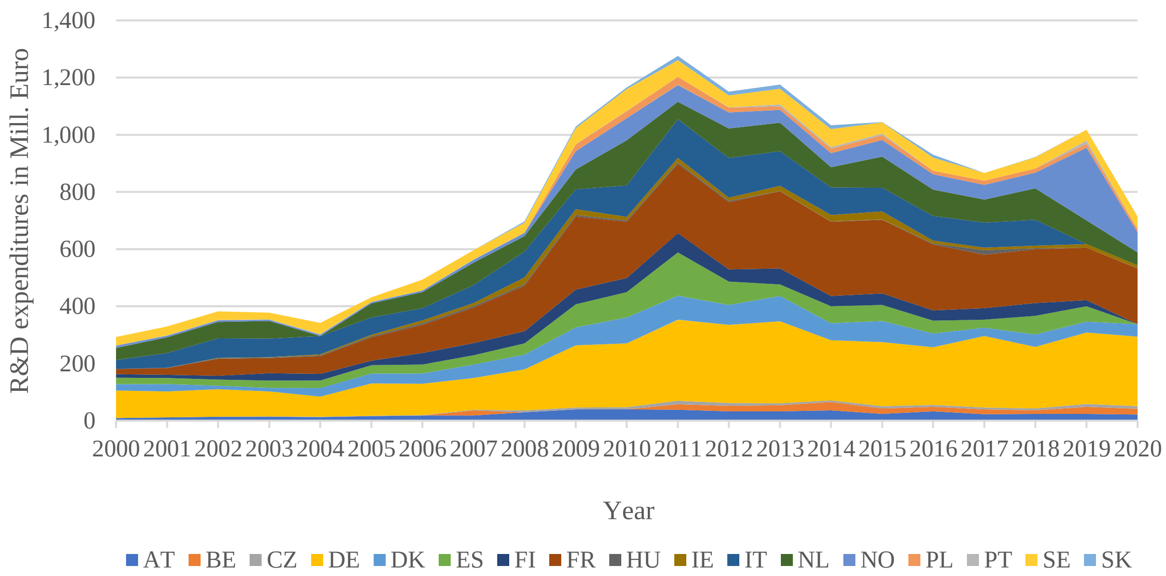

Figure 1. Country-specific development of national research and development expenditures for renewable energy technologies of 17 European countries from 2000 until 2020 (Mill. Euro) (2020 prices and exchange rates)

3.3. Budgets of the European Commission

Data on funding from the European Commission were accessed through the Community Research and Development Information Service (CORDIS) (EU Publications Office 2021). CORDIS provides detailed information on the EU's framework programmes for research and

[5] See Appendix 1, Figure A1.i for a sector-specific visualization of this development and Figure A1.ii for the country specific shares of total national RE R&D expenditures.

technological development (FPs). Approximately 85% of the R&D investments for the renewable energy sector from the EU have been issued through the EC's FPs (Bointner et al. 2016; De Negri et al. 2020). Therefore, and to avoid the risk of double-counting, the present analysis is limited to these FPs, in particular, to FP5 (1998-2002), FP6 (2002-2006), FP7 (2007-2013) and Horizon 2020 (2014-2020). Only for these most recent framework programmes data were available to a sufficiently detailed extent. Appendix 2 specifies the steps that had to be carried out to collect data on EC's R&D funding for renewable energy technologies. They resulted in a unique dataset that contains information on EC's country- and sector-specific R&D expenditures from 2000 until 2020, expressed in 2020 prices.

Figure 2 summarises these R&D expenditures from the European Commission[6]. From 2000 to 2020, EC's total R&D contribution for RE technologies increased by a factor of approximately 5. This increase is observed consistently across countries. The largest economies received the highest amounts of R&D funding for renewable energy technologies from the European Union. For example, Germany (DE) received 20% (more than one billion Euros) and Spain (ES) 16%. Most EC contributions targeted the solar energy sector, followed by wind and biomass[7].

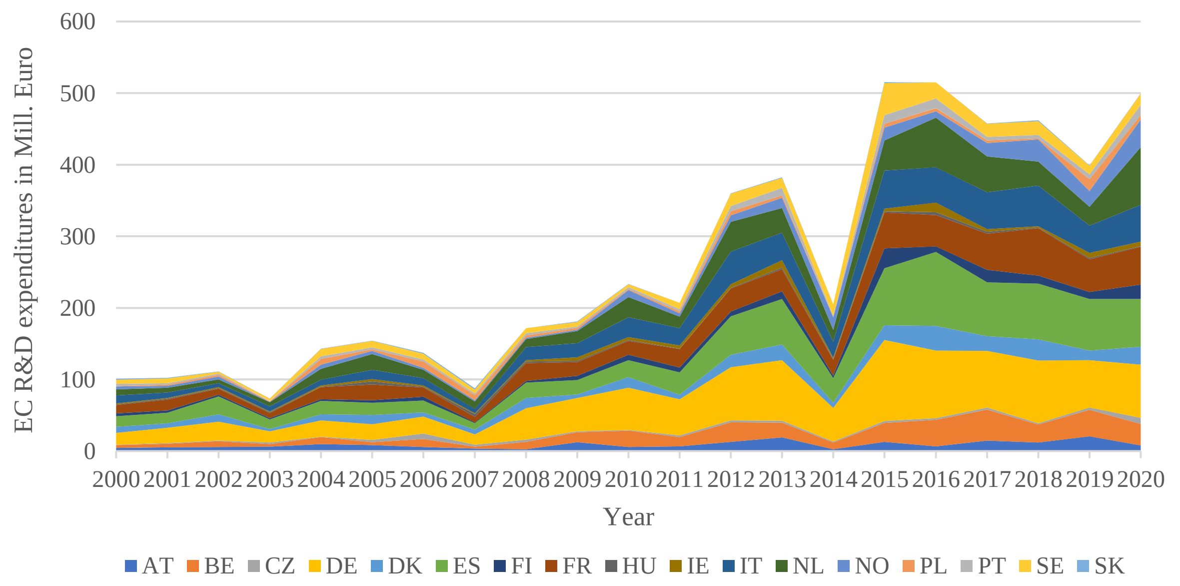

Figure 2. The European Commission's research and development expenditures for renewable energy technologies in 17 European countries from 2000 until 2020 by country (Mill. Euro) (2020 prices and exchange rates)

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[6] High volatility due to legislative fractionalization is frequent in the realm of public R&D expenditures on new energy technologies (Baccini and Urpelainen 2012). In the case of EC R&D expenditures, a high volatility and sudden drops (most clearly visible for the year 2014) stem from transition-periods between framework programmes (FPs). In the first year of new FPs, less funding is paid out as most projects are still in the application phase.

[7] Appendix 2 contains the similar Figure of EC expenditures over time by sector (Figure A2.i), as well as a visualisation of the shares of EC contributions by country (Figure A2.ii).

3.4. Total Public Research and Development Funding for Renewable Energy

At this point, the first part of the research question will be answered. EC expenditures are added to the national budgets to obtain a complete picture[8]. As Figure 3 illustrates, the largest economies by GDP lead on average yearly R&D expenditures for renewable energy technologies (Germany and France, followed by Italy, the Netherlands and Spain). However, the picture differs when countries' GDP is considered (Figure 4). Nordic countries lead in yearly public R&D funding available relative to GDP. In Denmark and Finland, public R&D funding available for renewable energy technologies (in % of GDP) had more than double the size of Germany or France. When expenses are measured relative to GDP, most large economies with high R&D expenditures move to the middle of the ranking. That is particularly striking for the case of Italy (moves from rank 3 to rank 13, among 17 countries included in the analysis) and Germany (moves from rank 1 to rank 9). The dataset of this piece also permits to shed light on the vast heterogeneity of the relative importance of EC funding. As shares of total public RE R&D funding between 2000 and 2020, the European Commission's contributions played the most critical role for Portugal (73%) (although a country with a meagre RE R&D budget), Belgium (63%) and Spain (46%). In the Slovak Republic (13%), France (15%) and Finland (18%), the share of EC contributions constituted the lowest share of total RE R&D funding compared to other countries.

[8] See Appendix 3 for the illustration of total RE R&D expenditures (EC + national) by country (Figure A3.i) and sector (Figure A3.ii), and for a visualization of the shares of total R&D contributions by country over the whole period 2000-2020 (Figure A.iii).

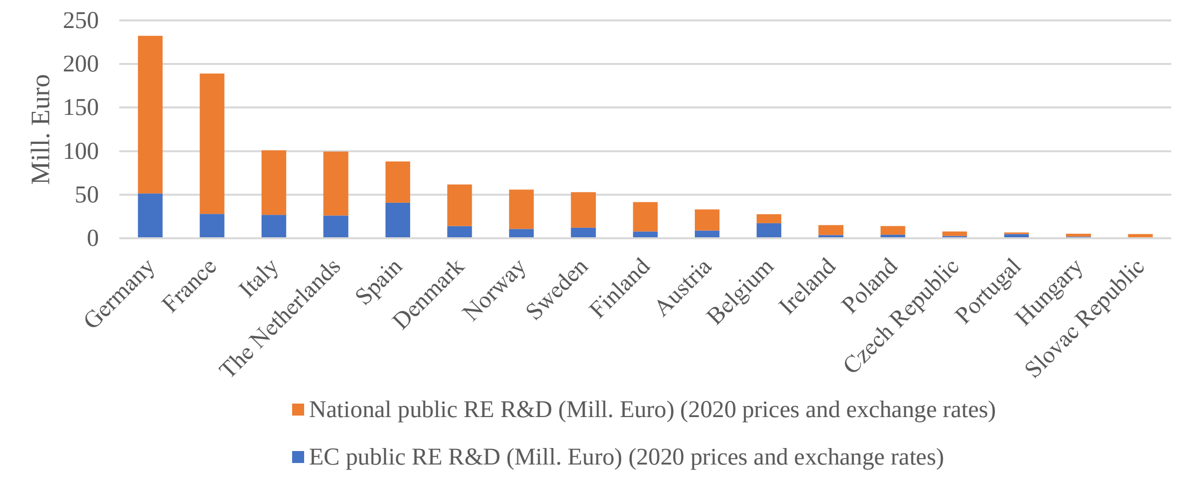

Figure 3. Averages of yearly total public research and development expenditures for renewable energy technologies by country (Mill. Euro) (2020 prices and exchange rates) (2000-2020)

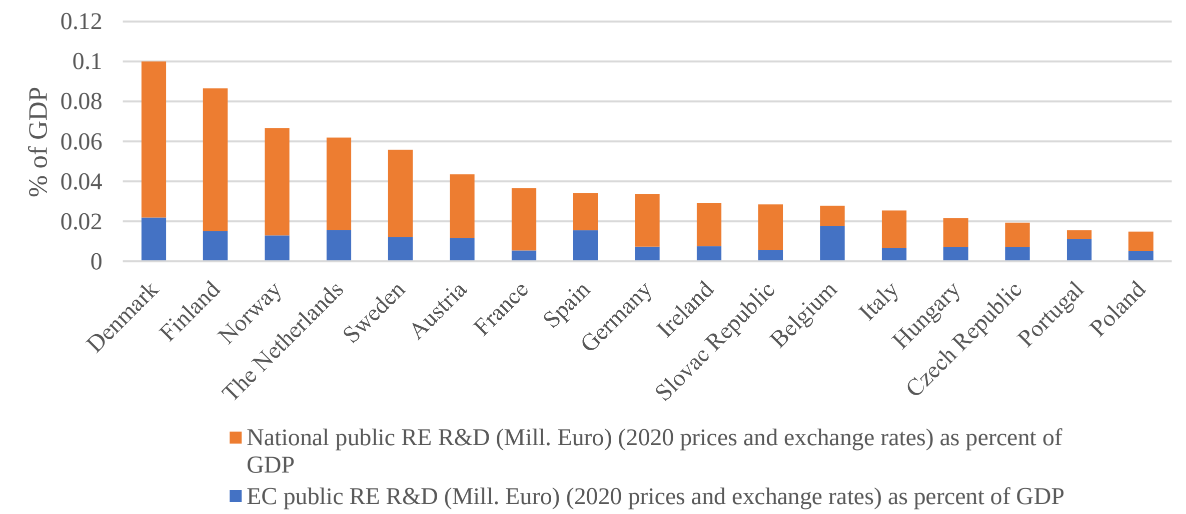

Figure 4. Averages of yearly total public research and development expenditures for renewable energy technologies by country (Mill. Euro) (2020 prices and exchange rates) (2000-2020), in percentages of GDP

Figure 5 displays changes over time. The graph describes the increasingly important and stabilizing role of EC expenditures for total public R&D funding across countries. The European Commission's funding (blue line) is added to national expenditures (orange line). The result forms the total public RE R&D expenditures over time (green line). From 2011 onwards, national R&D expenditures decreased or remained stable, while the European Commission's expenses continued to increase in all countries. Visually, these different trends over time result in both total expenditure curves converging from 2011 onwards. After merging both sources, total public R&D expenditures stabilize. Thus, the EC's expenditures significantly contributed to stabilizing total public R&D support for renewable energy technologies from 2011 onwards. In Norway, the Netherlands, Belgium and Portugal, the only countries that consistently increased their national budgets over time, available public R&D funding for RE technologies even increased. Hence, for all except those countries, stagnating public R&D funding is driven by decreasing national financing, while EC funding compensates for decreasing national budgets. None of the countries could double available public R&D support between 2015-2020, as stated in the MI initiative.

