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Abstract This article evaluates if and to which extent policy can steer innovation towards eco-friendly technologies. We construct a cross-country dataset on sectoral green innovation and complement it with data on policies designed to address environmental market failures: environmental taxes, regulation, and R&D subsidies. While all of these tools exert a positive effect on green innovation, our IV estimates reveal substantial heterogeneities across policies. Overall, green innovation reacts most strongly to R&D subsidies for renewables, but interaction effects between different policies need to be considered.

Keywords: *climate change, environmental policies, directed technological change, green patents, regulation, taxes, R&D*

JEL Codes: *Q54, Q55, Q58*

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1 Introduction

There is now a universal consensus that climate change is anthropogenic and that its consequences are appearing faster and getting more severe (IPCC, 2022). In order to comply with the goals set forth in the Paris Agreement and to limit the increase in average global temperatures to 1.5°C, policy makers need to guide consumers and companies towards a zero net-emission economy (Parry, 2020). Unfortunately, current technologies and mere behavioral changes will likely not be sufficient to achieve this task (IEA, 2020). New technologies will be decisive in attaining the required reductions in emissions and therefore, it is crucial to introduce efficient policies and research incentives as soon as possible. This paper studies which measures can steer innovation towards a greener path.

Most economists agree that the optimal policy to combat climate change is a combination of a carbon tax (or price) and research subsidies for green technologies (Acemoglu et al., 2012). A carbon price addresses the environmental externality, but does not achieve a first-best outcome (i.e. it does not minimize total consumption costs over the horizon of the policy), since it neglects the R&D externality (the social value of an innovation exceeds its private value). Thus, an R&D subsidy is required to raise innovation to the socially optimal level. Furthermore, since incumbent technologies relying on fossil fuels have been developed and optimized for a long time, they enjoy a productivity advantage over more recent, clean technologies. Thus, the research subsidy should be high enough to compensate this disadvantage and steer innovation towards green technologies.

Such a policy mix would internalize both the environmental externality, by putting a price on emissions, and the R&D externality, by subsidizing R&D as an optimal response to the public good nature of knowledge and to overcome the path dependency of innovation.[1] Most importantly, such a mix of policies would direct technological change towards green technologies needed to achieve the world's climate goals. However, due to a lack of political feasibility, these policies are not implemented by a majority of countries. Most countries either do not collect carbon taxes at all or do not set them sufficiently high.[2] Moreover, while nearly all countries

[1] The optimal policy would also include a carbon trade tax in the face of possible leakage problems, see e.g. Hémous (2021).

[2] For example, the Economist (2021) estimates that only 20% of global emissions are currently subject to a pricing scheme. In existing schemes, the median tonne of carbon emissions is priced at only 15$, way below all estimates of the social costs of carbon (SCC), most of which are beyond 50$. In February 2021, China's carbon trading market went live, however, coverage and price are still insufficient. In the USA, there is no carbon tax/price on a country wide basis, and only some states (e.g. California and the Regional Greenhouse Gas Initiative) have implemented carbon pricing schemes. In the EU, the carbon price surpassed €50 for the first time in 2021 and €100 in 2023, but was very low for over decade before that. The most notable exceptions are Sweden, Switzerland, and Norway, charging more than 100€, per tonne of CO2. However, even in these countries there are many exemptions from carbon taxation.

grant research subsidies specifically for green technologies, these subsidies are currently not high enough.[3] Instead, essentially all countries revert to regulating CO2 emitting technologies and activities.[4]

Our knowledge about which policy instruments are successful in directing technological change towards green innovation is limited. The fact that environmental policy tools – taxation/pricing, regulation and R&D subsidies – are used widely without robust estimates of their individual and interaction effects on directed technical change is worrying. This paper aims to contribute to this issue by analyzing the effects of environmental taxes, green research subsidies, and environmental regulation on green patenting activity in a cross-country, cross-industry panel setup. Specifically, we construct a dataset measuring green patenting activity at the country/sector/year level of observation for all of Europe, as well as the US and Canada. We use newly defined categories of innovation, allowing us to identify patents related to green technologies (Veefkind et al., 2012) and link these technologies to different sectors of the economy (Dorner and Harhoff, 2018).

