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Abstract

In this thesis, I investigate the effects of carbon taxes on the direction of innovation in the energy sector. Using patent data from the World Statistical Patent database and fossil fuel tax data from the Energy Prices and Statistics database, I exploit firm-level variation in the carbon taxes. The firm-specific tax rate is calculated on the basis of firms' different exposures to locations. The direction of innovation is defined as the difference of weighted patent counts between clean and dirty energy supply technologies, where clean refers to CO2-free or low-carbon technologies and dirty to carbon-intensive technologies. I find a strong and positive effect of the carbon tax on the direction of innovation. Moreover, firms innovating a lot in one type of technology are more likely to continue in this direction in the future, providing evidence for path dependency.

Zusammenfassung

In dieser Arbeit untersuche ich die Auswirkungen von CO2-Steuern auf die Richtung der Innovation im Energiesektor. Unter Verwendung von Patentdaten aus der World Statistical Patent Database und Daten zur Besteuerung fossiler Brennstoffe aus der Energy Prices and Statistics Database berechne ich die unternehmensspezifischen Unterschiede der CO2-Steuern. Der unternehmensspezifische Steuersatz wird auf der Grundlage der Verteilung der Unternehmen auf verschiedene Standorte bestimmt. Die Innovationsrichtung ist definiert als die Differenz der gewichteten Anzahlen der Patente für eneuerbare und herkömmliche Energieversorgungstechnologien, wobei Erneuerbare als CO2-neutrale oder kohlenstoffarme Technologien und Konventionelle als kohlenstoffintensive Technologien definiert werden. Ich finde einen starken positiven Effekt der CO2-Steuer auf die Richtung der Innovation. Darüber hinaus ist es wahrscheinlicher, dass Unternehmen, die in die Innovation bestimmter Technologien investieren, diese Investitionsrichtung auch in Zukunft beibehalten werden, was auf eine Pfadabhängigkeit hinweist.

1 Introduction

In recent decades one topic has consistently occupied the minds of both researchers and policymakers. Climate change, making extreme weather events like wildfires, droughts, and floods much more likely, threatens the livelihoods of millions of people around the world (Lee & Romero, 2023; WMO, 2023). The share of society agreeing on the urgency of mitigating the causes of climate change is rising. However, there is still great ambiguity regarding concrete solutions. In the long run, it is clear that carbon-intensive technologies will have to be substituted with emission-free or, if not possible, low-carbon technologies. This is a necessary step to preserve some of the world's global wealth that has been accumulated over the last centuries. Some economists are quick to recommend a carbon tax as the optimal policy, internalizing the causes of the negative externalities of climate change. Others favor subsidies to research and development in emission-free technologies or a mixture of the two policies. But how do these policies affect innovation in climate change mitigation technologies that are desperately needed? Addressing this question for the energy sector is particularly important, as its environmental impact is accountable for up to 40% of global emissions, depending on the definition of the industry (IEA, 2022; UN, 2014).

In this thesis, I want to provide insights into this issue by looking at the effects of carbon taxes on the direction of innovation in the energy sector. Specifically, I investigate the effects of taxes imposed on fossil fuels on the relative number of patents relating to climate mitigation technologies. I adopt definitions of clean and dirty patents, where clean patents relate to technologies that are associated with the supply of carbon-free energy commodities and the latter to innovations in carbon-intensive energy products. I define the difference between the two to be the direction of innovation. Using patents as indicators of innovation allows me to investigate the effects of carbon taxes on a firm level. I construct a firm-specific measure of carbon taxes, as proposed by Aghion et al. (2020), through the estimation of country weights, reflecting the firm's exposures to different locations. Additionally, patents are weighted by the number of references they receive from other patent documents, indicating the economic value of the patent (Harhoff et al., 1999). Furthermore, firms' innovation activities are likely to depend on the firm's path, meaning that the present direction of innovation is to some degree determined by past innovations (Popp, 2002). Similarly, a firm might experience knowledge spillover, i.e., is affected by the average patent portfolio of the countries it operates in. I review two theoretical models, compiled by Aghion et al. (2020) and Acemoglu et al. (2012), to guide the formulation of the empirical specifications and derive hypotheses about the estimated coefficients. Both models obtain path dependency by assumption of the specific productivity functions. Knowledge spillovers are implicitly assumed only in the model of Aghion et al. (2020). Finally, a fixed effects estimation that incorporates the possible predictors is deployed. The two main datasets used for this approach are the World Statistical Patent database (PATSTAT), managed by the European Patent Office (EPO), and the End-use prices dataset from the Energy Prices and Statistics database that is provided by the International Energy Agency (IEA).

The results obtained are in line with theory and similar to findings from recent works. I find a strong and positive effect of the carbon tax rate on the direction of innovation. A 10% increase in the carbon tax rate increases the relative number of clean to dirty patents by 1.5%-2.75%, on a firm level. Furthermore, the results corroborate the assumption of path dependency. Particularly clean patent stocks induce firms to innovate in clean technologies, as a 10% increase in the clean stock is associated with a 2.5% increase in the filing of clean patents. The estimated effects tend to be greater for firms that file a larger amount of patents.

In the following paragraph, I discuss literature related to the work of this thesis. Newell (1998) builds on Hick's induced innovation hypothesis to look into the effects of government efficiency standards on innovation (Hicks, 1932). In particular, they examine the energy efficiency of different appliances like air conditioners and water heaters through the use of catalog data. They find that regulations in these fields have decreased the operating costs of the appliances through innovations in energy efficiency. Popp (2002) continues the inquiry into the energy efficiency of technologies but also considers a broader spectrum of machinery related to classical pollution activities and renewable energy. Instead of efficiency standards, he considers energy prices to influence the direction of innovation. Being one of the first authors to utilize patents as indicators of innovation in this matter, he suggests that firms exhibit path dependency in their innovation activities. Moreover, he finds that only successful innovation, proxied by citation-weighted patents, is affected by changes in energy prices.

Recently, a lot of research has been discussing innovation in clean and dirty technologies. Calel (2020) investigates British firms subject to the European cap-and-trade regulation. He finds that firms patent to a greater extent in low-carbon technologies than their competitors, not subject to regulation. However, his results do not indicate that these firms reduce carbon emissions over the observation period. Fried (2018) deploys a general equilibrium model to explore the effects of a carbon tax on innovation in green technologies. He utilizes historical oil shocks to estimate departures of growth in technology from the initial growth path. The author finds positive changes in the growth path of green innovation and negative changes in fossil innovation after the implementation of a carbon tax. Acemoglu et al. (2012) formulate an endogenous growth model to explore the optimal policies in a world with clean and dirty inputs exhibiting environmental constraints. They find a mixture of a carbon tax and subsidies to clean research to be the most efficient policy. The result strongly depends on the elasticity of substitution between the two inputs as well as resource constraints on the dirty input. An extension of Acemoglu et al. (2012) can be seen in Acemoglu et al. (2016) distinguishing between clean and dirty technologies instead of inputs. They use US micro-data to simulate various policies and focus on the timing of interaction between a carbon tax and research subsidies. Finally, Aghion et al. (2020) study the effects of gasoline and diesel prices on firms' patent activity in the auto sector. They consider a microeconomic model, incorporating dynamics of fuel prices on the demand for different types of vehicles. They establish a new approach that uses firm-specific country weights to exploit differences in tax rates applicable to firms. They find strong evidence for the path dependency of firms in the auto sector and a positive effect of fuel prices on the patent activity of firms.[1]

This thesis is structured as follows. After the literature analysis above, section 2 briefly describes two theoretical models used to guide the empirical approach.

[1] Additionally, Gurun et al. (2020) investigate green energy production in the US and find that firms with particular low ESG scores drive patent activity in this industry. This might be relevant, as the firms investigated in the analysis are to a large extent, typical fossil fuel firms.

Section 3 depicts the empirical model. Section 4 describes the data being used and possible concerns related to data methodology. In section 5, I show summary statistics and discuss the results of the estimation of the empirical model. Section 6 discusses several robustness checks and limitations of my chosen approach. Section 7 concludes.

2 Theory

In the following section, I discuss different aspects of theory related to innovation activities in the energy sector. I outline some of the underlying assumptions for the chosen approach and discuss theoretical predictions from both a microeconomic and macroeconomic model aiming at the description of research activities of firms.

The model by Aghion et al. (2020) describes the behavior of firms operating in the automobile industry. Firms face consumers with quasi-linear preferences that choose between clean and dirty car bundle varieties, consisting of cars and energy for the specific car type. Firms can produce and innovate in clean or dirty car varieties, or both, where the decision to innovate incurs a cost. The number of varieties a firm can produce is fixed. Furthermore, it is assumed that clean/dirty varieties are more substitutable among themselves than dirty/clean varieties. The outside good, in turn, is less substitutable with different types of cars than the cars among themselves. Producers are local monopolists, where the number of cars produced using one unit of the outside good corresponds to the firm's productivity for the specific type of car and variety. Thus, innovation is cost-saving for producers[2]. The stock of technology determines the productivity for a given variety and type of car from the previous period and the current investment in innovation for this good. Firms decide on how much to invest in innovation and subsequently decide on production.