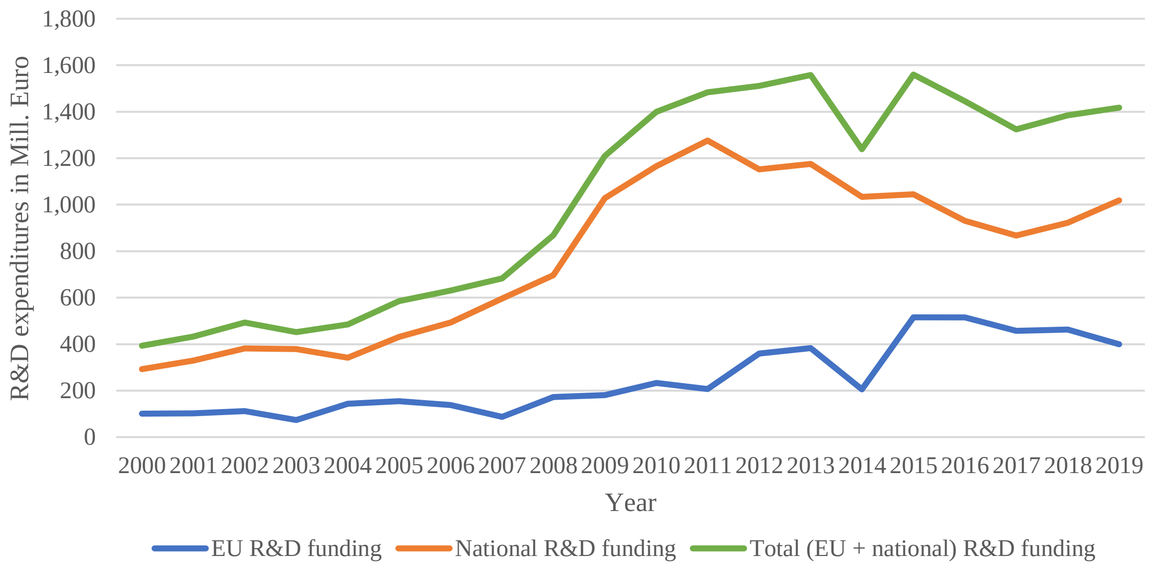

Figure 5. Convergence between the European Commission's and national research and development expenditures for renewable energy technologies, from 2000 until 2020 (Mill. Euro) (2020 prices and exchange rates). The European Commission's contributions becom

Furthermore, the stabilization of total public R&D funding for renewable energy technologies coincided with a substantial decrease in renewable energy patenting activity (Figure 6). However, a descriptive analysis alone is unlikely sufficient to make any conclusions on the general correlation between R&D expenditures and innovation outcomes. Other policy measures, such as demand-push measures, with the same environmental objective have been introduced as well. In addition, countries are vastly different in both R&D expenditures and patenting activity. With regards to the period after 2011, discerning a correlation between high-level stagnating R&D expenditures and decreasing patenting activities only based on descriptive analyses would be more than questionable as well. As will be discussed in more detail in Section 7.2, unobserved drivers, such as industry decline in the solar sector, are very likely to have caused the decrease in patenting for renewable energy technologies in that period. In the following, we shall go beyond descriptive analyses.

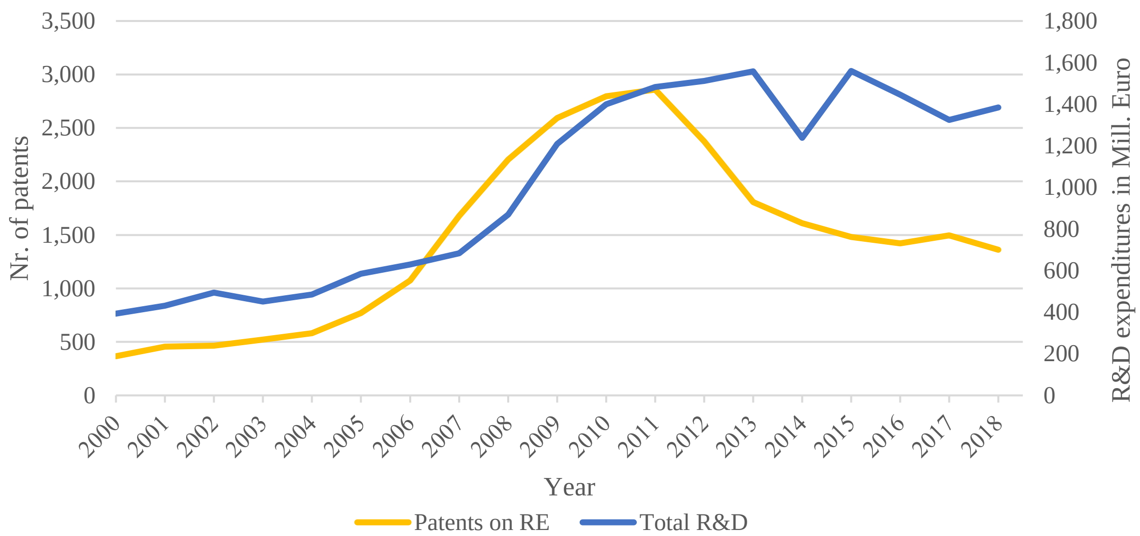

Figure 6. Total number of patents for renewable energy technologies in YELLOW and on left y-axis versus total research and development funding for renewable energy technologies (Mill. Euro) (2020 prices and exchange rates) in BLUE and on right y-axis.

4. Empirical Strategy and Data

Part one of the research question has been addressed in the previous section. An econometric approach shall now permit to address part two, the effectiveness of public RE R&D funding.

For 17 European countries[9] and 19 years (2000-2018)[10], data were available to a sufficiently detailed extent. Table A.4.i (Appendix 4) displays detailed descriptive statistics. The panel data allowed to estimate the following Baseline Equation (1) (which builds on existing contributions[11]):

$$\begin{aligned}(Patents\ RE_{i,t+1}) = ß_0 + ß_1\left(public\ R\&D\ expenditures_{i,t}\right) + \\ ß_2\left(energy\ consumption_{i,t}\right) + ß_3(electricity\ price_{i,t}) + \\ ß_4(Patents\ all\ technologies_{i,t}) + ß_5(Feed\_in\_tariffs_{i,t}) + \\ ß_6(Standards_{i,t}) + ß_7(Taxes_{i,t}) + ß_8(Trading\_schemes_{i,t}) + \\ \alpha_i + \mathcal{E}_{i,t} \qquad (1)\end{aligned}$$

The dependent variable that captures innovation output is the country-specific amount of patents for renewable energy technologies, lagged by one year ($Patent\ count\ RE_{i,t+1}$). *i = 1, ..., N* represent indexes for countries and *t = 2000, ..., 2015* represent time indexes. The regressor that is of main interest consists of ($public\ R\&D\ expenditures_{i,t}$) that directly target the development of renewable energies, measured in percentages of GDP. As will be explained in Section 4.2., the estimation includes the additional covariates $\left(energy\ consumption_{i,t}\right)$, $(electricity\ prices_{i,t})$ and $(Patents\ all\ technologies_{i,t})$, as well as data on the environmental stringency of other public policies than R&D expenditures through the covariates $(Feed\_in\_tariffs_{i,t})$, $(Standards_{i,t})$, $(Taxes_{i,t})$ and $(Trading\_schemes_{i,t})$. The econometric approach and how it allows controlling for time-invariant country fixed effects (α_i) will be described in Section 4.3..

[9] As mentioned, all countries, except Norway, are members of the European Union: Austria (AT), Belgium (BE), Czech Republic (CZ), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Hungary (HU), Ireland (IE), Italy (IT), The Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Sweden (SE), Slovakia (SK).

[10] While R&D data would have been available until 2020, limited availability of patent data and OECD's EPS index made it necessary to restrict the estimation to 2000-2015.

[11] Johnstone et al. (2010), Costantini et al. (2015), and Pitelis (2018).

4.1. Renewable Energy Patents as the Dependent Variable

While public R&D spending typically counts as an input measure that functions as a driver of innovation, patents count as an output measure (Groba and Breitschopf 2013). Data on the dependent variable ($Patents\ RE_{i,t+1}$) are extracted from OECD's (2021) Environment Database for Technology Development. OECD's (2021) patent statistics have been constructed using algorithms and avoiding double counting. The data were sorted by year in which the patent has been filed (being the closest moment to the actual invention) and by inventor's country of origin. The latter makes it more likely that patents can be traced back to policy measures in a country (such as public R&D support).

In line with existing literature (Johnstone et al. 2010; Costantini et al. 2015), the dependent variable is treated with a minimal lag of + one year ($t + 1$). Using lags takes into account that innovation needs time, and it reduces possible endogeneity (such as if the number of patents determined the amount of public R&D funding available, and not merely the other way around) (Costantini et al. 2015). Hall et al. (1983) support the choice of a small time-lag: "It does reconfirm, however, a statistically significant effect of R&D on patenting (with most of it occurring in the first year or two) […]" (Hall, Griliches, and Hausman 1983, p.2). Several authors go even further. Some neglect any substantial lag between public R&D support and patent applications (Peters et al. 2012; Brunnermeier and Cohen 2003; Hall, Griliches, and Hausman 1986).[12]

For different reasons, patent data are not necessarily a reliable measure of innovation. First, the filing of a patent must not reflect technology adoption. Indeed, most patents have little commercial value, and the adoption of the invention is often not widespread (Popp 2003). This piece focuses on sets of patents that were signed in at least two jurisdictions, which corresponds to a 'family size' equal to two or greater. Thus, it was possible to restrict the analysis to higher quality patents only (OECD 2009). Not only would it be unnecessarily costly to file patents for worthless inventions in more than one country (Putnam 1996). Also, evidence suggests that the family size of patents is, in general, strongly correlated with the economic value of an invention (Cremers et al. 2003).[13]

[12] Section 6.2. examines the robustness of the findings to alternative temporal treatments. Section 7 discusses the importance of the lag-choice as a potential source of limitations.
[13] Section 6.2. of this piece confirms the robustness of the main findings also to different family sizes.

Furthermore, not all inventions are protected by patents. A firm might prefer to keep its invention secret (Jaffe and Trajtenberg 2002). While this highlights how patent data cannot be a perfect measure, other advantages still support their use. Griliches et al. (1990) emphasise the strong relationship between private R&D spending (as a measure for innovative activity) and patents. Also, patent statistics permit a disaggregation to a detailed country and technology level (Popp 2003), an advantage that holds for this piece as well.

As anticipated, the number of patents filed in the 17 countries analysed increased from 2000 until 2011 (Figure 7). Thereafter, patenting activity in the renewable energy sector decreased. In 2018, only half of the patents were filed compared to 2011. Among all RE sources, the solar energy sector, followed by wind energy, are responsible for the largest share of total patenting and drive its decrease after 2011. In terms of patents, Germany (DE) is the largest renewable energy innovator among the countries studied[14] (Appendix 4, Figure A4.i). An increase in RE patenting activity followed by a substantial decrease is observed for all countries.

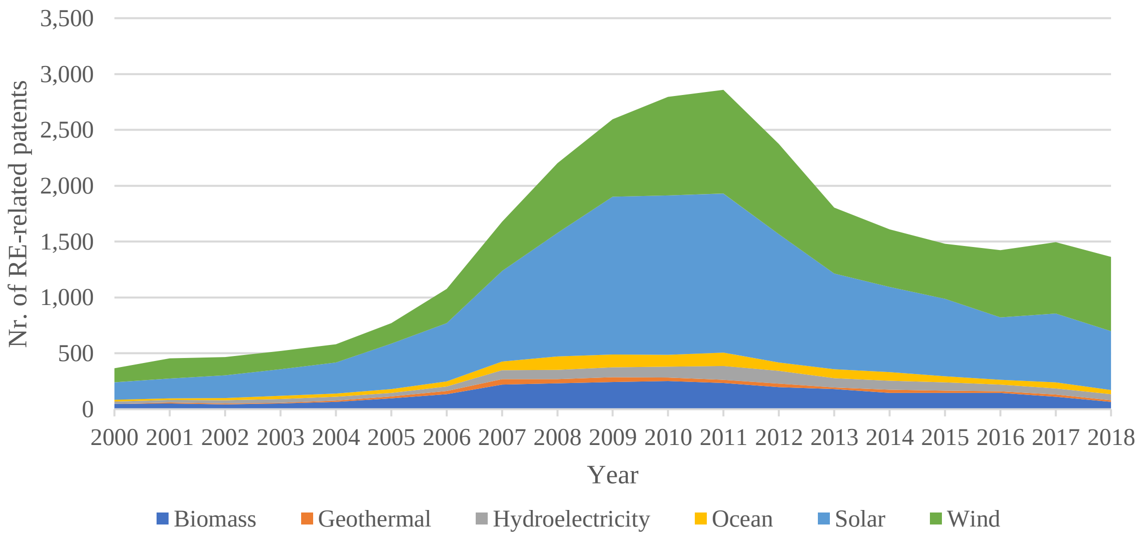

Figure 7. Total number of patents for renewable energy technologies from 2000-2018 in 17 European countries by sector.

4.2. Additional Covariates

Another argument against the use of patent data stems from differences between countries' patenting regimes and propensity to patent. In one jurisdiction, a single patent might be sufficient to protect an invention. In other countries, several patents for the same level of

[14] Among all OECD countries and from 1990 to 2018, the US, South Korea and Germany are the largest innovators in renewable energy technologies (in terms of patents) (Li and Shao 2021).

protection might be necessary (Johnstone, Haščič, and Popp 2010). The covariate ($Patents\ all\ technologies_{i,t}$) accounts for this and captures differences and changes over time in countries' innovative environment and propensity to patent (OECD's (2021) Environment Database for Technology Development).

($energy\ consumption_{i,t}$) and ($electricity\ price_{i,t}$) represent additional covariates (Eurostat 2021)[15]. Prices of fossil fuels as alternative factor inputs are an essential determinant of innovation in renewable energy technologies sources. Given that RES serve as substitutes for fossil fuels, higher prices for electricity produced by fossil fuels plausibly incentivise the adoption of and innovation in renewable energy technologies. The size of demand represents another critical driver of innovation and is measured through electricity consumption. In growing markets where demand is large, RE innovation is incentivized because it is easier to compensate initial investment costs. For both variables, a positive correlation with patenting is expected. (Johnstone, Haščič, and Popp 2010)

Indices for the policy measures ($Feed\_in\_tariffs_{i,t}$), ($Standards_{i,t}$), ($Taxes_{i,t}$) and ($Trading\_schemes_{i,t}$) control for changes in other policies that affect green innovation as well. OECD's (2016) environment statistics database provides internationally comparable indices for the country-specific environmental stringency of these policy measures. The environmental stringency of a policy measure is determined by its effect on the explicit or implicit price of environmentally harmful behaviour. As explained in Section 2.1., while R&D subsidies count as technology-push instruments, these additional covariates describe alternative demand-pull policy tools in so far as they affect demand directly. The OECD database (2016) also provides an EPS index for public research and development funding. OECD's definition of 'public', however, is the same as IEA's: it excludes EC sources. Contrary to existing research, this piece includes EC sources.[16]

[15] Eurostat's (2021) database provides a dataset on country-specific "electricity prices for domestic consumers". To avoid double-counting of policy measures, electricity prices exclude taxes and levies. In addition, to permit a cross-country comparison, prices are expressed in terms of Purchasing Power Standards. The dataset "final energy consumption" complements this information.

[16] The present analysis complements past literature that could not refer to such detailed and internationally comparable measures. Johnstone et al. (2010, p.10): "Unfortunately due to the heterogeneous nature of the data, it is not possible to construct continuous variables in which the level of „stringency" (or „support") is commensurable across policy types and countries."
Note that for 14 of the 17 countries, OECD's EPS did not provide data for the years 2013-2015. These missing values have been substituted estimating a linear trend based on past values.