Our empirical approach allows for environmental policies to be endogenously determined by using instrumental variables (IV) estimation, based on Hausman style instruments and a 2SLS estimation approach. We find encouraging results: all three policies - environmental taxes, environmental regulation and state-subsidized R&D in green technologies - significantly direct innovation towards green patenting. Doubling environmental taxes in an industry, on average increases green patenting by 6.7%. Doubling the stringency of environmental regulation in a NACE2 industry sparks a 16.4% increase in green patenting. Doubling direct state R&D subsidies leads to a 9% increase in green patent applications. An increase of R&D tax deductions by 1 percentage point increases green patent applications by 0.3%.

These clear-cut results, however, mask heterogeneous effects as well as interaction - or spillover - effects between the policies considered. For example, while the impact of environmental policies appears to be similar in North America and the EU, we find that their impact has strongly increased in more recent years. When investigating spillover effects, we find evidence for substitutive effects between environmental policies. In particular, R&D subsidies for green innovation appear to be less effective when applied in conjunction with environmental regulation.

[3]For example, Acemoglu et al. (2016, p.91) state that the (relative) research subsidy of 43% in the US is "insufficient to redirect technological change toward clean with no carbon taxes".

[4]Regulation on carbon emissions can take many forms. One useful distinction is between non-market-based and market-based regulation. Non-market-based regulation is characterized by specific state-imposed targets, limits or performance standards, which must be reached by producers or consumers within a certain time period. An example for this type of regulation is the EU's fleet regulation of passenger cars. Market-based regulation is characterized by using market-based mechanisms to reduce CO2 emissions. An example is the EU ETS pricing of emissions.

We further investigate sub-categories of the three main policies considered. Among environmental taxes, energy taxes most strongly affect green patents. When it comes to R&D subsidies, subsidies for renewable energy are especially effective in inducing green patenting. Market-based (MB) regulations have a positive effect, while the impact of non-market-based (NMB) regulations remains insignificant.

We contribute to the literature on directed technological change, which is constrained by a lack of comprehensive, broad-picture evaluations. To our knowledge, there is no paper that evaluates multiple policy tools in a cross-sector, cross-country dataset over time. Given the worldwide dimension of climate change and the heterogeneity of industrial activity, this appears to be a severe limitation.

The rest of this paper is organized as follows. In the next section we review the relevant literature. Section 3 briefly discusses the sources of externalities and the channels through which policy can influence the path of innovation. Section 4 describes the construction of the dataset, while the empirical strategy is detailed in section 5. Results of the empirical analysis are discussed in section 6 and section 7 concludes.

2 Literature review

In a closely related study, Aghion et al. (2016) use patents to estimate the effect of fuel prices on innovation in the automobile sector. The authors distinguish "green" (e.g. electric and hybrid vehicles), "grey" (e.g. energy efficiency increasing) and "dirty" (e.g. internal combustion) patents. Two main channels influence innovation activities: market size and (relative) prices. Innovation is directed to larger markets and to markets with higher prices. As the market for fossil fuels is one of the largest sectors, it attracts innovation over-proportionally. Green innovation is more expensive and therefore the gap between dirty and green innovation is not closed. Increasing fuel prices leads to more innovation in green technology, with an estimated elasticity of 0.97.

One of the first empirical studies dealing with innovation in the automobile sector is Crabb and Johnson (2010). It estimates the effects of expected oil prices and fuel economy regulations on energy efficient automotive patents from 1980-1999 in the United States. Findings show an elasticity of 0.24 between oil prices and patents, but no effects of fuel economy standards. We corroborate these findings in that we also find a positive sensitivity of green patents to fossil fuel prices and a lower effectiveness of NMB regulation.

Most studies find that market-based policies are more effective for innovation than other policy instruments (Magat, 1978, 1979; Milliman and Prince, 1989). Non-market-based policies penalize polluters but they do not reward emission efficient actors. However, Baumann and Lee (2008) show that under certain scenarios NMB regulations could lead to more innovation. MB policies may be more efficient if technologies are 'close to the market'. Wind energy, for example, is almost competitive with fossil fuel energy, since costs are already relatively low. Therefore, firms may be induced to invest in technologies which are relatively close to the market if a carbon price or tax additionally tips relative prices in their favour. Innovation in carbon capture, in contrast, may be further 'away from the market', therefore direct investment incentives/imperatives – such as induced by NMB regulations – may be more effective (Johnstone et al., 2010). We find that market based regulation increases green patenting across a broad range of industries.