Substituting car bundles through energy products yields an immediate applica-

[2]Extension to innovations improving energy efficiency can be found in subsection 2.3 of Aghion et al. (2020).

tion for the energy industry.[3] Analogous to Aghion et al. (2020), the change in the equilibrium innovation intensity of the clean energy product i is then given by

$$\widehat{x_{ci}} \propto (\varepsilon - \beta) \frac{P_d^{1-\varepsilon}}{P_c^{1-\varepsilon} + P_d^{1-\varepsilon}} \widehat{P_d} \tag{1}$$

where ε is the elasticity of substitution among clean and dirty energy products and β is the elasticity of substitution between the outside good and energy products.[4] P_c and P_d denote the price indices of clean and dirty energy products, defined as $P_z = \left(\int_0^1 (p_{zi} + \tau_z)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$ for $z \in \{c, d\}$ where σ is the elasticity of substitution of different varieties of clean and dirty products. Note that $\widehat{X} = \frac{dX}{X}$ and that τ_z is the potential tax on the type of energy z. This result implies that innovation in clean energy varieties increases if the average prices of dirty energy products get more expensive. Decreases in the price of clean products spur innovation in these technologies. The magnitude of these effects depends on the difference in the elasticities of substitution between different types of energy products and energy products and the outside good. The equilibrium innovation intensity in dirty energy products analogously increases in the price of clean products and decreases as dirty products get more expensive. Moreover, innovation depends on the existing technology stock in a given sector. The firms' innovation intensity in clean/dirty energy technology increases with the clean/dirty technology stock.[5] This result follows directly from the specific form of the assumed productivity function.[6] The size of this effect depends on the elasticity between different varieties of the same type of energy products as consumers switch from one variety to another. In an extension of the model, knowledge spillovers are introduced. Firms that operate geographically close to one another experience knowledge flows from other firms that potentially affect their own research activities. The result of this is that firms'

[3] Neglecting the energy efficiency of different types of cars and the additional energy input in the original model. The omission of these factors does not change the form of equilibrium intensities, as is directly apparent from the definition of the price index for dirty and clean car bundles and the inverse demand curve (Equation (2)) and equilibrium profits (Equation (3)) in Aghion et al. (2020)

[4] This result holds only for sufficiently small innovation intensities, which is assumed for the subsequent analysis.

[5] This hold only if the elasticity of substitution between varieties of a type of energy product is large enough. For a full description, see subsection 2.2.2 of Aghion et al. (2020).

[6] $A_{zi} = (1 + x_{zi})A_{zi0}$ where A_{zi} is the productivity, x_{zi} is the investment in R&D and A_{zi0} is the initial productivity of type z and variety i.

innovation intensity does not only depend on its initial stock of technology for the type of energy product but also on the average stock of technology in the locations the firm operates in.[7]

Acemoglu et al. (2012) employ a tractable growth model to delve into the dynamics of research activities in different sectors with environmental constraints. Note that the authors refer to different types of inputs instead of commodities, which does not change anything.[8] The model features three types of economic agents, workers, entrepreneurs, and scientists, that consume a unique final good and additionally derive utility from the quality of the environment. The final good is produced from clean or dirty inputs. The clean or dirty inputs are produced through the use of labor and clean/dirty machines.[9] Scientists decide in which technology to innovate and are successful with some probability η_j, with j being clean or dirty. If successful, the scientist subsequently becomes a monopolistic entrepreneur for one period. Productivity in sectors where innovation is successful increases. Production of the final good, using dirty inputs, deteriorates the quality of the environment. In the model's equilibrium, without any environmental policies, innovation in the sector that exhibits a larger stock of technology is more frequent. If the difference between the initial stocks is large, innovation occurs only in one sector.[10][11] Depending on the extent of substitutability between dirty and clean inputs, a temporary tax on dirty inputs and subsidies for clean machines induces scientists to switch from dirty to clean innovation.[12]

Summarizing the main predictions from theory, the relative innovation intensity of a firm depends on its initial stock in both clean and dirty energy technology as well as knowledge spillovers from other firms. The size of these effects is determined by the elasticity of substitution between different varieties of the same type of energy. Increases in prices of dirty energy products, e.g., due to changes in the tax rate, favor clean innovation activities of firms. The magnitude of this depends on the difference

[7]There is no distinction made between the location of business operations and that of research facilities where innovation takes place. Even if one would distinguish between the two, spillovers are likely to occur wherever the technology is finally applied.

[8]Energy commodities, in any case, are only being used as inputs.

[9]The original model also features the possible existence of an exhaustible resource, which I neglect for the simple description of the model.

[10]For a more detailed description, see Acemoglu et al. (2012).

[11]The two inputs have to be substitutes for the result to hold.

[12]This requires the discount rate to be sufficiently low.

between the elasticity of substitution between dirty and clean energy products and the elasticity of substitution between all energy products and the outside good (Aghion et al., 2020). The path dependency of firms' research is additionally shown to hold in the context of an endogenous growth model. Taxing dirty inputs and subsidies for the research of clean technologies induce future entrepreneurs to switch from dirty to clean innovation activities (Acemoglu et al., 2012).

3 Econometric model

In the following section, I describe the main empirical model used in the analysis as well as possible methods of estimation. I briefly formulate hypotheses for the model's coefficients, based on predictions from theory.

The following equation gives the main specification to be estimated:

$$\begin{aligned} InnovationDirection_{it} = {} & \beta_D CarbonTax_{it+3} + \beta_C CleanTax_{it+3} \\ & + \alpha_C Stock_{C,it} + \alpha_D Stock_{D,it} + \gamma_C Spillover_{C,it} + \gamma_D Spillover_{D,it} \\ & + \eta X_{it} + I_i + T_t + u_{it} \end{aligned} \tag{2}$$

where the dependent variable, $InnovationDirection_{it}$ is given by the log differences between the number of clean and dirty of patents, weighted by citations, for firm i at time t, i.e. $ln(1 + \#Clean\ Patents^{w}_{it}) - ln(1 + \#DirtyPatents^{w}_{it})$. Note that one is added to the weighted number of patents as the natural logarithm is undefined at zero. The first right-hand side term is the variable of interest, given by the firm's specific log carbon tax rate three years from today. This tax rate is calculated as the mean of taxes on fossil fuels weighted by the firm-specific country weights. The second term relates to the counterpart of taxes on electricity. The following two terms represent the firm's clean and dirty patent portfolio, that is, the depreciated sum of granted patents at time $t-1$. An additional dummy is included for both stock variables if they are equal to zero for at least two periods over the observation horizon. The spillover variables cover patent portfolios of countries weighted by the firm's specific country weights and the firm's number of R&D workers in that country. A collection of controls is summarised in X_{it}, including, e.g., government R&D

subsidies for energy production and transmission or related fields and an environmental policy indicator. As the control variables are only available at the country level, they are transformed in the same fashion as the tax rates, i.e., calculated as the mean weighted by the firm-specific country weights. Finally, the model includes firm- and time-fixed effects plus an error term that is allowed to vary across individuals and time. All "real" variables, not counting dummy and indicator variables, are log-transformed, with one being added wherever mathematically convenient.

The main advantage of this specification is the parsimony regarding dynamics. This model can be estimated using a two-way error component model, keeping the structure of the lags and errors relatively simple. For example, Baltagi (2021) shows that if the true model is of a two-way error component structure, the obtained estimates are consistent, unbiased, and even efficient, neglecting for a moment the possibility of heteroskedasticity and serial correlation in the errors.

In the presence of heteroskedasticity and/or serial correlation, the proposed model can be consistently estimated by generalized least squares (White, 1980). Furthermore, taking into account the missing observations, Baltagi et al. (2002) shows that simple Analysis of Variances, i.e., fixed effects estimation, is the preferred method of estimation.[13][14]

If the specified model yields estimates that are in line with what theory predicts, I expect the coefficients on the measure of carbon tax to be positive. The effect of a tax on clean energy is expected to be negative. The sign on the coefficients of the clean stock, clean spillover, and clean R&D is predicted to be positive and negative for the dirty counterparts. It is difficult to predict the magnitudes of the estimated effects, as in theory, they depend on the different elasticities of substitution, which are hard to estimate for the global energy sector.[15]

[13]Individual firm data are cohesive time series, where the PDF of the time of the series' first observation is approximately the exponential function.

[14]The measure of unbalancedness of the data, as proposed by Ahrens and Pincus (1981) is 0.718.

[15]Elasticities of substitution are likely sub sector-specific and may also greatly depend on the location, where distinct "end technologies" are being used.

4 Data

In this section, I refer to the different data used to estimate the model described above. As the present analysis greatly builds on the data methodology, I discuss specific topics in detail, such as citation weights and identification of patents associated with the energy sector.

4.1 PATSTAT Global 2022 (Autumn)

I use patent data from the PATSTAT Global 2022 (Autumn) bulk data set provided by the European Patent Office (EPO) and updated semi-annually. This data set contains detailed bibliographic information about patent applications and publications from 90 patent issuing authorities. It covers over 253,000 million patent-firm pairs from approx. 40 million firms dating back to the Mid-19th century. For the present analysis, I will use information on the date of application and filing, application authority, number of citing documents, technical classification, as well as detailed personal information on applicants and inventors.

4.1.1 Patent counts and citation weighting

Single entries in the PATSTAT database are associated with publications of patents or amendments to these publications. As patent publications differ by patent offices, I vary my inclusion parameters for publications by the relevant authority. For example, I include all patents filed at the EPO; however only consider patents granted by the USPTO. I follow this approach since patents filed with the USPTO were only finally published if granted, for the period prior to 2001 (EPO, 2022b).[16] It takes an average time of three years for a patent to get granted with the USPTO, in very few cases much longer OECD (2009).

Since I want to count patents by applicant rather than different publications of the same invention, I focus on the international patent family (IPF), for each family is endowed with a unique identifier. The purpose of IPFs is to describe a collection of patent documents that claim a single invention. This approach avoids double counts of the same patent. Particularly, only the priority right of inventors,

[16]For more information on data coverage of national patent authorities check PATSTAT Support, by EPO (2022a)

introduced in Article 4 of the Paris Convention for the protection of industrial property, makes it possible to file patents with claims on identical contents across different patent offices. As the earliest filing date of a patent publication relates only to the specific patent and not the corresponding patent family, I consider the earliest filing date of the original patent application (priority date) as the filing date of all patents in that same family. This date, as the earliest date associated with a single invention, gives the best proxy for the date of invention.