4.3. Econometric Approach

The data just introduced form a panel data set, which consists of repeated observations over time for the same countries. This made it possible to apply a fixed effects method, which is justified as follows. Unobserved characteristics of countries that do not change over time may be correlated with both public R&D expenditures and the innovation outcome. If they are not included in the regression, they may bias estimated coefficients ('omitted variable bias'). An example would be unobserved differences in the quality of labour forces within countries that affect both patenting activity and public R&D support. Another example would be that the covariate ($Patents\ all\ technologies_{i,t}$) is not sufficient to fully capture all differences between countries in innovative environments. In the fixed effects method employed in this paper, any influence from such country-specific factors that do not change over time (fixed effects α_i) is eliminated through differencing. Explained in a nutshell, 'differencing' means that the difference between Baseline Equation (1) where $t = a$ and Baseline Equation (1) where $t = b$ is calculated, whereby a and b are different moments in time. Through subtraction, time-invariant between-variation in α_i cancels out. Any change in the dependent variable must then stem from influences other than these time-invariant characteristics. (Wooldridge 2009, ch.14, p.481f.)

The random effects method is an alternative to the fixed effects approach. It implies the assumption that any variation between countries is random and not correlated with the explanatory variables. In the present case, this assumption is critical. The innovative environment in a country, in so far as not captured by other covariates and therefore part of the error term ($\mathcal{E}_i$), may well be correlated with public R&D expenditures. The Hausman test allows to test whether the random effects model is preferable over a fixed effects model. Its null hypothesis is that regressors are random, in the sense that time-invariant errors ($\mathcal{E}_i$) are not correlated with them. For the present analysis, the result of the Hausman test is clearly statistically significant (Table A.4.ii in Appendix 4). Hence, it indicates that the null hypothesis should be rejected and that a fixed effect model should be preferred. (Wooldridge 2009, ch.14, p.493)

In contrast to the random effect method, a requirement of the fixed effect method is that variation in R&D expenditures within countries over time is not minimal. If R&D expenditures were time-invariant, they would be absorbed by the intercept of a fixed effects model. In previous sections, it could already be observed that patents and R&D expenditures vary over time and between countries. Table 1. displays the extent of between and within variation more clearly. Naturally, the country ID varies only between countries, while the year variable varies only within countries (over time). We can observe that both patents and R&D expenditures vary between countries. This between-country variation/ standard deviation may stem from unobserved fixed effects, so a fixed effects method is relevant. Also, within variation is not minimal and can be exploited, making a fixed effects method possible.[17] (Wooldridge 2009, ch.14, p.481f.)

Table 1. Between Versus Within Variation

Variable	Mean	Standard Deviation	Observations
c_id	9.000	4.908	N = 272
between		5.050	n = 17
within		0	T = 16
year	2007.500	4.618	N = 272
between		0	n = 17
within		4.618	T = 16
Public R&D expenditures for RE (in % of GDP)	0.040	0.033	N = 272
between		0.025	n = 17
within		0.021	T = 16
Patents RE	86.899	177.944	N = 272
between		150.673	n = 17
within		101.085	T = 16

Note: Table 1 includes data from 2000 to 2015 used for the estimation. It displays between and within variation for the panel identifiers 'country ID' and 'year', and for the variables of primary interest 'public R&D funding for renewable energy technologies' and 'Patents in renewable energy technologies'. The table supports the relevance of the fixed effects method: first, variables of interest vary between countries and the fixed effects method can cancel out between variation that remains 'fixed' across time; second, within variation is not minimal, so that the fixed effects method can be applied.

Figures A.4.ii and A.4.iii (in Appendix 4) illustrate a presumed correlation between public R&D funding (in % of GDP) and RE patenting. In addition, the figures make the extent of between-country variation and the potential relevance of controlling for country fixed effects evident. As soon as Germany is omitted, the group of outliers highlighted in Figure A.4.ii disappears.

[17] Note that an inclusion of time-fixed effects (instead of only country fixed effects) resulted in a drastic decrease of within variation which undermined any exploitability.

To scrutinize more whether public R&D funding is indeed correlated with RE patenting, even after controlling for other factors and policy measures introduced, Baseline Equation (1) is estimated through a fixed effects Negative Binomial Regression Model (NBRM). This aligns with existing contributions (for example, Costantini et al. 2015; Johnstone et al. 2010; Pitelis et al. 2020). Different to other contributions, the dependent variable ($Patents\ RE_{i,t+1}$) of this piece is constructed and weighted through algorithms (OECD 2021). Therefore, it is not measured as pure counts but as a continuous variable. This would make using a more conventional 'Ordinary Least Square' (OLS) model less problematic than if we dealt with a count variable. Also, a violation of the assumption of homoskedasticity can be taken care of through robust standard errors. (Wooldridge 2009, ch.8)

However, for four reasons, this piece relies primarily on an NBRM. The first two reasons justify not using primarily an OLS model to estimate Baseline Equation (1). First, values of the dependent variable have a lower bound at 0. An OLS model cannot account for truncation at zero and may lead to negative results that make no sense for the non-negative dependent variable (patents on renewable energy technologies). The second more important reason is that OLS requires that residuals ($\mathcal{E}_i$) "[…] are independent of X and independently and identically distributed as Normal $(0, \sigma^2)$." (Wooldridge 2009, p.351). Figure 8 sheds light on the plausibility of this normality assumption when Equation (1) is estimated as a fixed effects OLS model with robust standard errors. It displays the Kernel density distribution of the residuals obtained compared to a normal density distribution. Clearly, OLS residuals are not normally distributed but asymmetric and left-skewed. The violation of the normality assumption does not bias estimates. Though, it undermines the possibility to interpret significance levels obtained from an OLS model reliably, especially if the sample size is small. However, a reliable interpretation of those is necessary to address part two of the research question. (Wooldridge 2009, ch.10)

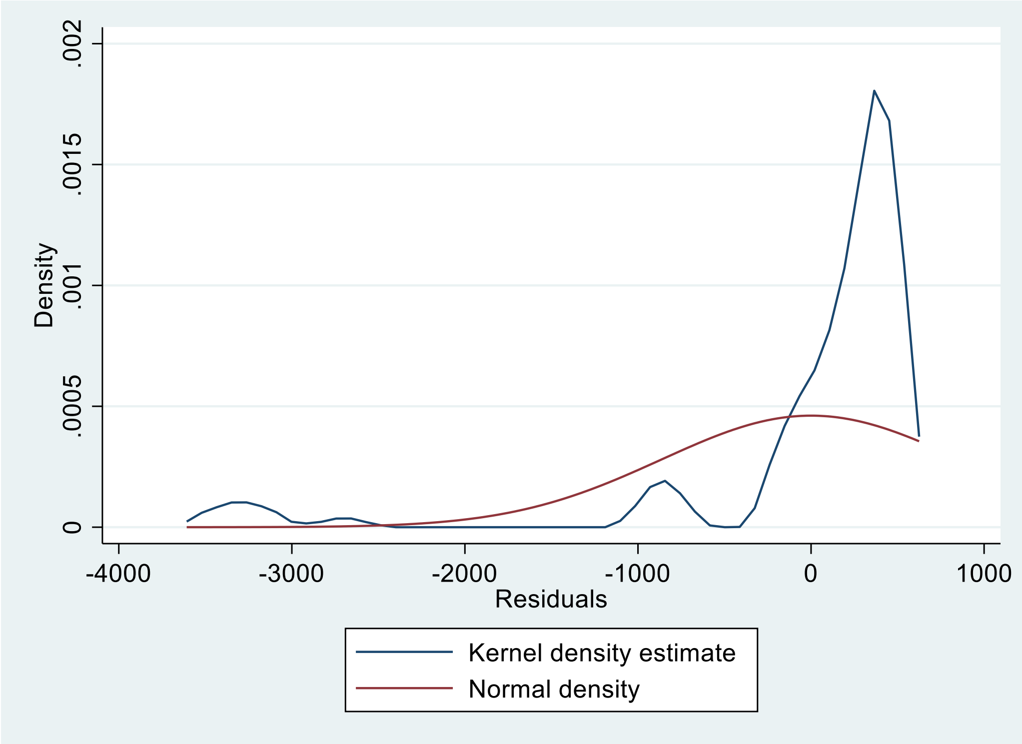

Figure 8. Density distribution of residuals obtained from estimating Equation (1) as fixed effects OLS model with robust standard errors. The Figure indicates a violation of the normality assumption.

The NBRM builds on the Poisson Regression Model (PRM). The third reason that justifies the choice of an NBRM represents an advantage it has compared to a PRM. Namely, the PRM excludes so-called 'conditional overdispersion' of the dependent variable by assumption. It assumes conditional equidispersion ($Var(y_i|x_i) = E(y_i|x_i)$): The conditional variance of y_i is assumed to be equal to the conditional mean[18]. Conditional overdispersion violates this assumption. It means that, after accounting for all predictors, the variance of the number of patents changes dependent on whether the mean of public R&D funding is high or low within a country. In other words, (all else equal) in years in which public R&D support is high in a country, RE patents in that country would vary more heavily than in years in which the country's public R&D support was low. This is plausible to expect, for example, due to the uncertainty innovation processes inhibit. The presence of conditional overdispersion does not bias PRM estimates in their sizes, but it biases standard errors and p-values downward (Costantini et al. 2015). Therefore, an NBRM is chosen over a PRM.

In an NBRM, it is assumed that the dependent variable follows a negative binomial distribution. Like in the PRM, the dependent variable is still assumed to follow a Poisson process. The

[18] This is different from the homoskedasticity assumption implied in OLS models, which means that the variance of residuals is constant across observations (but not equal to a mean).

difference to the PRM is that the NBRM introduces the possibility for heterogeneity in the variance of patents. It does so through the introduction of an unobserved error parameter η. More precisely, in this study, the variance of the dependent variable is specified as $Var(y_i|x_i) = E(y_i|x_i) \times (1+\eta)$, whereby η is positive. Compared to a PRM, where $Var(y_i|x_i) = E(y_i|x_i)$ must be true, the specification $Var(y_i|x_i) = E(y_i|x_i) \times (1+\eta)$ is more flexible, given that η can take on any positive value. (Cameron and Trivedi 1986)

Finally, and fourthly, Table A.6.i (in Appendix 6) displays the model-specific values for the Bayesian Information Criterion (BIC) (Schwarz 1978), a measure of model fit that is commonly used for model selection (Burnham and Anderson 2004). The lowest BIC value is attributed to the NBRM estimation of Equation (1). This again supports the choice of the NBRM.[19]

[19] Section 6.1 scrutinises the dependence of the main findings on the choice of model.

5. Estimation Results

Baseline Equation (1) is estimated through a fixed effect NBRM (Table 2), for 17 countries and for 2000-2015[20]. Thereby, different control variables are included, one after the other. For the whole period, public R&D funding (in % of GDP), which is categorised as a technology-push policy, has a positive and statistically significant effect on RE patenting. Covariates other than EPS indices do not affect the R&D estimate in size or statistical significance (compare Columns 1 and 2). The inclusion of EPS indices affects most estimates (Column 3). However, the R&D estimate remains statistically significant. In line with expectations, public policies other than R&D support affect RE patenting. Estimates for EPS indices are statistically significant and positive (except for Taxes). A comparison of BIC values supports the relevance of the inclusion of EPS indices in the model. Despite being a stringent overfitting model test, the BIC-value decreases after including EPS indices, indicating a lower penalty related to the inclusion of covariates. Again in line with expectations, estimates for electricity prices and energy consumption remain statistically significant and positive.

The Negative Binomial regression estimates can be interpreted as follows, in the same way as the output of a Poisson model. For Column 3, if total public RE R&D funding increased by 0.1 units (0.1 percentage points of GDP), keeping all other factors constant, expected RE patents would increase on average, across countries and years, by 60% (Wooldridge 2009, ch.17, p.600f)[21]. Notably, a 0.1 percentage points increase in public RE R&D funding would be a very large increase given that average RE R&D funding in % of GDP amounts to 0.04%. (see Appendix 4 Table A.4.i.)). Due to limitations such as temporal uncertainty of innovation outcomes and possible endogeneity (Section 7), quantitative interpretations of the estimates should be made with caution.

As shown in Columns 4 and 5 in Table 2, the piece also accounts for changing trends in public R&D support and patenting after 2011. For the period 2000-2011, the main results are not strongly affected. Public R&D funding still has a positive and statistically significant effect on RE patenting. However, results for the period 2012-2015 differ. The estimate for the association between R&D investments and patenting for that short period does no longer result statistically significant. However, the small within variation and the period 2012-2015 being very short (only four years and 68 observations) undermine drawing conclusions from a fixed effects

[20] While public R&D data would have been available until 2020, limited availability of patent data and the evaluation of different lag-structures made it necessary to restrict the main analysis to 2000-2015.
[21] More precisely, the log of expected patents would change, which approximates a percentage change. (Wooldridge 2009, ch.17, p.600f)

method (Wooldridge 2009, ch.14, p.481f.). Furthermore, the results are likely affected by unobserved drivers of patenting activity (e.g., mature technologies that do not require patent protection) and differ for other innovation outcome measures like academic publications. Section 7.2. will follow up on the discussion of the estimates for 2012-2015 more in detail.

Table 2. Negative binomial regression estimates for the effect of public research and development funding on innovation in renewable energy technologies (Equation (1)) (dependent variable: patents in the renewable energy sector (lag 1))

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Variable	**2000-2015**	**2000-2015**	**2000-2015**	**2000-2011**	**2012-2015**
Total public RE R&D in	12.660***	12.200***	6.058***	5.825***	-0.267
% of GDP	(0.00)	(0.00)	(0.00)	(0.00)	(0.89)
Electricity prices		7.509***	4.292**	8.160***	-7.074
		(0.00)	(0.00)	(0.00)	(0.15)
Energy consumption		0.033***	0.035***	0.020*	0.024
		(0.00)	(0.00)	(0.02)	(0.07)
Patents all technologies		0.000	0.000	-0.000	0.000**
		(0.23)	(0.70)	(0.29)	(0.00)
Feed-in tariffs			0.045	0.059*	-0.085
			(0.08)	(0.04)	(0.11)
Standards			0.153***	0.335***	-0.029
			(0.00)	(0.00)	(0.64)
Taxes			-0.034	0.007	-0.075
			(0.66)	(0.94)	(0.54)
Trading schemes			0.158***	0.094*	-0.038
			(0.00)	(0.01)	(0.53)
Constant	0.626***	-3.373***	-3.376***	-2.597**	2.471
	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)
Observations	272	272	272	204	68
BIC	2170.3	2145.5	2088.7	1473.6	382.6

Note. Table 2 shows negative binomial regression estimates for Baseline Equation (1). The first row displays estimates for the effect of public R&D support for renewable energy technologies (measured in % of GDP) on patents in the renewable energy sector. The dependent variable is the by the OECD constructed number of renewable energy patents per year and country, lagged by one year and restricted to patents of at least family size 2, which excludes low-quality patents (as described in Section 4.1.). The additional covariates (Section 4.2) include: final energy consumption and electricity prices for domestic consumers (expressed in Purchasing Power Standards) as measures of demand; the number of patents in all technologies (restricted to at least family size 2) as measure of the propensity to patent; OECD indices for the environmental policy stringency of feed-in tariffs, standards, taxes and trading schemes. Columns 1, 2 and 3 rely on all available years (2000-2015). Column 2 excludes alternative policy measures. These are included in Column 3, which displays a positive and statistically significant association of public R&D funding with patenting. Columns 4 and 5 differ from Column 3 only in the periods under scrutiny. They show that the positive and statistically significant association between public R&D support and patenting can only be confirmed until 2011, but not for the short period 2012-2015 in isolation.