On the micro level, Fischer and Newell (2008) and Gerlagh and Van der Zwaan (2006) evaluate a broader set of policies. Fischer and Newell (2008) evaluate emission-reducing policies in the energy sector and rank them in order of cost effectiveness: (1) emission price (most effective), (2) emission performance standard, (3) fossil power tax, (4) renewable share requirement, (5) renewable subsidy and (6) R&D subsidy. They show that a combination of emission pricing and R&D subsidies achieve significantly lower costs than any other policy. Gerlagh and Van der Zwaan (2006) using a top-down energy-economy model, in contrast, find that a carbon intensity portfolio standard (involving the recycling of carbon taxes to support renewables deployment) is the cheapest policy to reach different carbon stabilization goals. However, the Fischer and Newell (2008) and Gerlagh and Van der Zwaan (2006) do not analyze the effects of regulation on innovation.

Jaffe and Palmer (1997) estimate the relationship between (lagged) environmental compliance expenditures (a proxy for the stringency of environmental regulation) and total R&D expenditures, as well as the number of successful patent applications in U.S. manufacturing. They found a positive link with R&D expenditures (an increase of 0.15% in R&D expenditures for a compliance cost increase of 1%), but no statistically significant link with the number of patents. The analysis of Lanoie et al. (2011) draws upon a database that includes observations from approximately 4,200 facilities in seven OECD countries. In general, the authors using questionaire analysis find strong support for the "weak" version of the Porter hypothesis according to which more stringent regulation increases R&D expenditures. More flexible "performance standards" are more likely to induce innovation than more prescriptive "technology-based standards".

Calel and Dechezlepretre (2016) address the effect of the EU ETS on directed technological change. The authors show (1) that innovation increases if the EU ETS price rises and (2) innovation by firms not covered by the ETS is not influenced by the cap-and-trade system.

This is in line with our findings on the positive effects of carbon taxes and MB regulation on green patents.

Recently, Palage et al. (2019) find that renewable energy support policies for the solar photovoltaics (PV) technology increase patenting. For 13 countries over the 1978–2008 period, the analysis addresses one technology-push instrument, public R&D support, and two demand-pull instruments, feed-in tariffs (FIT) and renewable energy certificate (REC) schemes. The results indicate that: (a) both FIT and REC schemes induce solar PV patenting activity, but the impact of the former policy appears to be more profound; and (b) – consistent with our results – public R&D support has overall been more influential than FIT and REC schemes in encouraging solar PV innovation. A comprehensive survey of the empirical literature in this field is provided by Popp (2019).

Summarizing, the evidence on whether environmental policies direct technological change towards green innovation is encouraging. However, the literature so far lacks a comprehensive and broad-picture evaluation of different policies. Most papers only analyze specific aspects of policies (e.g. the EU ETS carbon pricing system), specific regulations (e.g. renewable portfolio requirements) or supply subsidies (e.g. feed in tariffs), in specific sectors (e.g. the automobile industry). This study extends the literature in several dimensions. We use a comprehensive classification of green patents covering all sectors of the economy of more than twenty countries, analyse recent technological advances until 2016, and evaluate a full set of environmental policies – and their interaction effects – rather than isolated measures.

3 Theory and channels for directing technological change

Economists have identified two market failures leading to the excessive emission of greenhouse gases and the sub-optimal level of technical change towards green inventions. The first market failure is an environmental externality. Consumers and firms do not pay the full social cost of polluting the atmosphere, leading to overconsumption, similar to a 'tragedy of the commons'-type situation. Moreover, since historically it has been cheap to use this resource, polluting technologies are better developed than technologies not causing environmental damage. Therefore, in the absence of policy intervention dirty technologies are favoured over green technologies.

The second market failure is due to the public goods nature of knowledge (Geroski, 1995). If a company innovates, the created knowledge may spill over to other, competing companies for free. That is, the investing company may not be able to appropriate the returns of its innovation and will therefore underinvest in new technologies. A fortiori, it will also underinvest in green technologies.[5]

As a first-best solution to the environmental market failure, economists advocate putting a price on emissions, leading households and firms to internalize these externalities (Stiglitz, 2019). This can be achieved through carbon pricing, e.g. by an emission trading system, or by direct taxation. Additional pros of market-based solutions are a lower need for information acquisition by the state than with specific regulatory limits, and the continuous nature of pricing/taxation.[6]

The second market failure can be addressed through R&D subsidies or other R&D promoting policies such as patent protection or state funding of basic research. Another argument in favour of R&D subsidies is to overcome the initial productivity disadvantage of green relative to dirty technologies. As mentioned in the introduction, these first-best solutions are not implemented by the majority of countries. Instead, most countries adopt environmental regulation to achieve their climate goals.