I group patent counts by the applicant, only considering legal persons that are firms.[17] If there is more than one applicant, I allocate fractional counts to the firms with applicant status.

Moreover, I restrict my sample to firms that have filed patents over at least five, not necessarily consecutive, years or firms that have filed at least ten patents over at least four, not necessarily consecutive, years. This restriction is essential to estimating the firm-specific location weights discussed in the next section.

I consider patents filed after 1980 and use 2018 as the cut-off, leaving me with almost three times the length of the publication lag between filings and latest publications. I do not consider the legal event data with information on transfer of ownership, revocation, or annulation of patents. Although this information might be relevant in some cases, generally, it applies in the least of cases.

Since sheer patent applications make for a poor measure of innovation, I retrieve for each patent the number of other patent documents citing the specific invention. A patent includes references to another patent if the corresponding contents are closely related to one another or if the invention builds on the contents of the other patent. The literature commonly considers the number of references from other patents to reflect, on average, the patent's technological importance and economic value (Hall et al., 2000; Harhoff et al., 1999; Harhoff et al., 2003). These references are typically outlined in a search report that accompanies a patent's application to ensure the legitimacy of the claim with respect to its uniqueness and usefulness. A legal examiner at the relevant patenting authority incorporates the final references

[17] A significant number of patents are issued by applicant individuals. However, patent counts by non-firm applicants are usually only a few single issuances, making for poor time series. Additionally, they receive, on average, fewer citations, indicating lower value.

included.[18]. The protocol in this regard is advantageous for statistical analysis, making the number of citations comparable within the same office. Nonetheless, there are stark differences between patent offices' citation practices and also changes in practices across years. The average number of citations for granted patents by the USPTO is, e.g., larger than for patents granted by the EPO. However, the number of patents that contain at least one reference to other patent documents is greater for EPO applications, pointing to differences in distribution (Callaert et al., 2006; OECD, 2009).[19] In order to factor in these artefactual differences, I group citations by patent office and year. I do not group by technological field, considering differences in this regard entirely value-based.[20] Accounting for differences among years does not only capture potential changes in patenting practices but, more importantly, considers citation lags. Naturally, most recent cohorts of patents have fewer citations on average than marginally older cohorts. This is due to the fact that there are more patents around that could have potentially cited contents from the older cohort, as they have been published for a longer time.

Patent citations being patent-specific indicators of value, it is most intuitive to use the number of citations as weights for the corresponding patent. E.g. Harhoff et al. (2003) propose value-weighted patents as indicators of innovation using citations and references to patent applications. The authors find that citation-weighted patents are viable indicators of innovation by comparing these measures to survey data from patent holders. Guellec and van Pottelsberghe de la Potterie (2000) and Harhoff et al. (2003) have shown that the number of forward citations, which are the citations received by a patent, is a good indicator of patent value. Sidak and Skog (2018) study different methodologies in determining a patent value for standard-essential patents, finding that citation weighting is beneficial regardless of the specific form of implementation.

I use the following weighting scheme proposed by Trajtenberg (1990)

[18]For applications at some patent offices, like the USPTO, it is required that applicants have already conducted a preliminary search report with references to other patent documents (at the USPTO, this is referred to as "duty of candour"). However, the final search report is always complemented and/or amended by an examiner of the patent office.

[19]For a discussion of trends in global citations across cohorts see OECD (2009).

[20]This assumption is arguable. One could potentially partially account for differences between types of technology, however, making things much more obscure.

Figure 1: Patents vs. Citation Weighted Patents for 15 largest firms

Note: Number of patents and citation-based patent indicator are in non-log form. The weighting scheme used for the variables in the right graph is given by Equation (3) for $\alpha = 1.1$

$$WPC_t(\alpha) = \sum_{i=1}^{n} (1 + C_i^{\alpha}), \quad \alpha > 0. \tag{3}$$

where WPC_t is the patent count weighted by citations at time t, and C_i are the number of citations received by patent i. The sparse literature on the specific form of weights, most importantly Harhoff et al. (2003), points to a non-linear weighting scheme with values of $\alpha > 1$. From here on, I thus set α to be equal to 1.1 for the subsequent investigation. Figure 1 shows on the left-hand side the number of dirty and clean patents for the 15 largest firms in the sample. The green line gives the differences between the two counts. The right-hand side shows the same measures after the implementation of the weighting scheme and rescaling. I find a rather stark spread between the two measures over time by looking at the two graphs in Figure (1). Under the assumption that the number of references from other patents reasonably reflects a patent's economic value, simple patent counts do not seem to be an appropriate measure of meaningful innovation on an aggregated level.

Finally, limitations in the use of patents as indicators for innovation are present if the respective industry can not be characterized as technologically intensive. If firms do not use a large stock of technology for their business operations, patents might fail as proxies for the new technologies, even for large firms. For most sub-sectors of the energy industry, this however, holds true (OECD, 2011b).[21]

[21] Alternatives to patents in the continuing appropriation of knowledge might be, e.g., secrecy as suggested by OECD (2009).

4.1.2 Country weights

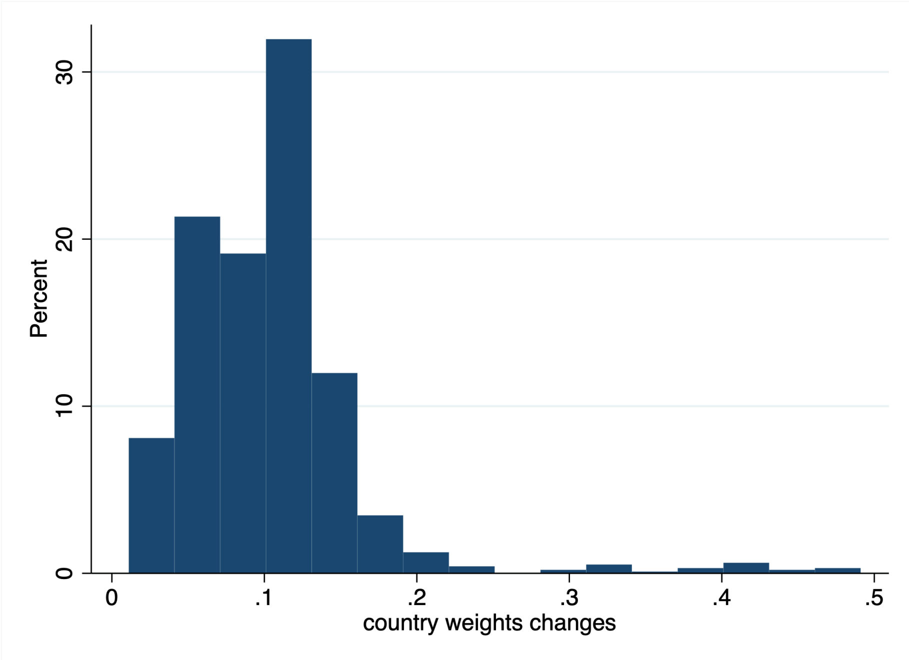
For the construction of a firm-specific carbon tax measure, I need, apart from the tax rate on the country level, the relative importance of a given country for the firm's operation. Such data on e.g., firm's revenue is hardly available on a large scale and, even if available, quite costly. I thus follow the idea of Aghion et al. (2020), who have come up with an alternative approach using patent data. The argument behind using patent data is their reflection on expected future profit opportunities in a given location. If a firm expects to operate in a given country, it will, if possible, restrict others from using its stock of technology. Arguably, patent data would then make for an even better measure of operation locations compared to, e.g., revenue data, which solely demonstrate present operations.

Based on a pre-regression sample, I calculate the country weights as the share of patents filed with different offices. For a firm that would, e.g., issue one patent in the US and Japan and another in Japan and the United Kingdom, the weights would be one-half for the US and one-fourth for Japan and the United Kingdom. As Aghion et al. (2020) note, the patent location could be influenced by shocks to innovation. Using a pre-regression sample for the calculation of them yields weakly exogenous country weights. The length of the pre-regression period being used depends on the total number of years that a firm filed patents. Firms issuing patents in only five years, the earliest two years are being used as the basis for the country weights. Three years are used if a firm filed patents in more than five but less than ten years. For firms with more than nine years of patent applications, country weights are calculated on the basis of the earliest four years.[22]

Furthermore, the sample only includes firms that filed at least 75% percent of their patents in the countries for which there is sufficient IEA energy tax data coverage and firms that do not have more than 10% of their patenting activity in a country not covered by the energy tax data. The residual share of the weight differs between countries and is apportioned evenly to the existing shares of weights. To make sure country weights are relatively time-invariant and weakly exogenous, I look

[22]Taking the earliest two to four years as the basis for the measure, depending on the patenting activity of the firm, covers on average 96% of application authorities the firm issues patents with over the total horizon. Patent applicants in the sample commonly issue patents only with a small number of different offices, as is typical for the energy sector.

Figure 2: Distribution of firms' country weights changes



Note: country weights changes on x-axis is given by Equation (4)

at changes in country weights, defined as the sum of absolute values of differences of existing country changes. For a firm whose country weights entirely changed over the observation period, this metric of change would then be equal to unity. The formula for this metric is given in Equation (4).

$$\sum_c |\omega_{c,t} - \omega_{c,T}| \quad \text{for} \ \ t = [t_{i,\min}, t_{i,(\min}+2,3,4)], \ T = [(t_{i,\max}-2,3,4), t_{i,\max}] \tag{4}$$

where $\omega_{c,t}$ is the country weight being used for the firm-specific tax rate and $\omega_{c,T}$ is the counterpart for the latest non-zero observations of the firm.