BIC-values as measures for model-fit are displayed at the bottom.

p-values are displayed in parentheses: *** Significance at the 0.1 percent level; ** Significance at the 1 percent level; * Significance at the 5 percent level.

For most countries (Appendix 5, Table A.5.i.), the positive and statistically significant effect of R&D funding is confirmed (except for Norway and Sweden). On a sector-specific level (Appendix 5, Table A.5.ii.), the positive and statistically significant effect is confirmed for all three renewable energy sources which currently provide the most renewable energy (biomass, solar- and wind energy).

6. Sensitivity Analyses

The following sensitivity analyses scrutinise the robustness of the finding of a generally positive effect of R&D expenditures on innovation in RE technologies.

6.1. Robustness to the Choice of Model

The choice of an NBRM over a PRM and an OLS model has already been justified (Section 4.3.). Nevertheless, the importance of the choice of model is also scrutinised for its relevance for the R&D result. In the literature, a general consensus has emerged that the difficulties of research on data that shows properties of count data (such as zero truncation) can be addressed through employing multiple methods (Sturman 1999).

In fact, for the whole period 2000-2015, the positive and statistically significant effect of public R&D funding on green innovation is robust to the choice of model, no matter whether an NBRM, a PRM or an OLS is chosen (see Table A.6.i in Appendix 6).[22]

However, the model choice still matters, which becomes apparent comparing the estimates for other policy indices. This motivates the alternative estimation of a fixed effects OLS model, which will be explained in the next subsection.

6.2. Robustness to Different Measures of the Dependent Variable

Two alternative measures for the outcome of innovation processes used in the literature would have been private R&D spending or the development of prices or costs (Groba and Breitschopf 2013). However, for the present purposes, none of these alternatives is feasible. As mentioned, reliable data on private R&D spending in the RE sector is not available. On the other hand, an analysis of industry-specific price and cost developments would have been beyond the scope of the piece. The different RE technologies accumulated in the present research imply different cost and price drivers.

Though, it was possible to evaluate the robustness of a positive and statistically significant effect for R&D support regarding three other modifications of the dependent variable.

First, as an alternative measure of the dependent variable, RE patents are replaced by the share of renewable technology patents of all technology patents filed in a country and a given year

[22] Although the statistically insignificant result for the period 2012-2015 appeared to be independent of the model choice as well, the period is too short for reliable conclusions.

(as has been suggested by Costantini et al. (2015) as an extension for future research). Equation (2) summarises this sensitivity analysis:

$$(RE\ Patent\ share_{i,t+1}) = ß_0 + ß_1(public\ R\&D\ expenditure_{i,t}) + ß_2(energy\ consumption_{i,t}) + ß_3(electricity\ price_{i,t}) + ß_4(Feed\_in\_tariffs_{i,t}) + ß_5(Standards_{i,t}) + ß_6(Taxes_{i,t}) + ß_7(Trading\_schemes_{i,t}) + \alpha_i + \mathcal{E}_{i,t} \quad (2)$$

This alternative measure indicates the importance of innovation in RE technologies relative to innovation in all technologies. The potential violation of the homoskedasticity assumption is tackled by using robust standard errors. And crucially, in contrast to the Baseline Equation (1), in this case, the assumption of normally distributed residuals could not be rejected, as is shown in Figure 9. Therefore, this alternative measure of the dependent variable made it possible to estimate Equation (2) as a fixed effects OLS model.

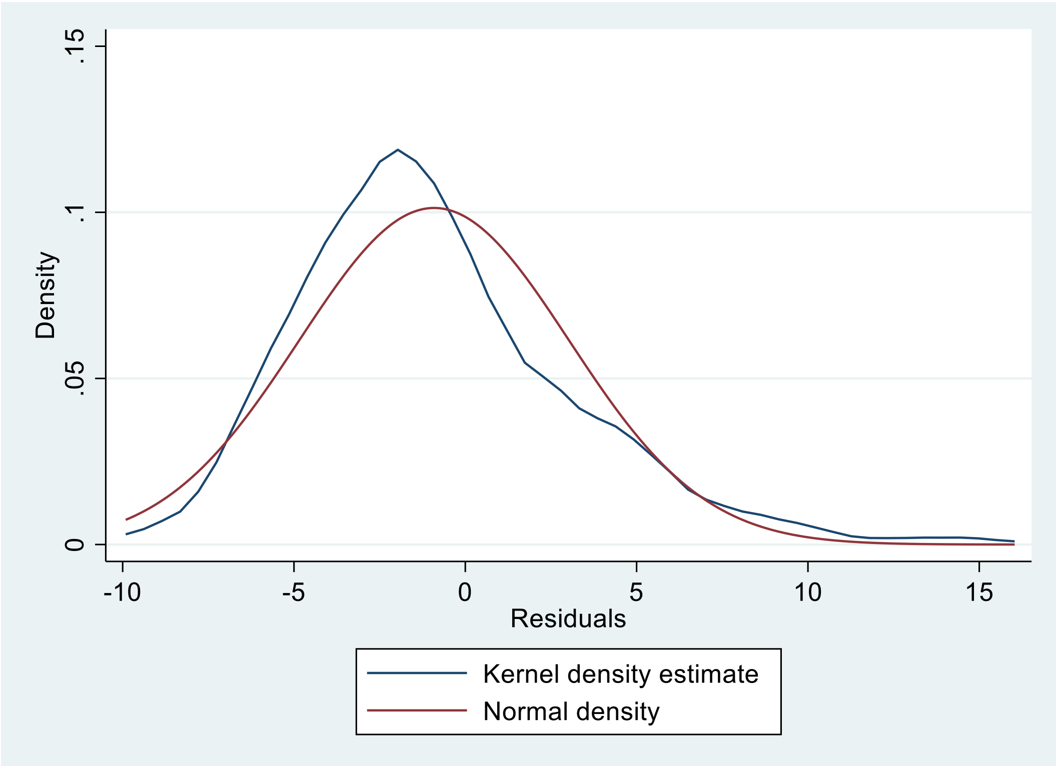

Figure 9. Density distribution of residuals obtained from estimating Equation (2) as fixed effects OLS model. The Figure indicates that the normality assumption is not strongly violated.

As shown in Table 3, again, a positive and (nearly) statistically significant effect of public R&D funding on innovation in the renewable energy sector is confirmed. As mentioned, quantitative interpretations of the estimates should be made with caution. This in mind, the coefficients in Column 3 can be interpreted as follows: on average and all else equal, if total public R&D support for RE increased by 0.1 units (0.1 percent of GDP), the share of RE patents would increase by 3 percentage points. This would be a very large increase considering that the average RE patent share across countries and years amounts to 2.8 percent (Appendix 4 Table A.4.i). Roughly, it would amount to a doubling of the RE patent share.

This result provides additional credibility for the findings obtained so far. Furthermore, analysing the period 2000-2011 in isolation, the statistically significant and positive effect for R&D can again be confirmed. The statistically insignificant effect for the very short period 2012-2015 reappears in this specification as well (just as in the NBRM, compare Table 2 in Estimation Results).

The here employed measure of the patent share is far from a perfect replacement. For example, assume patenting activity in all technologies strongly increased in a country due to unobserved reasons (e.g., potentially increased R&D subsidies for nuclear energy technologies), while RE patenting activity remained unaffected. As a result, the share of RE patents would decrease, although the number of RE patents has not changed. As the example suggests, this alternative measure is likely affected by unobserved factors. A thorough analysis of its drivers goes beyond the scope of this piece.

Table 3. Estimates for the effect of public research and development funding on innovation in renewable energy technologies derived from estimating Equation (2) through Ordinary Least Squares (dependent variable: patents in renewable energy technologies as a share of patents in all technologies)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Variable	**2000-2015**	**2000-2015**	**2000-2015**	**2000-2011**	**2012-2015**	**2000-2015 lag2**	**2000-2015 lag3**
Total public RE R&D	43.220*	43.500*	32.640	39.810	8.118	18.470	4.668
in % of GDP	(0.01)	(0.03)	(0.06)	(0.07)	(0.28)	(0.21)	(0.76)
Electricity prices		7.579	-3.084	1.640	-44.680	-9.154	-12.100
		(0.33)	(0.71)	(0.87)	(0.11)	(0.25)	(0.10)
Energy consumption		0.097*	0.093*	0.052	-0.095	0.139***	0.126**
		(0.03)	(0.03)	(0.16)	(0.55)	(0.00)	(0.00)
Feed-in tariffs			-0.095	-0.107	-0.189	-0.220	-0.283
			(0.58)	(0.51)	(0.37)	(0.27)	(0.34)
Standards			0.349*	0.683**	-0.290	0.569**	0.659**
			(0.02)	(0.00)	(0.42)	(0.01)	(0.01)
Taxes			0.576	0.918	-0.975	0.168	-0.192
			(0.31)	(0.14)	(0.40)	(0.67)	(0.63)
Trading schemes			0.170	0.047	-0.095	0.180	0.084
			(0.22)	(0.76)	(0.69)	(0.12)	(0.59)
Constant	1.222	-8.782	-9.417	-7.631	21.710	-12.400**	-9.526*
	(0.07)	(0.05)	(0.05)	(0.08)	(0.28)	(0.01)	(0.04)
Observations	272	272	272	204	68	272	272
BIC	1124.1	1121.2	1122.9	837.9	232.0	1098.0	1099.9

Note. Table 3 shows ordinary least square regression estimates for Equation (2). The first row displays estimates for the effect of public R&D support for renewable energy technologies (measured in % of GDP) on the share of RE patents. More specifically, the dependent variable is calculated as follows: the constructed number of renewable energy patents is divided by the number of patents in all technologies, per year and country, and restricted to patents of at least family size 2, which excludes low quality patents (as described in Section 4.1.). Except 'number of patents in all technologies', the additional covariates remain the same as in Baseline Equation (1): final energy consumption and electricity prices for domestic consumers (expressed in Purchasing Power Standards) as measures of demand; OECD indices for the environmental policy stringency of feed-in tariffs, standards, taxes and trading schemes. Columns 1, 2 and 3 display OLS estimates for all available years (2000-2015), while Columns 4 and 5 restrict the periods under scrutiny. Columns 1-5 can be compared to Columns 1-5 in Table 2. Indeed, statistical significance and direction of public R&D estimates remain similar. For the whole period, the overall effect of public R&D on RE patenting is still statistically significant and positive. In Column 6, the dependent variable 'RE patents' is lagged with plus 2 years and in Column 7 with plus 3 years. These columns are again based on the whole period 2000-2015. They highlight the importance of the chosen lag structure for the OLS estimates for the effect of public R&D.

BIC-values as measures for model-fit are displayed at the bottom.

p-values are displayed in parentheses: *** Significance at the 0.1 percent level; ** Significance at the 1 percent level; * Significance at the 5 percent level.

Second, the robustness of the statistically significant and positive effect of public R&D support is scrutinised concerning different temporal treatments of the dependent variable. In size, direction and statistical significance, the result is strongly dependent on the chosen lag structure, consistently across models (NBRM, PRM and OLS)[23]. While both theory and existing literature support the choice of a one- to two-year lag treatment (Section 4.1.), the high dependence of finding (a) on the temporal treatment of the dependent variable limits the persuasiveness of the results. The Discussion Section (7.1) elaborates on the implications of this inconsistency for future research.

Third, given the potential relevance of patent quality (Section 4.1.), Baseline Equation (1) is estimated on patents of various qualities. The statistically significant positive effect of public R&D expenditures on patenting is robust to choices of patent quality (family sizes ranging from one for low to four for very high quality) (Table 4, Columns 3-6). The BIC-values as measures of model-fit improved as soon as only higher-quality patents were included in the measurement of the dependent variable.

[23] For the alternative measure of the dependent variable mentioned above and estimated through OLS, this is shown in Table 2, Columns 6 and 7, and in Table 3 Columns 1 and 2 for the estimation of Baseline Equation (1) through a NBRM.

Table 4. Robustness-check of negative binomial regression estimates for the effect of public research and development funding on innovation (Equation (1)) for different patent qualities and temporal treatments of the dependent variable (patents in the renewable energy sector)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variable	**lag2**	**lag3**	**Family Size Two**	**Family Size One**	**Family Size Three**	**Family Size Four**
Total public RE R&D	1.480	-3.070*	6.060***	5.980***	6.350***	5.470***
	(0.299)	(0.034)	(0.000)	(0.000)	(0.000)	(0.000)
Electricity prices	2.070	-1.120	4.290**	4.650***	3.510*	3.120*
	(0.111)	(0.397)	(0.002)	(0.000)	(0.016)	(0.041)
Energy consumption	0.040***	0.040***	0.030***	0.030***	0.030***	0.030***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patents all technologies	0.0000017	0.0000024	0.0000048	0.0000048	0.0000110	0.0000109
	(0.896)	(0.857)	(0.705)	(0.714)	(0.412)	(0.446)
Feed-in tariffs	0.026	0.007	0.045	0.017	0.040	0.033
	(0.293)	(0.773)	(0.077)	(0.469)	(0.126)	(0.217)
Standards	0.170***	0.186***	0.153***	0.115***	0.150***	0.176***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Taxes	-0.065	-0.080	-0.034	-0.013	-0.080	-0.097
	(0.361)	(0.244)	(0.656)	(0.848)	(0.312)	(0.227)
Trading schemes	0.189***	0.163***	0.158***	0.159***	0.150***	0.149***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-3.185***	-2.278***	-3.376***	-2.382***	-2.541**	-2.434**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.003)
Observations	272	272	272	272	272	272
BIC	2084.1	2104.6	2088.7	2359.1	1902.3	1770.4

Note. Table 4 analyses the importance of the measurement of the dependent variable. It shows negative binomial regression estimates for Equation (1). The first row displays estimates for the effect of public R&D support for renewable energy technologies (measured in % of GDP) on patents in the renewable energy sector. All available years (2000-2015) are included for all columns. The additional covariates include: final energy consumption and electricity prices for domestic consumers (expressed in Purchasing Power Standards) as measures of demand; the number of patents in all technologies (restricted to at least family size 2) as measure of the propensity to patent; OECD indices for the environmental policy stringency of feed-in tariffs, standards, taxes and trading schemes. Importantly, the columns differ in the measurement of the dependent variable. In Columns 1 and 2, the dependent variable is lagged with plus two and plus three years instead of only one. This different temporal treatment affects the public R&D estimates. This also becomes evident in comparison with Column 3, where patents are lagged with only one year. Note that Column 3 here corresponds to Column 3 in Table 2, and on which the main results of this piece are based. In this vein, patents in Column 3 are restricted to patents with a family size of at least two. This means that those patents are filed in at least two jurisdictions, excluding low-quality patents. Column 4 does not apply this restriction and includes all renewable energy patents in measuring the dependent variable. Columns 5 and 6 are more restrictive in the quality of patents and include only those that are filed in at least three or four jurisdictions. Columns 3, 4, 5 and 6 show that the main results for public R&D do not depend on the quality of patents, approximated by family size.