Which effects are to be expected from the policies mentioned above? It is useful to follow the schematic framework of Nordhaus (1969) arguing that investments into the discovery of innovation rise with profits expected from successful discovery, i.e. there is a monotonic relationship between innovative investments and the probability of successful discovery.[7] Define I as the total level of investment in innovation, and $p(I)$ as the probability of a successful discovery, where $p'(I) > 0$ and $p''(I) < 0$. Define G as the state of the world in which a discovery in green technologies occurs, and D as the state in which no discovery occurs (i.e. the dirty technology prevails). $\mathbb{E}(\pi|G)$ is the innovator's expected profit in case of green invention, and similarly for $\mathbb{E}(\pi|D)$ for retaining dirty technology. Green innovation investment will be undertaken if and only if $\mathbb{E}(\pi|G) > \mathbb{E}(\pi|D)$. Firms may get subsidies so that they do not have to bear the whole cost of innovation - define $\phi(I) \leq I$ as the firm's private cost of investment. Finally, define r as the cost of capital. Then, the privately optimal level of innovation is given by the solution to:

$$\max_{I}\ p(I)\,\mathbb{E}(\pi|G) + (1 - p(I))\,\mathbb{E}(\pi|D) - (1 + r)\,\phi(I)$$

[5] Studies on the public-good-nature of knowledge are cited in Popp (2010), p. 5 f.

[6] On the negative side of taxation/pricing, Hepburn et al. (2020) enumerates four reasons why carbon pricing alone might not be sufficient. Carbon pricing may not achieve the task on the necessary timescale and the necessary scale of structural change. Moreover, regulation (e.g. a prohibition) may eliminate the burning of fossil fuels altogether, eliminating all deaths associated with it, whereas taxation/pricing may not. Further, regulation may give (more) confidence in new technologies such as solar, wind, or battery technologies characterized by large learning-by-doing effects and increasing returns to scale, than carbon pricing. Another drawback may be the lower political acceptance of carbon pricing than of regulatory intervention.

[7] The theory of Hicks (1963) stating that profit-motivated investment in innovation (R&D) is more attractive in sectors that can command higher relative prices is closely related to Nordhaus (1969).

Thus, policies can affect the decision to invest in green technologies via four channels. They can

1. increase the probability of successful innovation, $p(I)$,
2. increase the expected profits from green innovation, $\mathbb{E}(\pi|G)$,
3. decrease the expected profits from dirty technologies, $\mathbb{E}(\pi|D)$, and/or
4. reduce the private costs of investment, $\phi(I)$.

In the empirical analysis, we try to capture all four channels. Concerning channel (1), we expect the probability of successful innovation, $p(I)$, to be affected by the stock of knowledge amassed up to a specific point in time (Scotchmer, 1991). Channels (2) and (3) can be jointly examined by considering the expected profits from green innovation, relative to those from dirty innovation, $\frac{\mathbb{E}(\pi|G)}{\mathbb{E}(\pi|D)}$. This ratio increases if the expected profits from dirty technologies, $\mathbb{E}(\pi|D)$, decrease e.g. due to carbon pricing.

Regulation could also affect both types of profits, since the implicit cost ratio between dirty and green inputs is altered. A green portfolio standard should increase expected profits from green innovation, a ban on oil heating should decrease the expected profits from dirty technologies. In theory, however, the effects of regulation on green innovation are ambiguous. If fossil fuel use and green energy are gross substitutes, regulatory restrictions on fossil fuel use (e.g. via outright prohibition or portfolio requirements for green energy) increase the marginal product of green energy and demand for complementary technologies. This increases the returns to innovating in technologies that augment green energy relative to returns to fossil fuel augmenting technologies. Regulation in this case directs innovation towards green innovation (Acemoglu et al., 2016). If fossil fuel use and green energy are less substitutable, however, the overall scale of production in the economy may fall, reducing demand for all capital goods that complement energy. In this case, green regulation might reduce incentives for clean innovation (Gans, 2012). Which effect dominates can only be determined empirically.[8] Finally, related to channel (4), policies can reduce the private costs of investment. Policies can reduce $\phi(I)$ directly (via direct