To make sure that weights did not substantially change between the first and last patent applications, I conducted the same procedure for in-between periods. The distribution of country weight changes across firms is given in Figure 2, indicating very limited shifts of location. Only a handful of firms exhibit weight changes greater than 20%.

4.1.3 Stocks and spillovers

Stocks and spillovers, used to investigate path dependency, are given by depreciated sums of the individual history of patents and the location's history of patents. I fix the depreciation rate of R&D capital to be 15% per year as discussed in the related literature (Bernstein, 1988; Hall, 1992; Nadiri & Prucha, 1993; Oladunjoye, 2008). The spillovers, before depreciation, are counted as the weighted average of the location's aggregated sum of past patents, where the weights are again the firm-specific country measures.

4.1.4 Energy sector

The energy industry encompasses operations directly related to the supply of energy commodities. It can roughly be divided into two sub-sectors, namely, the fossil fuel industry and the renewable energy industry. Operations in the fossil fuel industry include, e.g., the exploration, extraction, and processing of fossil fuels. Activities related to the renewable energy industry cover utilizing natural forces like the wind and sun and producing hydrogen from water electrolysis. Furthermore, the transmission of energy commodities is also attributed to the energy sector. Neighboring industries, such as the auto industry that share related technology stocks are not included in the definition.

Identification of patents, comprising inventions in the energy industry would not have been possible without prior works of the OECD and the EPO (Haščič & Migotto, 2015; Ménière et al., 2021b; OECD, 2015, 2017a).[23] I build on the framework of Ménière et al. (2021b) as well as codes and search filters of Acker et al. (2013). Each patent receives at least one technical classification in line with the Cooperative Patent Classification (CPC).[24] The structure of the CPC resembles a tree with eight broad categories that break down into further subcategories.[25] Although there are approximately 250,000 sub-classes at the lowest levels in the CPC, identifying clean and dirty energy patents is impossible by only utilizing CPC information. Take the

[23]Particularly their works on the search of patents related to fossil fuel technologies, even made distinctions between sub-sectors possible.

[24]The CPC is an extension of the International Patent Classification (IPC) that was introduced by the EPO in cooperation with USPTO in 2013 to provide even more detailed information on the technical fields of the patent's contents (EPO & USPTO, 2013; WIPO, 2023).

[25]The complete tree can be found here: CPC search.

subclass E21B43/16 that encompasses technologies for "Enhanced recovery methods for obtaining hydrocarbons (fracturing E21B43/14,...)". This class contains e.g. patent US63730384A filed in 1984 by OXY METHANE DRAINAGE CORP and METHTEC INC, relating to an oil mining method for spaced-apart formations. Experts consulted by the EPO found this to be useful only for the exploration of fossil fuels. The patent US63244803A filed in 2003, falls in the same subclass and protects a method for pumping water from underground by the use of a downhole hydraulic ram. Although inventions are classified in the same technical field, experts of the EPO found the second patent not to be of exclusive use to the exploration of fossil fuels. Incorporating more exclusion parameters of the CPC can not solve this issue. This is why the EPO and OECD created a list of search parameters to be used on the patent's abstract, in combination with the CPC (Ménière et al., 2021b). An overview of the technical fields in fossil fuels is given in Figure 3. Figure 4 shows some of the CPC ranges and search queries for the identification of technologies in conventional oil and gas exploration and extraction. A list of the English version of search queries is given in Figure 5.

The identification method is similar for clean energy patents, yet more tractable, as patents related to climate change mitigation technologies are given a special tag in the CPC. The Y02 class of the CPC is complementary to other classes and includes technologies for the mitigation or adaption against climate change (EPO, 2023; EPO & USPTO, 2013). Furthermore, the subclass Y02E is particularly useful for the present analysis, comprising applications of energy generation, transmission or distribution that aim at reducing greenhouse gases (EPO, 2023). Few patents that are attributed to clean energy technologies are not classed as Y02E and are identified via methodologies of the OECD and EPO (Ménière et al., 2021a; OECD, 2011a, 2017b, 2020). Figure 6 shows some of the technical classes used for identification of clean energy patents in energy generation.[26]

In the initial search, which includes all applicants without restrictions, I identify 58,644 fossil fuel patents and 67,313 clean energy patents.[27] Firms operating in the energy sector are then defined to be the applicants of the patents, with the prior

[26] The extensive list can be found here: CPC - Y02

[27] A comparison between the number of fossil fuel patents obtained via my approach and the approach used by the IEA can be found in Figure 7.

exclusion of non-firm applicants. After the implementation of the restrictions, I am left with 26,941 clean patents and 21,503 dirty patents that were filed by 1,718 firms.[28] For the firms identified, 94% issued patent(s) related to fossil fuels first before issuing patent(s) related to clean energy technology.

4.2 IEA End-Use Prices

For data on fossil fuel taxes and electricity taxes, I use the end-use prices dataset from the Energy Prices and Statistics database provided by the International Energy Agency (IEA). The data set includes detailed information on quarterly end-use prices and taxes for OECD countries and Colombia. The time of availability of the data depends on the admittance of the given country into the OECD, with the earliest observations starting in 1978. Information on legal tax rates, as well as the share of taxes in the final prices for firms, is collected on the national level and pooled to estimate average effective tax rates for industry and consumers.[29][30] Value added taxes are accounted for at the country level depending on the design of the tax system. The methodology of the IEA aims explicitly at the estimation of measures that are comparable between countries. The final country tax rates are stated as excise tax rates in 2005 $US PPP[31]. For a few countries, final country rates are estimated as average legal rates.[32] In most countries, both firms that produce, and firms that subsequently use fossil fuels are subject to taxes.[33]

Tax rates for different fossil fuel products are highly correlated within countries. As data on gasoline taxes has the most observations across countries and time, I use this as an indicator of the tax on fossil fuels for consumers and diesel tax rates for industries, respectively. The average of the log measures is then taken to reflect

[28]It is only possible to match different patent applications under the same reported name in the application typed in by hand, making the matching process prone to errors. Even the harmonized person names reported in PATSTAT products observed some smaller errors. I corrected some misspellings and matched alternative names for patent cases in the final sample by hand. Ultimately, this led to a reduction of approx. 2% of individuals in the panel.

[29]The type of institutions collecting on the national level varies by country. Often, national banks and regulatory authorities conduct the data collection.

[30]This is done via pump surveys (survey data from petrol stations) and company surveys.

[31]PPP rates were estimated from data by the IMF, The World Bank and CHELEM database.

[32]Even for these locations, consulting IEA (2023) shows that reported legal rates are still well enough approximations to effective rates in the context of cross-country-time comparisons.

[33]For a detailed discussion on which parties are taxed in a specific country, see *Taxing Energy Use 2019: Using Taxes for Climate Action* (2019), and "World energy statistics (Edition 2019)" (2020).

the fossil fuel tax of the location.[34] Consumer and industry electricity taxes are analogously combined to construct the indicator for the tax on clean energy.[35]

The final firm-specific tax rate is computed as the sum of the products of country-specific fossil fuel tax rates and the corresponding firm-specific country weights (Aghion et al., 2020). For a few periods in some countries, the effective tax rates on some energy commodities are zero or negative, making a log transformation unfeasible. Portugal e.g., subsidized high sulfur fuel oil in the shipping industry until the late 1980s. In recent years, in response to a stark increase in the cost of living, especially energy costs, the Netherlands amply subsidized household electricity. Thus, I set the negative and zero values equal to the lowest tax rate larger than zero for the given year.[36]

4.3 Other data

Apart from the data described in the previous sub-sections, I use research development and demonstration (RD&D) budget data from the IEA, detailing government subsidies for energy producing, refining, transmitting, and distributing technologies both in clean and dirty energy products ("Energy Technology RD&D Budgets Data" (2023)). Depending on the econometric specification, I use the key indicators for clean and dirty energy government budgets and detailed measures of budgets divided into upstream, processing, downstream, and transmission and distribution technology budgets for clean and dirty energy.

Data on the Environmental Policy Stringency index, focusing on climate change and air pollution mitigation policies is obtained from the OECD's Environmental Policy database.[37]

GDP data is from the World Development Indicator database of the World Bank. Ultimately, information on the share of diesel cars in the total passenger car

[34]For most countries, this is in line with the shares of energy consumption of consumers and industry (IEA, 2021; "World energy statistics (Edition 2019)", 2020).

[35]Note that there are no taxes on other types of clean energy in the production or conversion process (*Taxing Energy Use 2019: Using Taxes for Climate Action*, 2019).

[36]The lowest tax rate on gasoline in the full sample was imposed by the US in the year 1978 with 0.035$ per liter (2005 $US PPP).

[37]For missing values in earlier years, I have used the approach suggested by Kruse et al. (2022)

fleet is collected from European Environment Agency.[38][39]

5 Results

In the following paragraphs, I show summary statistics and continue with the main results obtained by the econometric model estimation.

5.1 Descriptive statistics

A description of summary statistics of the main variables is given in Table 1. The mean of the log differences between clean and dirty patents is 0.109. This specific value would be realized if a firm would issue approx. nine clean patents and eight dirty patents in a given year.[40] Using patent data and especially data on tax rates in regression analyses is often times difficult, as variation in these data is generally low across individuals and time. However, the relatively high standard deviations given in Table 1 raise hope for a feasible estimation in this regard.