BIC-values as measures for model-fit are displayed at the bottom.

p-values are displayed in parentheses: *** Significance at the 0.1 percent level; ** Significance at the 1 percent level; * Significance at the 5 percent level.

6.3. Robustness to Alternative Measures of Covariates

In the following, the robustness of sign and statistical significance of the R&D estimates obtained is evaluated with respect to the inclusion of three alternative measures of covariates.

First, OECD's (2016) overall market-based EPS index replace single EPS indices for market-based, demand-pull policies, represented by the variables $(Feed\_in\_tariffs_{i,t})$, $(Taxes_{i,t})$ and $(Trading\_schemes_{i,t})$. This replacement is performed to account for concerns of multicollinearity. Several different EPS indices are included in the baseline Equation (1). It could be the case that different environmental policies are strongly linearly correlated. For example, they could have been introduced or strengthened in the same year. In the regression, the effect of public R&D support is obtained by holding the other regressors constant. However, if EPS indices shared variability with public R&D funding, ‘holding other factors constant’ would decrease the variability of public R&D funding in so far as shared with the other regressors. This potential loss of information and variability can result in less accurate estimates through increased standard errors, both for public R&D funding and individual EPS indices (Wooldridge 2009, ch.3, p.95f.).

Calculating Pearson correlation indices for all regressors in Baseline Equation (1) (compare Appendix 6, Table A.6.ii), the regressor of interest, public R&D funding, results as not strongly linearly correlated with any of the other regressors. Although a quantitative interpretation of estimates is not the purpose of this analysis, concerns of multicollinearity can still be ruled out for the R&D estimate. However, the EPS index for Trading Schemes is linearly correlated with the EPS index for Standards at a critical level of 0.58 (while a value of 1 would indicate a perfect linear correlation of the two variables). Therefore, to mitigate multicollinearity concerns for Standards, the variables Trading-Schemes, Taxes, and Feed-in Tariffs are replaced by the cumulative index for market-based EPS. This replacement reduces the correlation between the EPS index for Standards and the EPS index for market-based policies to 0.4 (see Appendix 6, Table A.6.iii). As expected, the estimates for total public R&D expenditures are robust to this replacement in size, direction and statistical significance. In contrast, estimates for Standards increase slightly in their size (Table 5, Column 2 compared to Column 1).

This piece focuses on whether public R&D has been an effective driver of innovation. As mentioned, Pitelis et al. (2020) found that sometimes, RE R&D funding as a technology push policy is effective only in combination with other demand-pull policies. Thus, as an extension, R&D funding is interacted with the index for market-based EPS (Table 5, Column 3). A positive and statistically significant effect is found only for the interaction term. This is in line with past evidence on the importance of combining technology-push and demand-pull policies.

Second, the total number of patents in all technologies is replaced by an alternative measure for the innovative system. Namely, as an alternative, the knowledge stock created by all patents related to renewable technologies is estimated (as similarly done by Costantini et al. (2015) for biomass only). The knowledge stock represents a measure of the presumed, accumulated knowledge created by past patents. Klaassen et al. (2005), Kobos et al. (2006) and Bointner (2014) provide a detailed description of the methodology. The method goes beyond a pure sum of patent counts. While Equation (1) already implied assumptions concerning time lags, calculating the cumulative knowledge stock for RES permits it to go further. Namely, it implies assumptions both on knowledge spillovers (ρ) and depreciation rates of knowledge (δ). It consists of both the accumulated knowledge stock of the past period, depreciated and multiplied by a spill-over effect, as well as the amount of RE patents for period t. This is illustrated by the following Equation (3):

$$KS\_RE\_Pat_{t,i} = \sum_{i=1}^{n} (1+\rho) \times (1-\delta) \times KS_{(t-1),i} + RE\_Pat_{t,i} \qquad (3)$$

The reasoning which justifies accounting for depreciation of knowledge is that the further in the past knowledge has been created, the lower is its value for current inventions. Based on existing contributions by Bointner (2014) and De Negri et al. (2020), a depreciation rate of 10% for knowledge on renewable energy technologies is assumed. Furthermore, it is assumed that knowledge creation of one party facilitates innovation by other parties. Thus, new knowledge can, at least in parts, be traced back to past innovations and their positive externalities (Jaffe, Trajtenberg, and Fogarty 2000). In line with De Negri et al. (2020) and based on the European Commission's (2017) technical study on energy spillovers of clean technologies, a knowledge spillover rate of 35% is assumed.

The estimated values for the RE-patenting knowledge stock are then used to replace the total number of patents in all technologies. The R&D estimate remains statistically significant and positive (Table 5). Thus, the estimate of public R&D funding proved robust to the inclusion of a knowledge stock measure for green innovation. The estimates for the knowledge stock are also statistically significant and positive. This is in line with expectations, as one would expect green patenting to be positively affected by the amount of knowledge accumulated in the past in that sector.

Third, OECD's (2016) Environmental Policy Stringency index for public R&D subsidies is added. The index replaced the total amounts of public R&D funding, the regressor of main interest in this paper. Notably, OECD’s index for the environmental stringency of public R&D funding differs from the latter in an important way: in the calculation of the index, the government’s budget allocations to R&D on renewable technologies are used, in line with IEA’s definition of “public” (Botta and Koźluk 2014, p.18). This, though, does not include R&D funding on renewable technologies distributed through the European Commission (Section 3.2). As the results in Table 5 illustrate, the positive and statistically significant effect of public R&D funding is confirmed with (Column 1) and without EC funding considered (Column 5). This supports not only the reliability of the R&D measure that has been constructed and employed in this study for the first time. It also indicates the robustness of the main finding of a positive and statistically significant effect of public R&D support to alternative, more incomplete measures of that variable.

Table 5. Robustness-check for negative binomial regression estimates for the effect of public research and development funding on innovation after including alternative measures for covariates

Variable	(1) Baseline Equation	(2) Market-based EPS	(3) Total public RE R&D # Market-based EPS	(4) RE Patent Knowledge Stock	(5) EPS for R&D Support
Total public RE R&D in % of GDP	6.058***	6.038***	2.910	5.151***	
	(0.00)	(0.00)	(0.31)	(0.00)	
Electricity prices	4.292**	4.543***	4.775***	4.132**	4.803***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Energy consumption	0.035***	0.042***	0.043***	0.037***	0.031***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Patents all technologies	0.000	-0.000	-0.000		0.000
	(0.70)	(0.75)	(0.75)		(0.84)
Feed-in tariffs	0.045			0.059*	0.047
	(0.08)			(0.02)	(0.06)
Standards	0.153***	0.199***	0.234***	0.131***	0.146***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Taxes	-0.034			-0.010	0.005
	(0.66)			(0.90)	(0.94)
Trading schemes	0.158***			0.175***	0.177***
	(0.00)			(0.00)	(0.00)
Market-based instruments		0.232***			
		(0.00)			
Total public RE R&D # Market-based instruments			1.771		
			(0.07)		
RE Patent Knowledge Stock				0.00008*	
				(0.04)	
EPS for national R&D Support					0.142***
					(0.00)
Constant	-3.376***	-4.456***	-4.330***	-3.515***	-3.265***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	272	272	272	272	272
BIC	2088.7	2085.9	2097.0	2085.2	2086.7

Note. Table 5 shows negative binomial regression estimates for Baseline Equation (1) with different measures for the covariates. The dependent variable remains the by the OECD constructed number of renewable energy patents per year and country, lagged by one year and restricted to patents of at least family size 2. All columns rely on the whole available period (2000-2015). For comparison, Column 1 displays the main results of the Baseline Equation (1) and corresponds to Column 3 in Table 2. In Column 2, to control for multicollinearity, the market-based environmental policy stringency index replaces separate market-based policy measures (taxes, trading schemes and feed-in tariffs). In Column 3, this market-based EPS is interacted with public R&D funding. In Column 4, the knowledge stock created by renewable energy patents replaces the number of patents in all technologies as a measure of the innovative environment. In Column 5, OECD's EPS index for national R&D support replaces total public R&D funding. For all columns, estimates for public R&D funding remain statistically significant and positive. In Column 3, public R&D estimates are statistically significant at a 10 percent level only if interacted with market-based policy instruments.

BIC-values as measures for model-fit are displayed at the bottom.

p-values are displayed in parentheses: *** Significance at the 0.1 percent level; ** Significance at the 1 percent level; * Significance at the 5 percent level.

7. Discussion, Limitations and Policy Recommendations

Addressing part two of the research question, an overall positive and statistically significant effect of public (EC + national) R&D support on green innovation has been found. The result is robust across models and different measures for the dependent variable and covariates. However, the importance of temporal treatment and statistically insignificant results for 2012-2015 motivate the author to be reluctant to quantitative interpretations. These results provide the case to discuss three main limitations of this piece before policy recommendations are formulated.

7.1. Limitation One: Temporal Uncertainty

The main results are based on lagging patents by one year. Hall, Griliches, and Hausman (1983) support this choice. They found that most of the effect of R&D spending on patenting occurs in the first and, to a smaller extent, in the second year. The choice is also in line with other contributions (Johnstone et al. 2010; Costantini et al. 2015). At the same time, a different temporal treatment affects the results, independent of the chosen model. This reflects a challenge identified by Pless et al. (2020), who stress the long and uncertain times between receiving R&D support and the manifestation of measurable innovation outcomes. Pitelis (2018) justifies his reluctance to a quantitative interpretation of estimates with the dependence of results on chosen lag structures.

Future research should address this challenge, first, through recognising the different stages of current innovation processes. Different levels of technology advancement imply different time spans for R&D activities to produce innovation outcomes. Second, through data-collection: Although extensive data-collection over several years (such as in this piece) forms the basis to address the challenge of temporal uncertainty successfully, here, a limitation is set by future innovation outcomes not yet being observable. The patent data analysed in the present piece are only available until 2018. Future research should collect data on more extended periods post policies to address the temporal uncertainty challenge.

7.2. Limitation Two: The Quantification of the Causal Effect

Another challenge the evaluation of energy innovation policies commonly faces is the reliable quantification of causal effects (Pless, Hepburn, and Farrell 2020). This challenge underpins an interpretation of the statistically insignificant estimates from 2012 onwards. The challenge consists of the following: to identify a causal effect of a policy, influences from other factors on the innovation outcome need to be stripped out. Ideally, the innovation outcome would be compared to a counterfactual: the potential outcome had the entity/ country not received public R&D funding. This potential outcome, though, is by definition unobservable. Instead, the regression method with fixed effects employed in this piece aims to 'strip out' relevant differences between countries other than public R&D subsidies that are likely to affect green innovation. However, at least two statistical problems still threaten the isolation of marginal effects and their quantitative, causal interpretation. (Pless et al. 2020)

The first is commonly known as 'selection bias'. It refers to systematic differences between groups that 'cause' outcomes to differ. For example, countries might vary systematically in their propensity to innovate. Firms that have been innovative in the past are more likely to apply for patents successfully. In this piece, different measures for the innovative environment (the number of all technology patents, the RE Knowledge Stock) and the fixed effects method cope with this challenge at least partly. The RE Knowledge Stock controls for the estimated knowledge available in a country and technology sector. (Pless et al. 2020)

'Simultaneity bias' represents the second statistical problem that threatens a causal interpretation: changes in policies may coincide with other changes over time. For example, research efforts of firms may be driven directly by expectations about future demand and the reputations of these technologies within society. At the same time, governments may respond to these societal interests as well. They might introduce policies that favour renewable energy technologies. Thus, green innovation would be driven 'simultaneously' by both firms' direct responses to political interests and the introduction of more stringent policies by governments. (Pless et al. 2020)

For the period from 2012 to 2015, next to simultaneity bias and selection bias, R&D estimates are likely unreliable for several reasons. The period is very short, and stable total public R&D expenditures reflect a small within variation. This makes a reliable application of a fixed effects method questionable (Wooldridge 2009, ch.14, p.481f.). Also, sector-specific price drops and general industry declines are not included in the analysis. These factors are likely to have caused the decrease in patenting activity for that very recent period instead of stable public R&D funding. For example, between 2006 and 2016, the (inflation-adjusted) price of rooftop photovoltaic systems in Germany decreased by approximately 72% (Fraunhofer ISE 2021, p.44), which was mainly caused by massive production by Chinese manufacturers (Li and Shao 2021). Maturity levels of renewable energy technologies may represent additional unobserved drivers of green innovation, especially for 2012-2015. RE technologies have advanced over time, which may have affected the impact of public R&D support (Costantini et al. 2015). In Section 7.4., lacking data on maturity levels of technologies will be further discussed as a separate limitation. For these various reasons, the statistically insignificant R&D estimates for 2012-2015 should not be interpreted as undermining the relevance of public R&D support. Instead, for that period, RE patenting is likely driven by other factors.

Overall, the fixed effects method and covariates can remove some endogeneity. Nevertheless, it is simply impossible to know whether all relevant information and sources of endogeneity are included in the analysis. This impossibility is one of the reasons that motivate the author to be reluctant to formulate quantitative interpretations.

Possible simultaneity- and selection bias and some unobserved drivers of innovation, especially for the period from 2012 onwards, shed light on promising realms for future research. Adapting the design of new energy innovation policies can make it easier to account for potential simultaneity- and selection bias. For example, policy design can facilitate randomised control trials (Athey and Imbens 2017) through randomising specific requirements of R&D grant funding (e.g., whether the applicant collaborates with certain types of firms or institutions). Alternatively, determining the distribution of public R&D support through grades or rankings can permit the evaluation through 'Regression Discontinuity Designs' (D. S. Lee and Lemieux 2010). Innovation performance of firms just above and below the cut-off, which is assumed to be similar in relevant characteristics, can be compared. For example, Bronzini and Piselli (2016) and Agrawal, Rosell, and Simcoe (2020) have already successfully implemented Regression Discontinuity Designs in the context of evaluating energy innovation policies. (Pless et al. 2020)

Finally, regarding unobserved drivers of patenting activity, which may be particularly relevant from 2012 onwards, the inclusion of alternative measures of innovation outcomes may provide beneficial insights in future research. These alternative measures include private R&D spending, which will be discussed in the next section, price or cost development, and academic publications (all measures were not available for the purpose of this study) (Groba and Breitschopf 2013). Indeed, in contrast to patents, the EU's share of global academic publications in RE sectors remained constant from 2012 onwards (Hoogland et al. 2019).

7.3. Limitation Three: Private R&D Funding

For this piece, country-specific data on private R&D funding were not available. Public R&D funding can affect private R&D spending, which is why the latter represents an alternative measure for innovation output in RE technologies (Groba and Breitschopf 2013). Theory and recent evidence on the relationship between private and public R&D funding shed light on why the lack of private data likely biases the size of the public R&D estimates.

First, the lack of private R&D data is a challenge that coincides with Limitation Two. Regarding selection bias, a firm that is innovative and successful in applying for patents is likely one that has spent significant amounts on innovation activities. At the same time, such a firm is also likely successful in receiving public R&D funding (Jaffe 2002). Thus, the 'true' estimates for the impact of public R&D spending on patents may be smaller than in the output of this piece. While the fixed effects approach allows capturing unobserved variation between countries in their levels of private spending, it cannot capture unobserved changes in private spending over time (Section 4.3.). And this is critical if one recalls that global private R&D funding for RE technologies has increased heavily in recent years and represents an essential part of total R&D spending (IEA 2020a) (Section 3.1.). Thus, changes in patenting activity may be partly driven by changes in private R&D spending. Regarding simultaneity bias (Pless et al. 2020), as discussed, public reputations of RE technologies may simultaneously affect private and public R&D spending. And both private and public expenditures affect RE innovation. Thus, the true effect of public R&D may be smaller than if private spending was omitted.

Second, besides issues related to simultaneity- and selection bias, firms may alter their spending decisions if they receive public support. This so-called 'additionality question' concerns how public R&D funding affects private R&D spending. In a simple theoretical framework, one may suggest that public spending crowds out private spending. If marginal costs remain constant, a firm that maximizes its profits will not invest more in innovation activities and instead reduce private spending. However, cost-sharing or co-funding requirements for public support can mitigate crowding out by reducing marginal costs. A profit-maximizing firm is incentivized to invest more until the marginal productivity of R&D spending decreases sufficiently so that marginal benefits again equal marginal costs (Wallsten 2000). Also, in so far as private funding reflects a firm's long-term commitments, it is not affected by fluctuating public support (Becker 2015). Furthermore, firms may free-ride on the public funding decision conceiving of it as a certification of high quality and therefore invest more in these projects (the so-called 'halo' effect) (Diamond 1999). Thus, public funding may even 'crowd-in' private funding. Recent empirical evidence predominantly supports the hypothesis that, in general, public R&D support crowds-in and stimulates private R&D spending. Thereby, the effectiveness of public R&D spending is found to be larger for smaller firms that face financial constraints, while larger firms are likely to invest anyways. (Jaffe 2002; Becker 2015)

Overall, the implication of omitting private R&D data for the public R&D estimates is ambiguous. Selection- and simultaneity bias may imply that true public R&D estimates are smaller. However, recent empirical evidence predominantly supports the crowding-in hypothesis. Public R&D support generally drives innovation in interaction with and ‘through’ stimulating private investment (Becker 2015). This recent evidence suggests that the piece’s main result on public R&D’s general effectiveness is not threatened by the omission of private data. Provided the availability of private R&D data is enhanced, future research should analyse this relationship for the case of RE technologies.

7.4. Limitation Four: Stages of Technology Development

An additional challenge stems from the dependence of the impact of public R&D support on the stage of technology development. For example, Grubb (2004) emphasises that public R&D support is vital during the early phases of the technology development and continues to be effective during the demonstration phases until commercialisation in a niche market. While market-pull policies should generally be combined with R&D funding, market-pull policies are crucial during later stages to support full market commercialisation. Johnstone et al. (2010) support this finding, arguing that R&D support is especially effective for early-stage RE technologies since it incentivizes very specific technologies. An OECD publication (OECD 2011) adds stringent environmental standards as effective drivers for early-stage technological development. Standards stimulate innovation that makes it less costly to comply with the new regulations. Costantini et al. (2015) discriminated between two generations of technologies in the biofuels sector. They found that only second-generation technologies in the biofuels sector reacted positively to technology push policies (such as R&D support). They suggest that demand-pull policies can effectively incentivise risky and exploratory innovation investments on first generation-technologies by affecting a firm’s expectations towards the growth of demand.

All these findings indicate that the stages of development and the generation and advancement of technologies matter for policies’ effectiveness. In this piece, due to data limitations, it was impossible to clearly discriminate between different stages of development or technology generations. Doing so would be a relevant extension for future research. Regarding the period 2012-2015, a closer analysis of the commercialisation stages of RE technologies can provide valuable insights on the relationship between maturity levels of RE technologies and the decrease of renewable energy patenting in Europe.

7.5. Policy Recommendations

The descriptive analysis in this piece resulted from an extensive data collection effort. It revealed a high heterogeneity across countries in the relative importance of the European Commission's R&D contributions for renewable energy technologies, ranging from 15% (France) to 63% (Belgium). The National Energy and Climate Plans (NECPs), which all EU Member States must submit, address the necessity to align national support for R&D in renewable energy technologies (EU 2018b). However, alignment does not mean equality. Path-dependence and divergence in the governments' R&D efforts or the allocation of EC funding may be of little concern for green innovation (Grafström et al. 2020). Overall, drawing normative conclusions from biases of the allocation of EC funding towards certain countries goes beyond the scope of this piece. Instead, (**policy recommendation 1**) to facilitate the transparency and alignment of public R&D efforts, the accessibility of data on EC and national contributions should be improved. Furthermore, the availability of private R&D data should be enhanced so that the relationship between private and public R&D funding can be analysed. In relation to this, the vital role international organizations such as the IEA play in providing such data and knowledge services and in mobilizing other agencies to support renewable energy technologies should be recognized (Li and Shao 2021).

In line with existing contributions, the estimation results on the overall effectiveness of R&D funding for RE are statistically significant, positive, and diverse across sectors and countries. From this follows **policy recommendation 2**: the size of public R&D support for renewable energy technologies should be determined recognizing the local conditions and policies in place. For example, Denmark has many wind resources and already relies on wind power generation. However, despite the countries' local conditions, ocean energy generation is an underdeveloped sector with potential that deserves more attention (Li and Shao 2021). Another example of a technology-specific factor that affects the impact of R&D support is the complementarity to other energy innovation policies in place. Acemoglu et al. (2012) show that an effective carbon price should complement public R&D subsidies for environmental regulation to be effective. Furthermore, the extent to which R&D support measures should be complementary to demand-pull instruments should, among others, depend on the current stages of development of specific RE technologies (Groba and Breitschopf 2013; Costantini et al. 2015).

Policy recommendation 3 addresses the necessity to quantify marginal effects: the design of energy innovation policies should recognise the need to identify marginal effects and quantify the effectiveness of measures, such as through implementing lotteries or rankings. Finally, **policy recommendation 4** relates to this and addresses the temporal uncertainty of innovation outcomes. As discussed, (quantitative) results highly depend on the temporal treatment. Therefore, it is recommended that energy innovation policies are provided consistently over time and coupled with reporting processes of innovation impacts maintained for several years. Reporting processes can provide critical data to capture middle- to long-term effects. (Pless, Hepburn, and Farrell 2020)

Conclusion

The EU and its Member States widely acknowledge the importance of public research and development support for renewable energy technologies. For example, they committed to double public R&D investment from 2015 until 2020 and to increase the renewable energy share to at least 35% by 2030. That provides the case to address the following research question: *what was the size of public R&D funding for renewable energy sources in 2000-2020 and its effect on knowledge and innovation?*

Public (the EC's + national) R&D funding for renewable energy technologies were analysed from 2000 to 2020 and across 17 European countries, on both a country- and sector-specific level and over time. Based on this (to the author's knowledge) so far uniquely detailed panel dataset on a country-level, the piece provides strong support for the relevance of public R&D funding. In addition, it aims to incentivize future research and policy-making. The research question is answered as follows:

(a) Concerning the first part of the research question, yearly averages for public R&D funding for RE technologies have been the highest in the largest economies (DE, FR). Nordic countries lead when the sizes of the economies are taken into account. The piece made it possible to shed light on the vast heterogeneity of the relative importance of EC contributions (as shares of total public R&D funding for renewable energy technologies): Belgium received 63% and Spain 46% of their total public R&D support for renewable energy technologies from the European Commission. In contrast, France received only 15% and Finland only 18% from the EC. Regarding changes over time, all countries experienced an increase in total public R&D funding until 2011. From 2012 onwards, for most countries, the strong increase in EC contributions coincided with and compensated decreasing national budgets. This resulted in overall stable total public R&D support in most countries since 2012. Hence, on a detailed country level, the piece highlights the vital role of EC expenditures in stabilizing public R&D support for renewable energy technologies. In Norway, the Netherlands, Belgium and Portugal, total available public R&D funding for RE technologies even increased after 2012. However, none of the countries could double available public R&D support between 2015-2020, despite their commitment to the MI initiative.

(b) Concerning the second part of the research question, estimates for the overall average effect of total public R&D support on green innovation are statistically significant and positive. Based on precise data for the very recent period 2000-2015 and including the European Commission's contributions, existing evidence derived from indices and without the consideration of EC contributions is therefore confirmed. Furthermore, the effectiveness and relevance of public R&D support is confirmed for nearly all countries and the largest sectors (biomass, solar- and wind energy), whereby the size of the estimates is heterogeneous. However, for the most recent years 2012-2015, the association between public R&D funding and patenting in renewable energy technologies is statistically insignificant. Statistically, the estimates for that period are unreliable: the period is too short and within variation too small. Also, the decrease in patenting activity contrasts with the development of other innovation output measures such as academic publications on RE technologies. Overall, various factors not included in this analysis may have affected patenting activity in those years, such as the industry decline in the solar sector and less need for patenting due to, for example, technology advancement.

(c) The piece also contributes to existing findings by confirming the general relevance of public R&D support through a range of sensitivity analyses. The overall positive and statistically significant result is robust: across alternative model-choices (for OLS, NBRM and PRM); across different measures for the dependent variable (RE patents as a share of all technology patents and different patent-qualities); against concerns of multicollinearity; when controlling for the knowledge stock created by renewable energy patents; and including OECD’s Environmental Policy Stringency index for (only) national R&D subsidies as a replacement for the unique, more complete measure constructed for this piece.

(d) Overall, the piece shares four limitations with existing studies: the manifestation of innovation outcomes remains uncertain; the precise quantification of marginal effects remains critical; the advancement of technologies is heterogeneous; data availability (particularly for private R&D funding) remains limited. These limitations have been addressed. The discussion, so the author hopes, incentivizes future research and policymaking.

Appendix

Appendix 1 on National Research and Development Expenditures

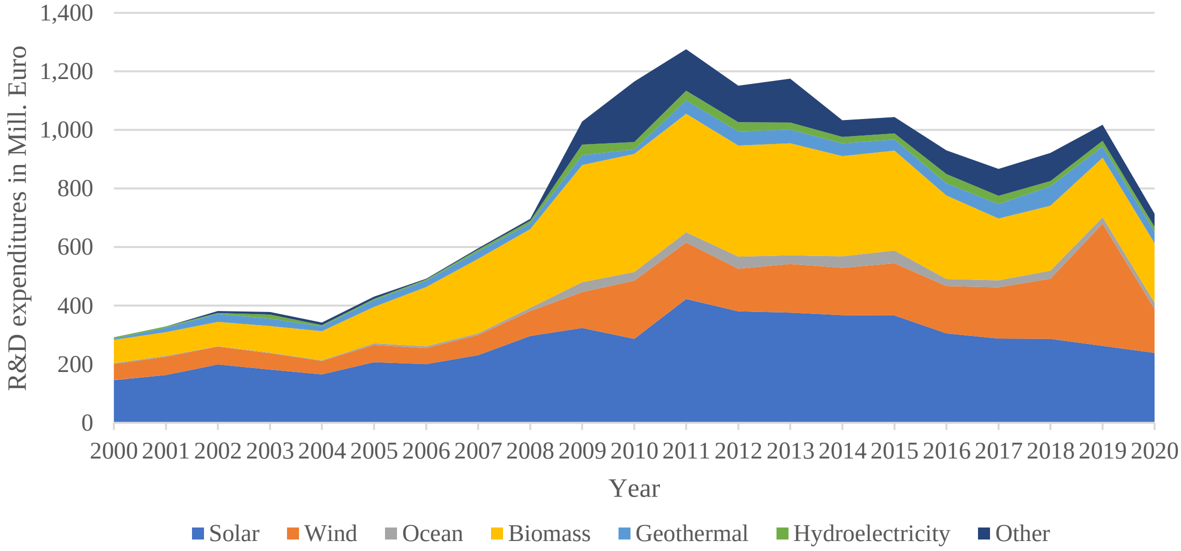

Figure A1.i. Sector-specific development of national research and development expenditures for renewable energy technologies of 17 European countries from 2000 until 2020 (Mill. Euro) (2020 prices and exchange rates)

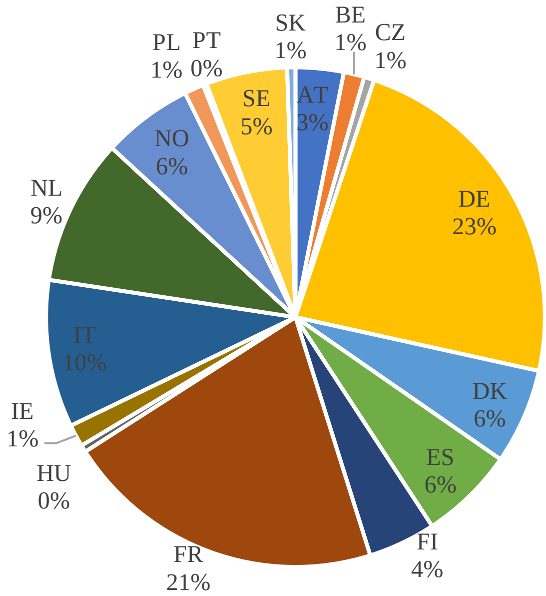

Figure A1.ii. Shares of national historical research and development expenditures for renewable energy technologies from 2000-2020, by country (Mill. Euro) (2020 prices and exchange rates)

Appendix 2 on the European Commission's Research and Development Expenditures

Description of data collection for the European Commission's research and development expenditures for renewable energy technologies:

The analysis of this piece is based on a unique dataset that is the result of an extensive data collection effort. Namely, the framework programme-specific datasets accessed through CORDIS still had to be attributed to both the RE-sector and subsectors (such as wind or solar energy), as well as to countries. The attribution of R&D projects to the RE-sector and subsectors has been carried out through a detailed, automated keyword search. Each project's title and objective description were automatically skimmed for matches with a list of 99 keywords. Based on the resulting matches, the projects were then attributed to respective RE-subsectors.