The timeline for household taxes on gasoline for various countries is given in Figure 8. Similarly, Figure 9 shows the industry taxes on diesel over time. Although the country taxes observe strong correlations over time, there is enough variation among them to be exploited for subsequent regression of the effects of tax rates. Especially the periods prior to 1995 and after 2005 observe high variations across countries' tax rates. Figure 10 shows the total number of clean and dirty energy patents for the period being used in the regression. As one would expect, the number of clean patents filed started to grow rapidly only in the last two decades. The number of patents related to fossil fuel technology experienced a stark increase in 2010, coinciding with unexpected reductions in fossil fuel tax rates. Note that the most recent years are not representative of the actual number of filings of patents because of publication lags.

[38] Information on this is used to estimate the measure of the fossil fuel taxes more precisely in the main regression specification.

[39] Data for countries outside the EU were collected on the national level.

[40] $exp(0.109 + ln(1 + 8)) - 1 \approx 9$. This example is given only for the fostering of intuition and does not in any way relate to a representative firm in the sample. In fact, in over 91% of cases where at least one patent was issued by a firm, only one of two types of patents is being issued by the firm.

Table 1: Summary Statistics

Variable	Observations	Mean	Sd	Min	Max
Innovation Direction	34872	0.109	0.669	-3.593	2.918
Clean Stock	34872	-0.216	0.589	-5.389	5.897
Dirty Stock	34872	0.059	0.611	-6.175	4.553
Clean Spillover	34872	3.075	0.948	-9.502	9.597
Dirty Spillover	34872	4.591	1.087	-7.560	8.483
Carbon Tax	34872	-1.571	0.821	-4.090	0.749
Clean Tax	34872	0.973	1.167	-5.907	4.724
Clean RD&D	34872	6.716	0.463	1.151	7.743
Dirty RD&D	34872	5.049	0.490	-0.617	6.460

Notes: These are the variables used in the main regression. All variables are log-transformed, with one being added wherever mathematically convenient.

5.2 Main results

The results of the main specification are given in Table 2. Column (1) gives the responding coefficients for the basic specification, Column (2) extends the model with more control variables, including, e.g., an environmental policy stringency index and emission regulation measures. Finally, Column (3) gives the coefficients for the inclusion of country-year fixed effects. The interpretation of coefficients of log-log models is straightforward, giving the respective elasticities between dependent and independent variables.

The estimates obtained indicate a strong, significant, and positive effect of the carbon tax rate on the direction of innovation. Thus, a 10% increase in the carbon tax rate would lead to an increase in relative patenting of approx. 1.5%-2.75%, depending on the coefficients considered.

Moreover, there is strong evidence for the path dependency hypothesis. Firms that have applied for a lot of patents in one direction in the past are more likely to patent in this direction again today.[41] This effect is less ambiguous and substantially larger for the stock of patents related to clean energy technology. The magnitude of

[41] Models that covered an interaction term of the clean and dirty stock variables yielded a significant, however small, positive effect on the direction of innovation. Theory in principle, has little to say about the potential sign of this coefficient.

Table 2: Main Results

Innovation Direction	(1)	(2)	(3)
Carbon Tax *(Gasoline & Diesel)*	0.213***	0.204***	0.187**
	(0.063)	(0.059)	(0.086)
Clean Tax *(Electricity)*	-0.093**	-0.101	-0.097
	(0.058)	(0.098)	(0.092)
Clean Stock	0.266***	0.232***	0.220**
	(0.080)	(0.079)	(0.099)
Dirty Stock	-0.173**	-0.170**	-0.166*
	(0.077)	(0.077)	(0.098)
Clean Spillover	0.096*	0.095*	0.158
	(0.053)	(0.053)	(0.172)
Dirty Spillover	0.079	0.005	0.197
	(0.090)	(0.104)	(0.284)
Clean RD&D	0.067**	0.051**	0.029
	(0.030)	(0.029)	(0.074)
Dirty RD&D	-0.020	0.019**	-0.001
	(0.073)	(0.009)	(0.048)
Extended Controls	No	Yes	Yes
Country $\times$ Year fixed effects	No	No	Yes
Observations	34872	34872	34872

Notes: p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm fixed effects included and standard errors clustered at the firm-level.

the effect is in line with the theoretical considerations, as firms that mainly operate in one type of energy commodity are faced with high costs of infrastructure and inventory costs.

There is no clear evidence of the effects of spillovers on the dependent variable. Although the coefficient on clean spillovers is significant at 10%, it is small in magnitude and becomes insignificant after including country-year fixed effects. A potential issue in this regard could be the relatively low variation across individuals after the inclusion of the more vigorous fixed effects.

Finally, the effects of the clean tax rate, as well as that of the RD&D expenditures, are ambiguous. None of the coefficients is significant even at the 10% level in the third Column. All controls are preceded by insignificant coefficients or coefficients that are small in size. Regarding the specific significance levels the estimates were obtained on, one must keep in mind the hybrid type of data being used. For relative patenting, the stock and spillover variables are micro-economic data whereas the remaining variables are only synthetic micro-economic data.

The Within-R^2 for the within estimator is calculated as the ordinary R^2 from the mean-deviated regression. The Within-R^2 for Table 2 is fairly constant across the three specifications and equal to 0.106. Typically, the overall R^2, analogous to the standard OLS R^2, is very small for applications with large variations across groups. As this is the case for the data sample being used, I do not find the Overall-R^2, equal to 0.011, discouraging.

Table 3 gives the coefficients on different measures of carbon taxes. The standard measure, that is, the mean of household and industry taxes on the mean of gasoline and diesel used in Table 2 is repeated in the first row. The different columns relate to the same specifications employed in Table 2.

Table 3: Main model: Different Carbon Tax Measures

Innovation Direction	(1)	(2)	(3)
Carbon Tax *(Gasoline & Diesel)*	0.213***	0.204***	0.187**
	(0.063)	(0.059)	(0.086)
Carbon Tax *(Natural Gas & Fuel oil)*	0.188**	0.157**	0.151
	(0.085)	(0.078)	(0.130)
Carbon Tax *(Gasoline & Diesel)*	0.287***	0.269***	0.201**
adjusted for "Dieselation"	(0.069)	(0.084)	(0.084)
Extended Controls	No	Yes	Yes
Country × Year fixed effects	No	No	Yes

Notes: p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm fixed effects included and standard errors clustered at the firm-level. Estimates from different rows are not based on the same number of observations. *Dieselation* as the share of diesel cars in the total passenger car fleet by country. Data used by European Environment Agency.

The carbon tax measure based on natural gas for households and fuel oil for industry indicates smaller effects on relative patenting. Although the estimate after the inclusion of country-year fixed effects becomes insignificant, the sizes of the coefficients from Columns (1) and (2) are in line with theoretical predictions. The coefficient on the carbon measure based on natural gas and fuel oil is slightly smaller in size compared to the results from Table 2. The differences in magnitude between the different estimates are perfectly in line with the share of consumption of the underlying commodities. Gasoline and diesel products together account for a significantly larger share of total energy consumption than natural gas and fuel oil.[42]. The effects of the fossil fuel tax adjusted for "dieselation" are estimated to be marginally greater than the original estimates.

6 Robustness and limitations

In the following paragraphs, I discuss various modifications of the original specification and examine the robustness of the results concerning these changes. Essential in this regard are the country weights, citation weighting scheme as well as lag dynamics of the model, as was argued by Aghion et al. (2020).

Since the sample includes some groups with observations over very long periods of time, e.g., 20 years, I conduct a Breusch-Pagan Lagrange-Multiplier test that checks for cross-sectional dependence (Breusch & Pagan, 1980). The p-value for this test statistic is zero until at least the fourth digit after the comma, thus firmly rejecting the null hypothesis of cross-sectional dependence. However Pesaran (2021) and Sarafidis et al. (2009) show that the Breusch-Pagan Lagrange Multiplier test has undesirable properties for estimations where the time dimension is smaller than the cross-sectional dimension. Although the time dimension is large for some groups, the number of groups is of considerably greater size. Thus, I also conduct a Pesaran cross-sectional dependence test and find that the p-value is similar in size (Pesaran, 2021). A Wooldridge test for autocorrelation firmly rejects the null hypothesis of no autocorrelation. The p-value of this test statistic is zero until at least the fourth digit after the comma.

In Table 5, I display regression estimates for randomly altered country weights. The change metric refers to Equation (4) and is given at the top of each Column. In total, I estimate 25 different regressions with different samples for both a 10% change and 15% change in the metric. Table 5 includes two randomly chosen outputs for the 10% and 15% scenario in the country weights. All scenarios estimated, produced comparable coefficients for the carbon tax rate. Coefficients on the carbon tax rate

[42]Precise shares can be found here: Key World Energy Statistics 2021: Final Consumption, IEA

observed p-values < 0.1 across all scenarios.

Table 6 gives the regression outputs for different sub-sample of firms. In Column (1), the smallest 20% of firms by number of patents filed were excluded. Column (2) gives the estimates for the exclusion of the 7.5% and 10% top patent filing firms. The coefficients indicate a substantially stronger effect of carbon taxes for firms that file a lot of patents. The estimates for path dependency also seem to be decreasing for the sample of firms that patent less. No significant differences were found between the effects of mostly clean versus mostly dirty patent filing firms.

To show that the specific weighting scheme does not drive the results, I interchange the dependent variable with the log differences of simple patent counts between clean and dirty energy patents. The outcome of this is displayed in Table 7. The coefficients obtained add to the evidence for a significant and positive effect of the fossil fuel tax rate on relative patenting.

Table 8 - 10 show the different estimation specifications for various lag orders. They indicate a persistent effect through the lags of minus one to as far as positive ten. There is no clear pattern by which the size of the coefficients changes.