In general, a keyword method could be biased. For example, it might include irrelevant projects or exclude relevant ones (Johnstone, Haščič, and Popp 2010, p.7). However, the keyword search method applied in this piece is likely reliable. The risk of excluding relevant projects has been mitigated not only through a long list of different keywords (nearly a hundred). Furthermore, the method did not require precise matches, but the single keywords could also match parts of terms used in the project titles or descriptions. This again effectively minimised the risk of leaving out relevant projects. On the other hand, the risk of including irrelevant projects has been mitigated through a manual examination of descriptions of matched projects' abstracts.

In a subsequent step, the categorised projects had to be attributed to countries. Initially, lacking data on countries' participation formed a significant obstacle to the feasibility of the present analysis. Fortunately, after several inquiries at the Helpdesk of the Publications Office of the European Union, the required CORDIS data has been made available to a sufficiently detailed extent. The published data also contained the precise amounts that countries received through their participation in EC R&D projects. This information could be merged with the sector attribution obtained from the keyword method.

Finally, given that the raw data on EC funding only contained nominal values, they still had to be adjusted for inflation. This adjustment was carried out in reference to Harmonised Indices of Consumer Prices (HICP), which are published by the European Statistical Office (Eurostat 2021). HICP provide comparable measures for inflation across Europe, both on a country level and over time. The year 2020 was used as a reference year to transform the nominal values into real values.

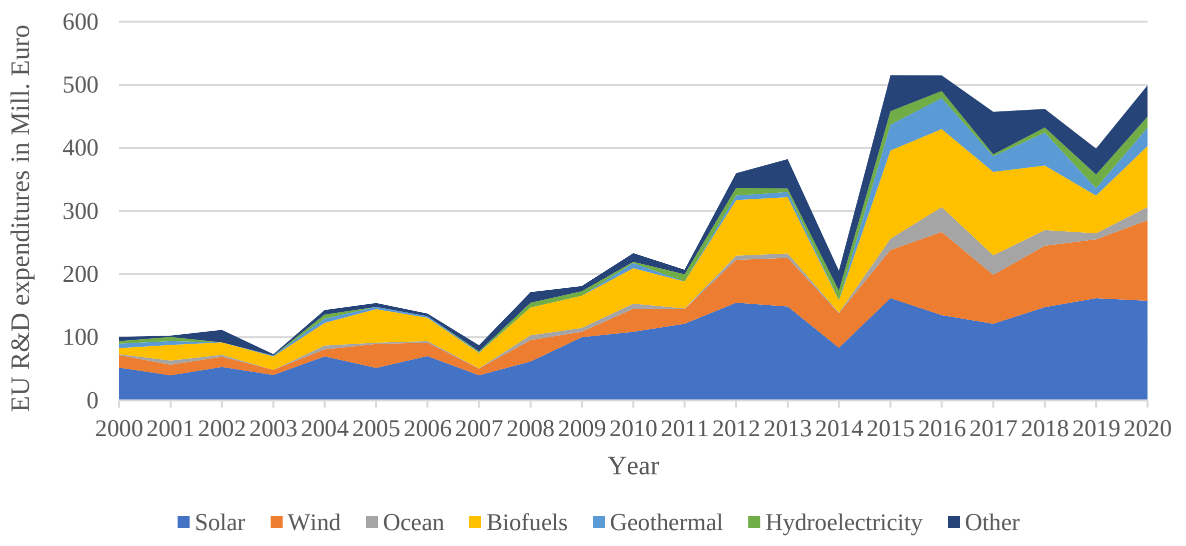

Figure A2.i. Research and development expenditures for renewable energy technologies of the European Commission in 17 European countries from 2000-2020 by sector (Mill. Euro) (2020 prices and exchange rates)

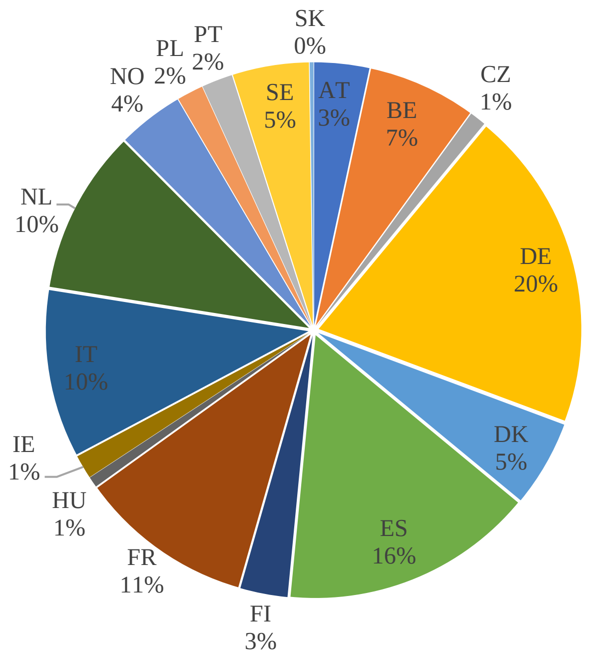

Figure A2.ii. Countries' shares of historical research and development funding for renewable energy technologies received from the European Commission in the period 2000-2020 (Mill. Euro) (2020 prices and exchange rates)

Appendix 3 on Total Research and Development Expenditures

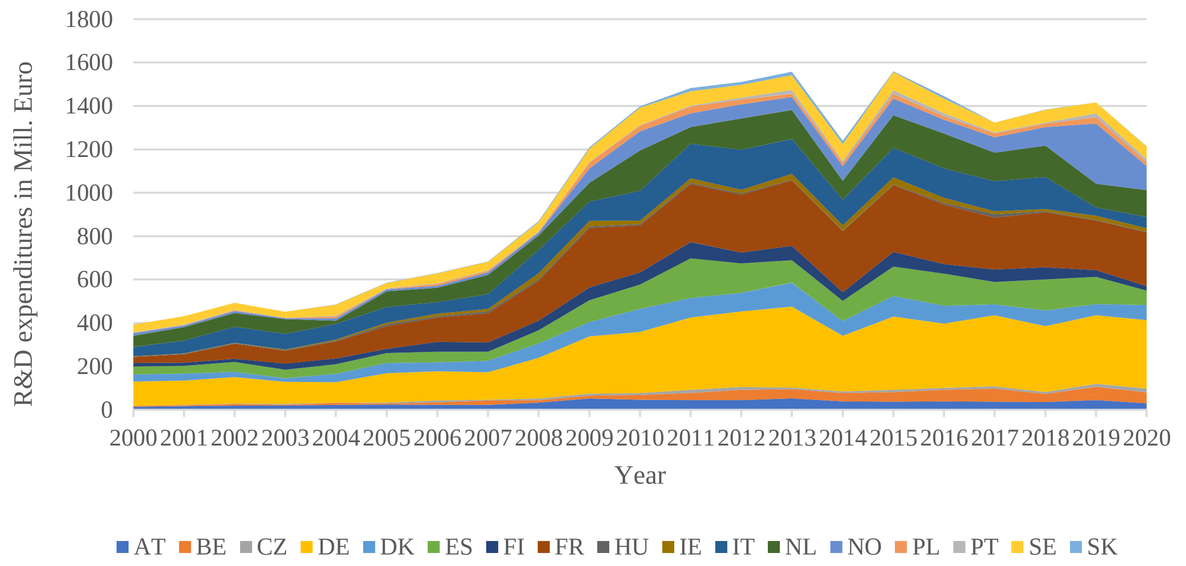

Figure A3.i. Total (the European Comission's + national) research and development expenditures for renewable energy technologies, in 17 European countries and from 2000-2020 by country (Mill. Euro) (2020 prices and exchange rates)

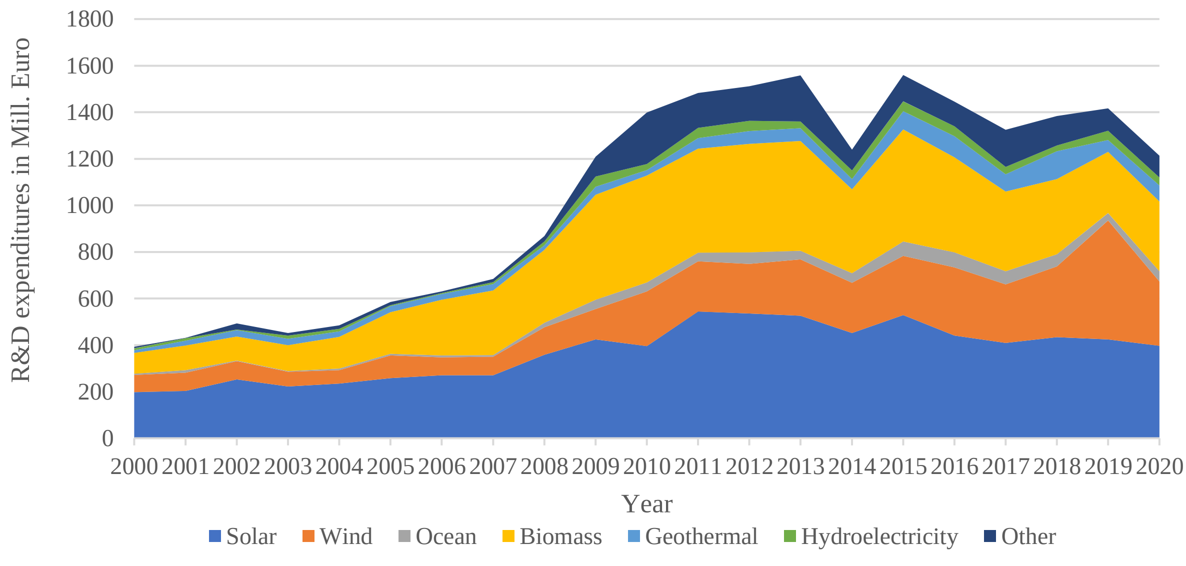

Figure A3.ii. Total (the European Comission's + national) research and development expenditures for renewable energy technologies in 17 European countries from 2000-2020 by sector (Mill. Euro) (2020 prices and exchange rates)

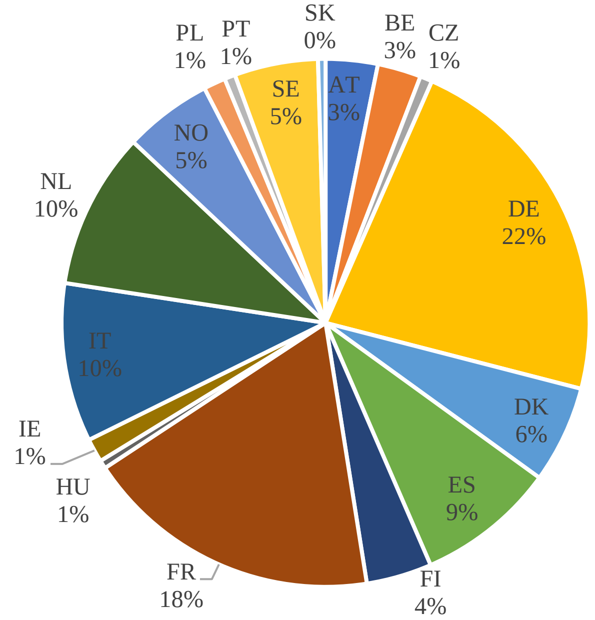

Figure A3.iii. Shares of total (the European Comission's + national) historical research and development expenditures for renewable energy technologies from 2000-2020 by country (Mill. Euro) (2020 prices and exchange rates)

Appendix 4 on Empirical Strategy and Data

Table A.4.i. Descriptive statistics (for the period included in the estimation: 2000-2015)

Variable	**Obs.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Patents RE	272	86.899	177.944	0	1282.920
Patents RE as % share of all technology patents	272	2.818	2.887	0	19.638
Total public R&D expenditures for RE in Mill. Euro	272	55.081	70.599	0.234	372.022
Total public R&D expenditures for RE in % of GDP	272	0.040	0.033	0.001	0.177
Energy consumption	272	96.588	5.625	80.900	113.300
Electricity prices	272	0.126	0.043	0.052	0.235
Feed-in Tariffs	272	2.003	1.912	0	6.000
Standards	272	4.019	1.338	1	6.627
Taxes	272	1.733	0.806	0.637	4.335
Trading Schemes	272	1.497	1.248	0	5.281
Market-based instruments	272	1.744	0.754	0.250	3.433
R&D Stringency	272	2.578	1.460	0.919	6.728
Patents RE Knowledge Stock	272	476.128	1026.011	2.350	6716.002
Patents Solar Energy	272	42.733	105.462	0	762.090
Patents Wind Energy	272	26.661	58.979	0	349.000
Patents Biomass	272	8.632	13.310	0	81.790
Patents Ocean Energy	272	3.721	5.670	0	38.000
Patents Geothermal Energy	272	1.320	3.195	0	27.000
Patents Hydroelectricity	272	3.828	6.896	0	59.830
Total public R&D for Solar Energy in Mill. Euro	272	20.858	30.179	0	140.600
Total public R&D for Solar Energy in % of GDP	272	0.011	0.008	0	0.054
Total public R&D for Wind Energy in Mill. Euro	272	8.205	12.734	0	75.941
Total public R&D for Wind Energy in % of GDP	272	0.007	0.011	0	0.073
Total public R&D for Biomass in Mill. Euro	272	17.245	22.575	0	140.532
Total public R&D for Biomass in % of GDP	272	0.016	0.018	0	0.103
Total public R&D for Ocean Energy in Mill. Euro	272	1.366	2.755	0	15.834
Total public R&D for Ocean Energy in % of GDP	272	0.002	0.004	0	0.032
Total public R&D for Geothermal Energy in Mill. Euro	272	2.002	4.585	0	24.706
Total public R&D for Geothermal Energy in % of GDP	272	0.001	0.001	0	0.013
Total public R&D for Hydroelectricity in Mill. Euro	272	1.273	2.347	0	12.731
Total public R&D for Hydroelectricity in % of GDP	272	0.001	0.003	0	0.029
GDP Deflator	272	145603.8	173140.7	5418.9	745226.0