There are several minor limitations to the approach that I have chosen. Taking the log of variables does not permit a clear distinction between negative and positive values of the original measures. As there are very few observations of tax rates with values smaller than zero, I have set them to be equal to the smallest value larger than zero in the sample. In principle, one could also add an arbitrary constant. However, this heavily skews the data if there are a lot of observations with relatively small values, which is the case for the tax data being used.

Likely the greatest drawback of the approach used in this thesis, is that there is no distinction between the effect of tax rate on industry products and household products. This is owed to the strong correlation between the two tax rates, making coefficients on both of them simultaneously infeasible due to perfect multicollinearity. To tackle these issues, one would potentially need detailed firm-level information regarding the firm‘s specific business model across time and countries.

7 Conclusion

In this work, I use tens of thousands of patents issued by over 1,000 different firms to investigate the direction of innovation in the energy sector at the firm level. In this regard, I show that a more parsimonious approach to data methods still identifies most of the relevant energy patents. The main exogenous presumed factor of influence concerning the direction of innovation is the carbon tax. As carbon taxes are only available at the country level, I have combined the common country-level measure with information from patent data to construct a firm-specific carbon tax measure (Aghion et al., 2020). Results from various specifications give strong evidence for a significant and positive effect of carbon taxes on the relative number of clean energy patents. The coefficients from the main estimation suggest an increase of 1.5%-2.75% in the relative number of clean energy patents if carbon taxes increase by 10%.

Furthermore, the results obtained indicate strong evidence for path dependency of firms. This holds true particularly for "clean paths", which significantly outweigh other effects in magnitude. I find no clear effects for clean or dirty spillovers. The impact of government RD&D budgets and the tax on electricity on the direction of innovation is similarly inconclusive.

I show, that the approach proposed by Aghion et al. (2020) for estimating the effect of carbon taxes on the direction of innovation can be extended to firms operating in the energy sector. From the analysis, it is also clear that significant effects, in line with the literature, were found via the use of the more tractable model (i.e., not using a count data model).

As the world is likely to breach 1.5C rise in global temperatures, measures like increases in carbon tax rates, along with expansions of investments in carbon neutral infrastructure, have to accelerate (Lee & Romero, 2023). Considering the main estimated effects, an increase in the carbon tax rate effectively contributes to the promotion of clean innovation activities among firms. As further indicated by the results, increases in tax rates predictably do not have to be persistent, as once firms switch from research in dirty- to research in clean technology, they are far more likely to continue down this path. Nevertheless, the temporary increases in the tax rate have to be sufficiently large in order to induce firms with dirty paths to shift their innovation activities to more sustainable technologies.

Future research on this topic would profit from a theoretical formulation of the dynamics between carbon taxes and innovation activities of energy-producing firms. The elasticity of substitution between clean and dirty energy products seems especially important, which is likely to depend on end technologies that require different inputs. Moreover, the utilization of a count data model seems natural, as the effect on the absolute direction of innovation, i.e., the total number of patents issued, can not be addressed via the approach I have chosen. Another issue is that theory and the literature has little to say about the timing of decisions related to innovation and research. Finally, it would be compelling to see a similar strategy to the one that was used in this thesis, in combination with sales data of firms, to distinguish between the effects of consumer and industry tax rates.

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APPENDIX

Table 4: Company revenue by market compared to weights derived from patent data for four of the world's largest energy companies

Company	markets	Revenue	Patent weights
Eni S.p.A.	Italy	0.43	0.36
	United Kingdom	0.23	0.18
	United States	0.05	0.11
ExxonMobil Corporation	United States	0.51	0.41
	Canada	0.11	0.10
	Japan	0.11	0.14
	United Kingdom	0.09	0.08
	France	0.09	0.07
Shell plc	United States	0.27	0.27
	Netherlands	0.15	0.11
	United Kingdom	0.14	0.09
	Germany	0.05	0.09
TotalEnergies SE	France	0.24	0.22
	Rest of Europe	0.44	0.39
	United States	0.09	0.08

Source: respective annual revenue reports from the years 2014 for Eni S.p.A. and ExxonMobil Corporation, 2015 for TotalEnergies SE and 2018 for Shell plc.

Table 5: Country Weights - Robustness

	(1)	(2)	(3)	(4)
Innovation Direction	10%	10%	15%	15%
Carbon Tax *(Gasoline & Diesel)*	0.251**	0.185***	0.329*	0.224**
	(0.104)	(0.061)	(0.235)	(0.086)
Clean Tax *(Electricity)*	-0.190*	-0.084**	-0.083	-0.176
	(0.072)	(0.030)	(0.076)	(0.128)
Clean Stock	0.270***	0.206***	0.191***	0.318***
	(0.080)	(0.064)	(0.050)	(0.097)
Dirty Stock	-0.151***	-0.174**	-0.096*	-0.166***
	(0.055)	(0.081)	(0.060)	(0.057)
Clean Spillover	0.004	0.122*	-0.025	-0.191
	(0.015)	(0.070)	(0.031)	(0.186)
Dirty Spillover	-0.219	0.172	0.052	0.003
	(0.365)	(0.252)	(0.049)	(0.003)
Clean RD&D	0.101	0.031**	0.098**	-0.194
	(0.089)	(0.016)	(0.048)	(0.162)
Dirty RD&D	-0.410	0.093	-0.186	-0.335
	(0.381)	(0.163)	(0.226)	(0.462)
Extended Controls	Yes	Yes	Yes	Yes
Country × Year fixed effects	No	No	No	No
Observations	34872	34872	34872	34872

Notes: p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm fixed effects included and standard errors clustered at the firm-level.

Table 6: Sub sample of firms - Robustness

Innovation Direction	(1)	(2)	(3)
Carbon Tax *(Gasoline & Diesel)*	0.229**	0.173**	0.131**
	(0.105)	(0.089)	(0.086)
Clean Tax *(Electricity)*	-0.089*	-0.086*	-0.117*
	(0.064)	(0.053)	(0.070)
Clean Stock	0.319**	0.256**	0.199**
	(0.138)	(0.112)	(0.082)
Dirty Stock	-0.207*	-0.164**	-0.154**
	(0.094)	(0.074)	(0.070)
Clean Spillover	0.284	0.097	0.127
	(0.295)	(0.127)	(0.121)
Dirty Spillover	0.009	-0.032	-0.107
	(0.011)	(0.040)	(0.142)
Clean RD&D	0.054*	0.069*	-0.042
	(0.033)	(0.043)	(0.044)
Dirty RD&D	0.019	0.042	-0.038
	(0.052)	(0.047)	(0.039)
Extended Controls	Yes	Yes	Yes
Country × Year fixed effects	No	No	No
Observations	28944	30877	29730

Notes: p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm fixed effects included and standard errors clustered at the firm-level.

Table 7: Simple Patent Counts - Robustness

Innovation Direction (simple patent counts)	(1)	(2)	(3)
Carbon Tax *(Gasoline & Diesel)*	0.582***	0.563***	0.499***
	(0.274)	(0.216)	(0.186)
Clean Tax *(Electricity)*	-0.277***	-0.269**	0.091**
	(0.125)	(0.122)	(0.041)
Clean Stock	0.253***	0.201***	0.167***
	(0.097)	(0.077)	(0.064)
Dirty Stock	-0.101*	-0.083	-0.007
	(0.062)	(0.075)	(0.007)
Clean Spillover	0.242	0.199	0.176
	(0.259)	(0.204)	(0.104)
Dirty Spillover	-0.050	0.008	-0.001
	(0.102)	(0.011)	(0.002)
Clean RD&D	0.009***	-0.040	-0.029
	(0.002)	(0.030)	(0.024)
Dirty RD&D	0.035	-0.017	-0.002
	(0.040)	(0.020)	(0.002)
Extended Controls	No	Yes	Yes
Country × Year fixed effects	No	No	Yes
Observations	34872	34872	34872

Notes: p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm fixed effects included and standard errors clustered at the firm-level. Innovation Direction measured as simple patent counts.

Table 8: Lag Robustness: No Full Controls & No Country-Year Fixed Effects

Innovation Direction$_t$	(1)	(2)	(3)	(4)	(5)
Carbon Tax$_{t-1}$	0.384***				
	(0.096)				
Carbon Tax$_t$		0.259**			
		(0.081)			
Carbon Tax$_{t+3}$			0.213***		
			(0.063)		
Carbon Tax$_{t+6}$				0.306***	
				(0.077)	
Carbon Tax$_{t+10}$					0.261***
					(0.077)
Extended Controls	No	No	No	No	No
Country × Year fixed effects	No	No	No	No	No
Observations	34872	34872	34872	33129	30438

Notes: p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm fixed effects included and standard errors clustered at the firm-level.

Table 9: Lag Robustness: Full controls

Innovation Direction$_t$	(1)	(2)	(3)	(4)	(5)
Carbon Tax$_{t-1}$	0.197***				
	(0.071)				
Carbon Tax$_t$		0.183**			
		(0.074)			
Carbon Tax$_{t+3}$			0.204***		
			(0.059)		
Carbon Tax$_{t+6}$				0.271***	
				(0.068)	
Carbon Tax$_{t+10}$					0.236***
					(0.078)
Extended Controls	Yes	Yes	Yes	Yes	Yes
Country × Year fixed effects	No	No	No	No	No
Observations	34872	34872	34872	33129	30438

Notes: p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm fixed effects included and standard errors clustered at the firm-level.

Table 10: Lag Robustness: Full Controls & Country-Year Fixed Effects

Innovation Direction$_t$	(1)	(2)	(3)	(4)	(5)
Carbon Tax$_{t-1}$	0.114**				
	(0.060)				
Carbon Tax$_t$		0.128**			
		(0.069)			
Carbon Tax$_{t+3}$			0.187**		
			(0.086)		
Carbon Tax$_{t+6}$				0.155*	
				(0.093)	
Carbon Tax$_{t+10}$					0.153***
					(0.081)
Extended Controls	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	34872	34872	34872	33129	30438

Notes: p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm fixed effects included and standard errors clustered at the firm-level.

Figure 3: Fossil fuel technology fields: overview

Table 1.1

Overview of upstream technology fields

Field	Definition	Examples
Conventional oil and gas exploration and extraction	Technologies related to the exploration and extraction of conventional oil and gas	Seismography, offshore platform, earth drilling
Unconventional oil and gas exploration and extraction	Technologies related to the exploration and extraction of unconventional oil and gas	Fracking, directional drilling
Coal and solid fuels exploration and mining	Technologies related to the exploration and mining of coal	Coal separating plant, mine cars

Table 1.2

Overview of processing and downstream technology fields

Field	Definition	Examples
Oil refining	Technologies related to refining of oil into combustible products for the end-user	Cracking of Hydrocarbons, Refining of Hydrocarbons
Gas conditioning	Technologies related to conditioning of gas into combustible products for the end-user	Purifying combustible gases
Solid fuel conditioning	Technologies related to conditioning of coal into combustible products for the end-user	Methods of shaping, briquetting
Coal-to-gas	Technologies related to the transformation of coal into gas for application as combustible products	Coke ovens, cooling or quenching coke
Coal-to-liquids and gas-to-liquids	Technologies related to the transformation of coal into liquids or gas into liquids for application as combustible products	Production of combustibles gases containing carbon monoxide from solid carbonaceous fuels
Hydrogen fuel production	Technologies related to the production of hydrogen as source of fuel for the end-user	Production of hydrogen by decomposition of gaseous or liquid organic compound

Table 1.3

Overview of transmission and distribution technology fields

Field	Definition
Liquid fuel pipelines	Technologies related to transport of liquid fuel by means of pipeline
Gas fuel pipelines	Technologies related to transport of gaseous fuel by means of pipeline
Liquid fuel tanker shipping	Technologies related to transport of liquid fuel by means of ships
Liquefied gaseous fuel shipping	Technologies related to transport of gaseous fuel by means of ships
Compressed gaseous fuel shipping	Technologies related to transport of compressed gaseous fuel by means of ships
Solid fuel shipping	Technologies related to transport of solid fuel by means of ships
Road tanker liquid fuels transport	Technologies related to transport of liquid fuel by means of road vehicles
Road tanker gaseous fuels transport	Technologies related to transport of gaseous fuel by means of road vehicles
Rail tanker liquid fuels transport	Technologies related to transport of liquid fuel by means of trains
Rail tanker gaseous fuels transport	Technologies related to transport of gaseous fuel by means of trains
Rail solid fuel transport	Technologies related to transport of solid fuel by means of trains
Underground liquid fuels storage	Technologies related to underground storage of liquid fuel
Underground gaseous fuels storage	Technologies related to underground storage of gaseous fuel
Stationary tank storage for liquids	Technologies related to surface storage of liquid fuel
Stationary tank storage for gases	Technologies related to surface storage of gaseous fuel
Solid fuel storage	Technologies related to storage of solid fuel
Liquid fuel distribution (gas stations)	Technologies related to distribution of liquid fuel
Gaseous fuel distribution	Technologies related to distribution of gaseous fuel

Source: Methodology for identifying fossil fuel supply related technologies in patent data, EPO & IEA

Figure 4: Fossil fuel technology fields: CPC classes

Fossil fuel supply category	Fossil fuel supply subcategory	CPC class/range	Filtering including queries (Chapter 4)	Filtering excluding queries (Chapter 4)
Upstream	Conventional oil and gas exploration and extraction	E21B43/003	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099
		E21B43/006	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099
		E21B43/01/low	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099
		E21B43/02/low to E21B43/12/low	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099
		E21B43/14	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099
		E21B43/16/low	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099
		E21B43/25/low	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099
		E21B43/28/low to E21B43/34/low	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099
		E21B44/00/low to E21B49/00/low	[1], [2], [4], [8]	E21B43/26/low OR E21B7/04/low OR E21B7/06/low OR E21B43/16/low OR E21B43/24/low OR E21B43/006 OR E21B41/0099

Source: Methodology for identifying fossil fuel supply related technologies in patent data, EPO & IEA

Figure 5: Fossil fuel technology fields: English search queries

4.1 English queries

To be applied to the corresponding CPC Fields

Queries in English	Corresponding short label
fossil OR (non w renewable) OR hydrocarbon? OR petrol+	[1]
petroleum OR (crude w oil) OR oil	[2]
coal OR mineral? OR coke OR peat OR BKB OR briquette OR asphaltite OR ortholignite OR metaanthracite OR lignite OR hardcoal OR browncoal OR (brown w coal) OR (oil 2w deposit) OR (oil w bear+) OR bitumen OR bituminous OR (tar w sand) OR (oil w sand)	[3]
methane OR (natural w gas) OR hydrate? OR (petroleum w gas+) OR hydrogen OR (boil 2w gas+) OR BOG OR LNG OR LPG OR (liqui+ 2w (fuel? OR petroleum)) OR (liqui+ 2w gas+) OR (gaseous w fuel?)	[4]
LNG OR LPG OR (liquid w fuel?) OR diesel OR gasoline OR (jet w fuel?) OR (fuel w oil) OR (bunker w fuel?) OR kerosene OR (oil w product?) OR octane OR cetane OR propane OR butane	[5]
methane OR (natural w gas+) OR CNG OR LNG OR PLNG OR propane OR butane OR LPG OR Hydrate? OR (petroleum w gas+) OR hydrogen OR liquefied OR (compressed w gas+)	[6]
coal OR BKB OR briquette OR asphaltite, ortholignite OR metaanthracite OR lignite OR hardcoal OR browncoal	[7]
drilling OR offshore OR onshore OR oil OR hydrocarbon? OR gas+ OR subsea OR seabed OR reservoir OR petroleum OR methane OR formation OR riser? OR (well w head) OR bop OR (blowout w prevent+) OR fracturing OR frack+ OR ((bottom OR down) w hole)	[8]
(oil 3w (spill?, containment?)) OR hydrocarbon? OR petrol+ OR (crude w oil) OR (light w oil) OR (hazardous w material?) OR chemical? OR (raw w oil) OR tanker? OR (liquid w pollutant?) OR ((subsea OR underwater) w emission?)	[9]
biomass OR biofuel OR bioethanol OR biodiesel	[10]
plastic OR (floating w debris) OR (floating w waste) OR leaves OR (solid w waste) OR (waste w matter) OR (floating w matter) OR pollutant?	[11]
(wind w turbine) OR tower OR mast OR ((power OR electric) 3w generat+)	[12]
(tar w sand?) OR (oil w sand?) OR (bituminous w sand?) OR frack+ OR (produced w water) OR drilling	[13]

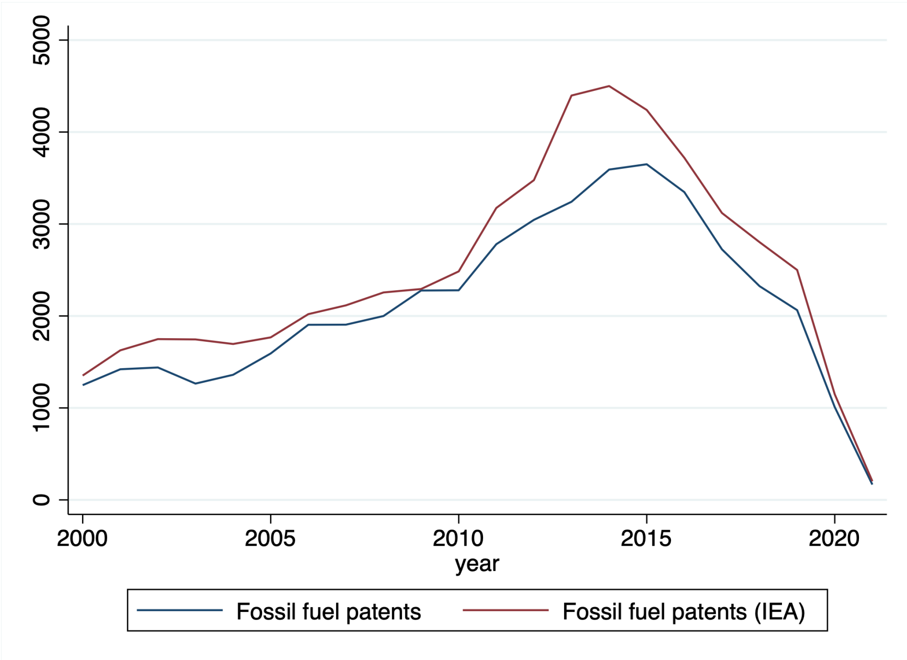
Source: Methodology for identifying fossil fuel supply related technologies in patent data, EPO & IEA