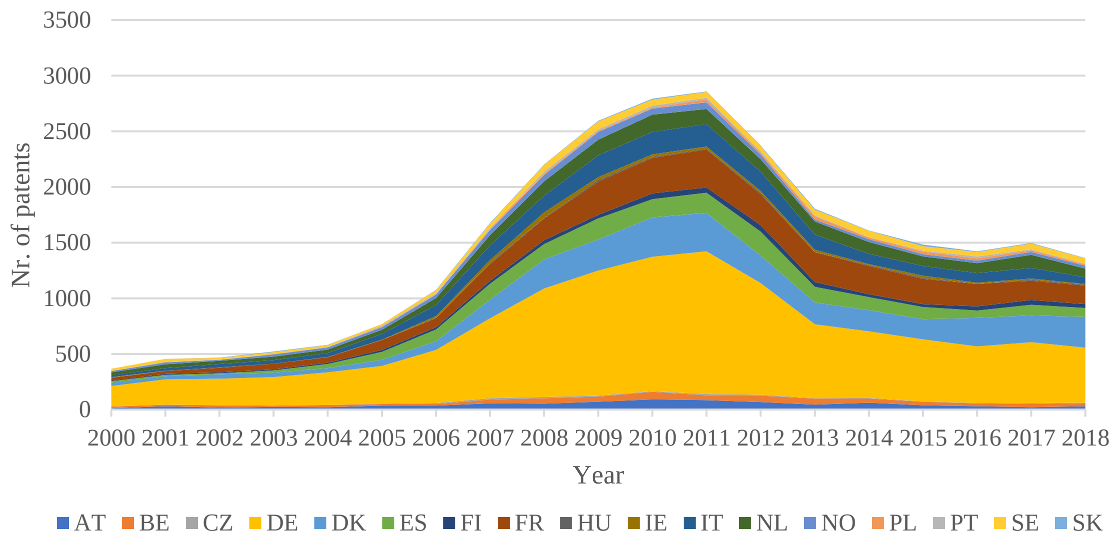

Figure A.4.i. Total number of patents for renewable energy technologies from 2000-2018 in 17 European countries by country.

Table A.4.ii: Output of Hausman Test of H0: Difference in coefficients not systematic	
chi2(8)	= (b-B)'[(V_b-V_B)^(-1)](b
	= 91.70
Prob > chi2	**= 0.0000**
(V_b-V_B is not positive definite)	

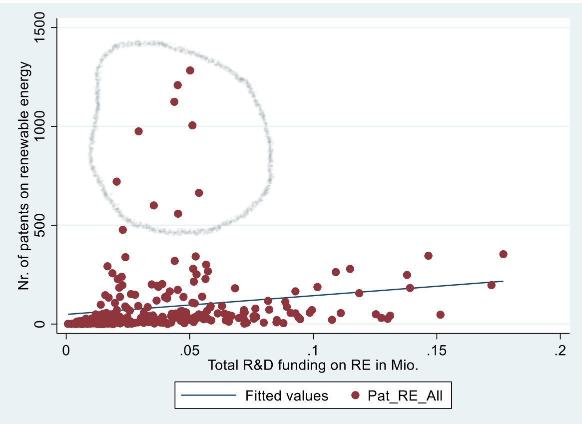

Figure A.4.ii. Scatterplot for renewable energy research and development funding and renewable energy patents (lagged by one year) (all 17 countries, 2000-2015).

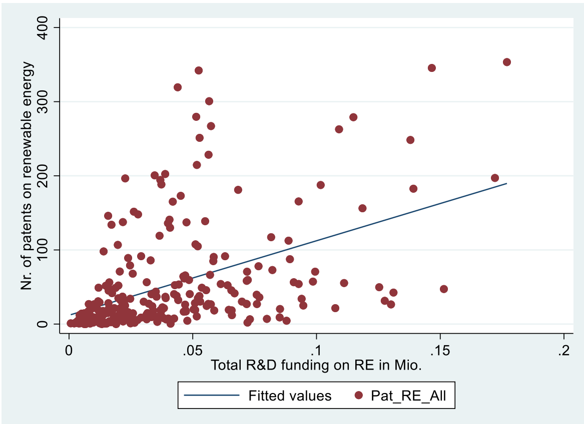

Figure A.4.iii. Scatterplot for renewable energy research and development funding and renewable energy patents (lagged by one year) (16 countries **except Germany**, 2000-2015).

Appendix 5 on Estimation Results

Table A.5.i: Comparison of negative binomial regression estimates for the effect of public research and development funding on innovation in renewable energy technologies between ***countries*** (Equation (1)) (dependent variable: patents in the renewable energy sector (lag 1))

	(1)
Variable	**2000-2015**
Total public RE R&D	17.410**
	(0.00)
Country=AT # Total public RE R&D	0.000
	(.)
Country=BE # Total public RE R&D	-15.180***
	(0.00)
Country=CZ # Total public RE R&D	3.007
	(0.73)
Country=DE # Total public RE R&D	1.327
	(0.80)
Country=DK # Total public RE R&D	-10.320*
	(0.03)
Country=ES # Total public RE R&D	-0.492
	(0.90)
Country=FI # Total public RE R&D	-6.034
	(0.22)
Country=FR # Total public RE R&D	-10.040
	(0.11)
Country=HU # Total public RE R&D	-2.537
	(0.36)
Country=IE # Total public RE R&D	-4.641
	(0.05)
Country=IT # Total public RE R&D	-10.400
	(0.39)
Country=NL # Total public RE R&D	-14.500**
	(0.00)
Country=NO # Total public RE R&D	-21.330***
	(0.00)
Country=PL # Total public RE R&D	-3.189
	(0.56)
Country=PT # Total public RE R&D	-12.560
	(0.32)
Country=SE # Total public RE R&D	-18.340***
	(0.00)
Country=SK # Total public RE R&D	-5.672
	(0.49)
Electricity prices	-1.798
	(0.69)
Energy consumption	0.028
	(0.14)
Patents all technologies	0.000***
	(0.00)

Feed-in tariffs	0.019
	(0.73)
Standards	0.165***
	(0.00)
Taxes	0.043
	(0.60)
Trading schemes	0.145***
	(0.00)
Constant	
Observations	272

Note. Table A.5.i displays country-specific negative binomial regression estimates for Baseline Equation (1) for the whole period 2000-2015. More specifically, and equally to Table 2 Column 3, this table displays estimates for the effect of public R&D support for renewable energy technologies (measured in % of GDP) on patents in the renewable energy sector (lagged by one year and restricted to at least family size 2, which excludes low quality patents). The additional covariates (Section 4.2) include: final energy consumption and electricity prices for domestic consumers (expressed in Purchasing Power Standards) as measures of demand; the number of patents in all technologies (restricted to at least family size 2) as measure of the propensity to patent; OECD indices for the environmental policy stringency of feed-in tariffs, standards, taxes and trading schemes. The baseline country is Austria (AT), for which the association between public R&D funding and patenting is statistically significant and positive. For Belgium (BE), the coefficient remains positive and statistically significant (17.41-15.18=2.23). The positive and statistically significant effect of public R&D funding is confirmed for most countries (except for Norway and Sweden).

p-values are displayed in parentheses:

*** Significance at the 0.1 percent level.

** Significance at the 1 percent level.

* Significance at the 5 percent level.

17 European countries are included: Austria (AT), Belgium (BE), Czech Republic (CZ), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Hungary (HU), Ireland (IE), Italy (IT), The Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Sweden (SE), Slovakia (SK).

Table A.5.ii: Comparison of NBRM estimates for the effect of public research and development funding on innovation in renewable energy technologies (Equation (1)) between ***sectors*** (dependent variable: patents in the renewable energy sector (lag 1))

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variable	**Biomass**	**Wind**	**Solar**	**Ocean**	**Geothermal**	**Hydroelectricity**
R&D Biomass	7.906**					
	(0.01)					
Electricity prices	4.517	7.996***	3.687*	6.151*	-3.931	1.934
	(0.05)	(0.00)	(0.03)	(0.01)	(0.42)	(0.46)
Energy consumption	0.029**	0.024*	0.044***	0.042***	0.036	0.016
	(0.00)	(0.02)	(0.00)	(0.00)	(0.05)	(0.20)
Patents all technologies	-0.000	0.000	-0.000	-0.000***	0.000***	-0.000
	(0.63)	(0.09)	(0.79)	(0.00)	(0.00)	(0.33)
Feed-in tariffs	0.056	0.013	0.056	0.036	0.032	-0.021
	(0.10)	(0.70)	(0.07)	(0.45)	(0.61)	(0.64)
Standards	0.135**	0.156***	0.177***	0.209***	0.135	0.288***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)
Taxes	-0.075	-0.055	0.006	-0.118	0.163	-0.212
	(0.43)	(0.61)	(0.95)	(0.31)	(0.40)	(0.12)
Trading schemes	0.225***	0.125**	0.197***	0.120*	0.174*	0.130*
	(0.00)	(0.00)	(0.00)	(0.04)	(0.01)	(0.03)
R&D Wind		13.490*				
		(0.03)				
R&D Solar			15.080**			
			(0.00)			
R&D Ocean				-18.780		
				(0.14)		
R&D Geothermal					17.130	
					(0.77)	
R&D Hydroelectricity						-27.300
						(0.23)
Constant	-2.288*	-2.868*	-4.672***	-3.340*	-4.173	-0.931
	(0.05)	(0.01)	(0.00)	(0.01)	(0.05)	(0.51)
Observations	272	272	272	272	256	272

Note. Table A.5.ii displays sector-specific negative binomial regression estimates for Baseline Equation (1) for the whole period 2000-2015. More specifically, and equally to Table 2 Column 3, this table displays estimates for the effect of public R&D support for renewable energy technologies (measured in % of GDP) on patents in the renewable energy sector (lagged by one year and restricted to at least family size 2, which excludes low quality patents). The additional covariates (Section 4.2) include: final energy consumption and electricity prices for domestic consumers (expressed in Purchasing Power Standards) as measures of demand; the number of patents in all technologies (restricted to at least family size 2) as measure of the propensity to patent; OECD indices for the environmental policy stringency of feed-in tariffs, standards, taxes and trading schemes. The effectiveness of public R&D funding on patents in the specific RE sectors is estimated separately for all RE sectors (biomass, wind energy, solar energy, ocean energy, geothermal energy, hydroelectricity). The positive and statistically significant effect of public R&D funding is confirmed for all three renewable energy sources which currently provide the most renewable energy (biomass, solar and wind).

p-values are displayed in parentheses: *** Significance at the 0.1 percent level; ** Significance at the 1 percent level; * Significance at the 5 percent level.

Appendix 6 on Sensitivity Analyses and Robustness Checks

Table A.6.i: Negative binomial regression estimates for the effect of public research and development funding on innovation in renewable energy technologies compared to Poisson regression estimates and Ordinary Least Square regression estimates (Equation (1)) (dependent variable: patents in the renewable energy sector (lag 1))

Variable	**(1)** **NBRM** **2000-2015**	**(2)** **PRM** **2000-2015**	**(3)** **OLS** **2000-2015**
Total public RE R&D in % of GDP	6.058***	8.701***	832.800*
	(0.00)	(0.00)	(0.05)
Electricity prices	4.292**	-0.058	-263.800
	(0.00)	(0.98)	(0.18)
Energy consumption	0.035***	0.021	-0.418
	(0.00)	(0.23)	(0.74)
Patents all technologies	0.000	0.000***	0.136***
	(0.70)	(0.00)	(0.00)
Feed-in tariffs	0.044	-0.021	-9.674
	(0.08)	(0.62)	(0.26)
Standards	0.153***	0.158***	-1.098
	(0.00)	(0.00)	(0.84)
Taxes	-0.034	-0.093	-14.670
	(0.66)	(0.25)	(0.48)
Trading schemes	0.158***	0.140***	5.817
	(0.00)	(0.00)	(0.13)
Constant	-3.376***		-373.200**
	(0.00)		(0.00)
Observations	272	272	272
BIC	2088.7	4701.5	3163

Note. Table A.6.i compares negative binomial regression estimates (NBRM) for Baseline Equation (1) with poisson regression estimates (PRM) and ordinary least square estimates (OLS). All available years (2000-2015) are included. As in Table 2, the dependent variable is the by the OECD constructed number of renewable energy patents per year and country, lagged by one year and restricted to patents of at least family size 2, which excludes low quality patents (as described in Section 4.1.). The additional covariates (Section 4.2) include: final energy consumption and electricity prices for domestic consumers (expressed in Purchasing Power Standards) as measures of demand; the number of patents in all technologies (restricted to at least family size 2) as measure of the propensity to patent; OECD indices for the environmental policy stringency of feed-in tariffs, standards, taxes and trading schemes. Estimates for ‘Total public RE R&D’, the variable of main interest, indicate the effect of public R&D support for renewable energy technologies (measured in % of GDP) on patents in the renewable energy sector. The estimates reveal that the finding of a positive and statistically significant effect of public R&D funding is independent of the chosen model. For other covariates, however, the choice of model matters. The main reliance on the NBRM in this piece is justified in Section 4.3.

BIC-values as measures for model-fit are displayed at the bottom.
p-values are displayed in parentheses: *** Significance at the 0.1 percent level; ** Significance at the 1 percent level; * Significance at the 5 percent level.

Table A.6.ii: Correlation matrix

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(1) Total public RE R&D	1							
(2) Feed-in tariffs	-0.07	1						
(3) Standards	0.33	0.13	1					
(4) Taxes	0.17	-0.15	-0.06	1				
(5) Trading schemes	0.33	-0.13	***0.58***	0.18	1			
(6) Electricity prices	-0.35	0.12	0.01	0.08	0.01	1		
(7) Energy consumption	0.01	-0.35	-0.04	-0.01	0.18	-0.24	1	
(8) Patents all technologies	-0.02	0.28	0.17	-0.17	-0.07	-0.11	0.11	1

Table A.6.iii: Correlation matrix replacing variables "Feed-in tariffs", "Standards" and "Taxes" with overall "Market-based EPS"

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) Total public RE R&D	1					
(2) Market-based EPS	0.18	1				
(3) Standards	0.33	***0.41***	1			
(6) Electricity prices	-0.35	0.14	0.01	1		
(7) Energy consumption	0.01	-0.20	-0.04	-0.24	1	
(8) Patents all technologies	-0.02	0.14	0.17	-0.11	0.11	1

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