Figure 6: Clean energy technology fields: CPC classes

GENERAL TAGGING OF NEW TECHNOLOGICAL DEVELOPMENTS; GENERAL TAGGING OF CROSS-SECTIONAL TECHNOLOGIES SPANNING OVER SEVERAL SECTIONS OF THE IPC; TECHNICAL SUBJECTS COVERED BY FORMER USPC CROSS-REFERENCE ART COLLECTIONS [XRACs] AND DIGESTS	Y
TECHNOLOGIES OR APPLICATIONS FOR MITIGATION OR ADAPTATION AGAINST CLIMATE CHANGE	Y02
REDUCTION OF GREENHOUSE GAS [GHG] EMISSIONS, RELATED TO ENERGY GENERATION, TRANSMISSION OR DISTRIBUTION	Y02E
Energy generation through renewable energy sources	Y02E 10/00
Geothermal energy	Y02E 10/10
Hydro energy	Y02E 10/20
Energy from the sea, e.g. using wave energy or salinity gradient	Y02E 10/30
Solar thermal energy, e.g. solar towers	Y02E 10/40
Heat exchange systems	Y02E 10/44
Conversion of thermal power into mechanical power, e.g. Rankine, Stirling or solar thermal engines	Y02E 10/46
Mountings or tracking	Y02E 10/47
Photovoltaic [PV] energy	Y02E 10/50
PV systems with concentrators	Y02E 10/52
CuInSe2 material PV cells	Y02E 10/541
Dye sensitized solar cells	Y02E 10/542
Solar cells from Group II-VI materials	Y02E 10/543
Solar cells from Group III-V materials	Y02E 10/544
Microcrystalline silicon PV cells	Y02E 10/545
Polycrystalline silicon PV cells	Y02E 10/546
Monocrystalline silicon PV cells	Y02E 10/547
Amorphous silicon PV cells	Y02E 10/548
Organic PV cells	Y02E 10/549
Power conversion systems, e.g. maximum power point trackers	Y02E 10/56
Thermal-PV hybrids	Y02E 10/60
Wind energy	Y02E 10/70
Wind turbines with rotation axis in wind direction	Y02E 10/72
Offshore wind turbines	Y02E 10/727
Onshore wind turbines	Y02E 10/728
Wind turbines with rotation axis perpendicular to the wind direction	Y02E 10/74
Power conversion electric or electronic aspects	Y02E 10/76

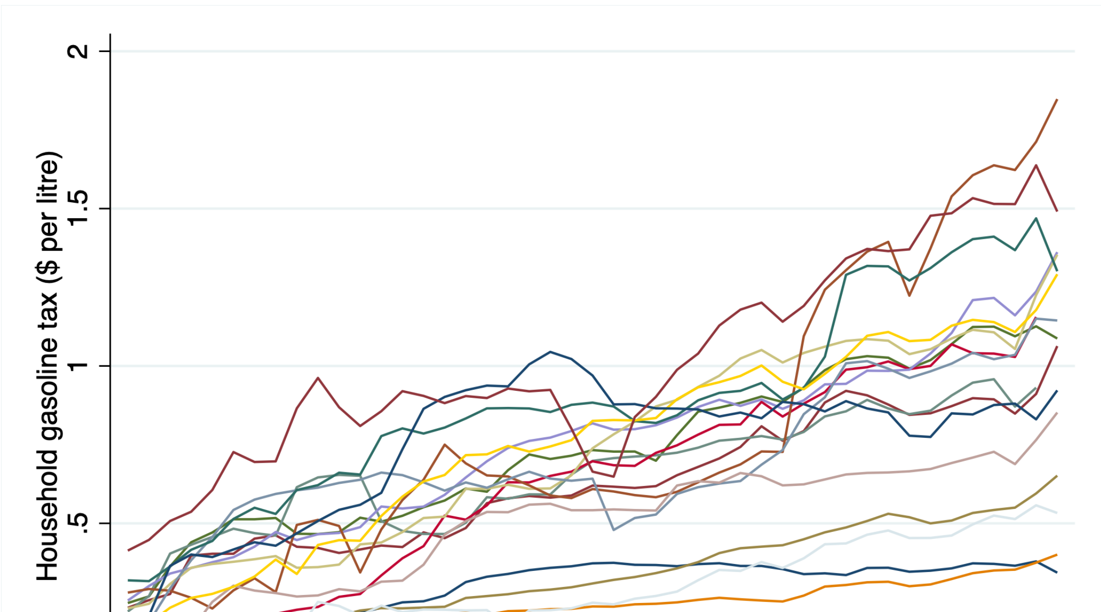
Source: Methodology for identifying technologies related to the supply of clean energy in patent data, EPO & IEA

Figure 7: Number of fossil fuel patents



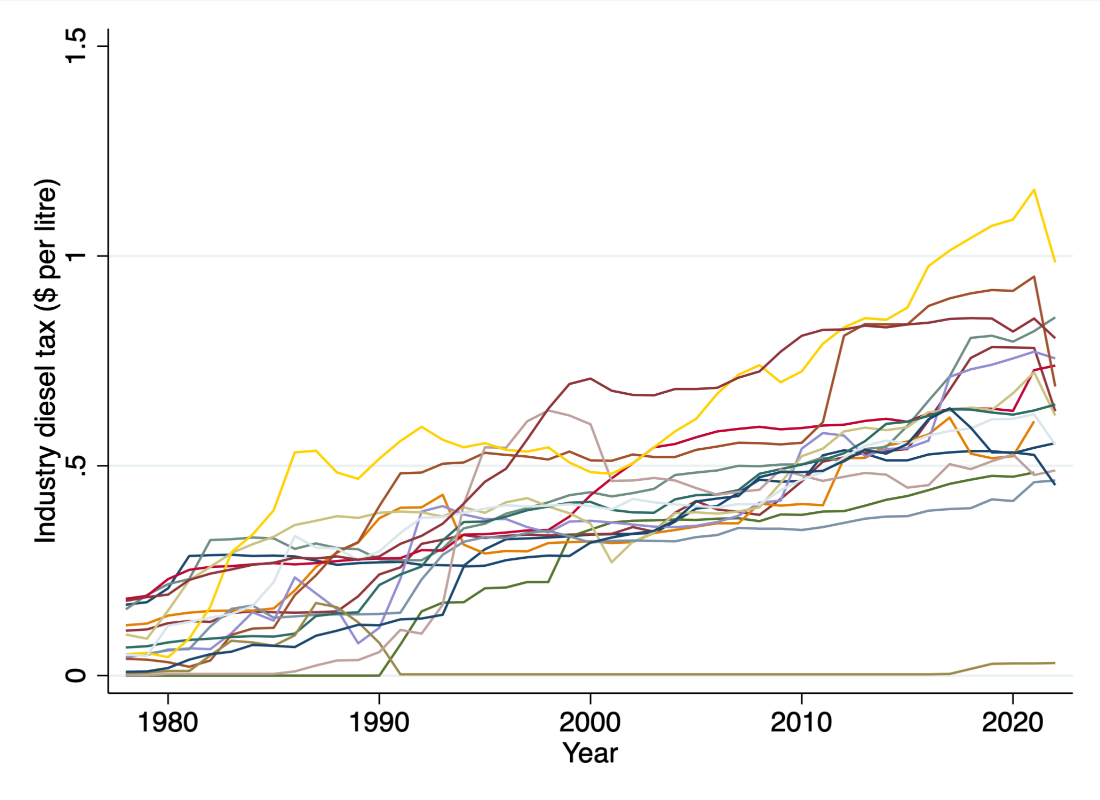
Source: own dataset & IEA.
Notes: Data from IEA only available starting in 2000. These are not the number of dirty patents used in the analysis but rather all fossil fuel patent identified via the data methodology without imposing further restrictions on e.g. firm size etc..

Figure 8: Household tax on gasoline



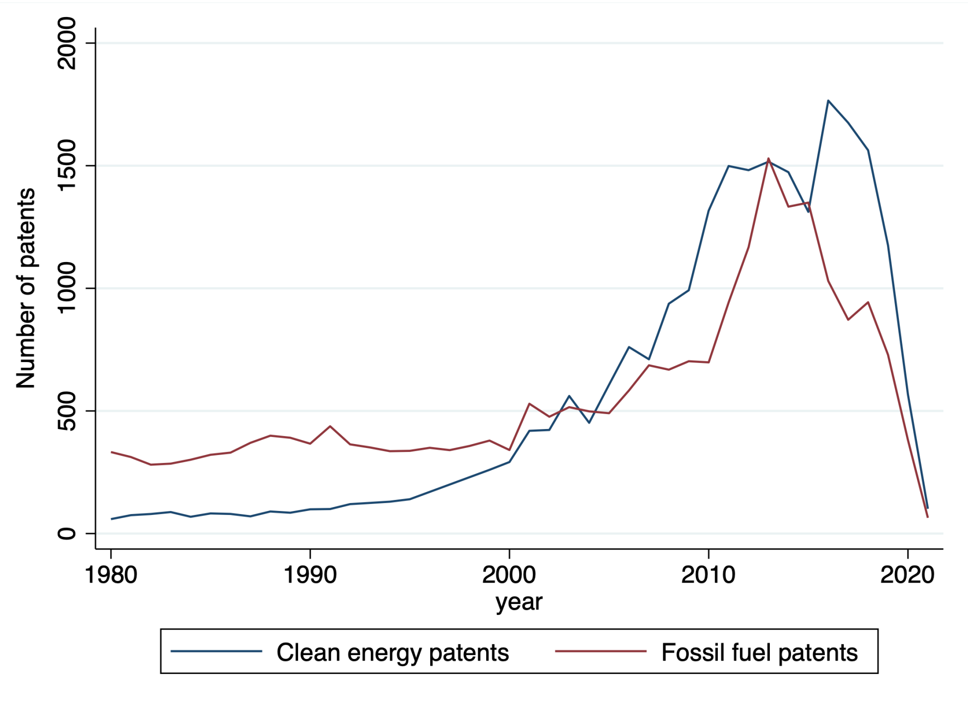
Source: IEA.

Figure 9: Industry tax on diesel



Source: IEA.

Figure 10: Clean and dirty energy patents



Source: own dataset.
Notes: Data used for main regression estimation.