[8]Moreover, the effects of regulation may depend on its specific implementation. For example, a limit on fleet emissions or a green portfolio standard may induce efforts by companies until the threshold is reached, but not beyond. Thus, effects could be non-linear, i.e. increasing innovation up to a point but then - when a specific target is achieved - tapering off. See Aghion et al. (2021) for recent evidence of a threshold effect of labor regulation on innovation for small French companies. Likewise, regulation punishes polluters but does not (directly) reward emission efficient actors. Thus, effects may depend on how exactly regulation is implemented (e.g. NMB or MB). Environmental regulation, such as stipulating renewable energy quotas or subsidies for green technologies, may also have unintended consequences. For example, subsidies for renewables may reduce the electricity price via increased supply of electricity, leading to more consumption of energy. On the positive side, environmental regulations may convey a stronger signal to markets and firms that this policy is here to stay, reducing adoption uncertainty.

subsidization or direct state R&D) or indirectly (via the tax system), thereby subsidizing green R&D. This would help internalize the public goods nature of the knowledge externality.[9]

Figure 1: Policy channels for directed technological change

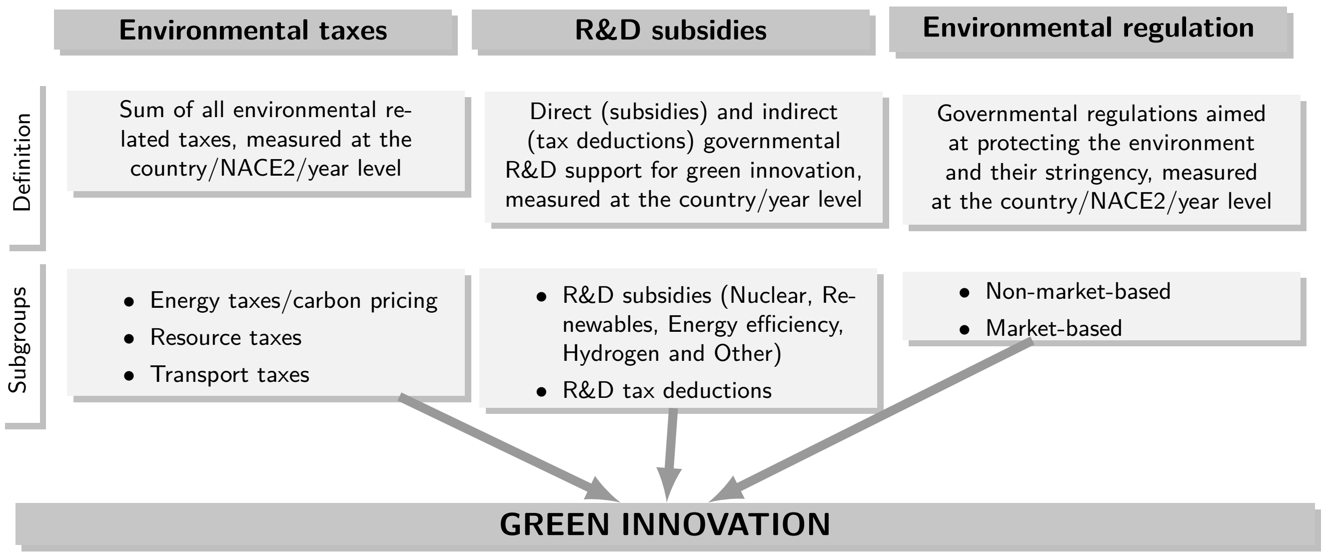


Figure 1 summarizes the policy channels potentially leading to green innovation and lists different types of environmental taxes, R&D subsidies and regulatory measures included in the empirical analysis. In the following sections we econometrically analyse the effects of the three main policy instruments.

4 Data

4.1 Green patents

The patent data are drawn from the European Patent Office PATSTAT global spring 2020 version, containing all worldwide patents (including those granted by non-European patent authorities). Based on the Veefkind et al. (2012) classification, we select all Y02 ("green") patents in all available countries (see also Haščič and Migotto (2015)). Three different types of green patents are included in our dataset: (i) zero emission, (ii) emission reducing technologies and (iii) negative emission technologies. These include climate change mitigation technologies related to energy, transportation and buildings as well as capture, storage, sequestration or disposal of greenhouse gases. Examples of zero emission technologies are patents for renewable

[9]Some green policies may concern more than one channel. For example, a policy that guarantees some form of stable revenue for renewables, such as contracts for difference or guaranteed feed-in tariffs would not only concern channel (2) but also lower the cost of capital (due to a lower investment risk), thereby impacting channel (4).

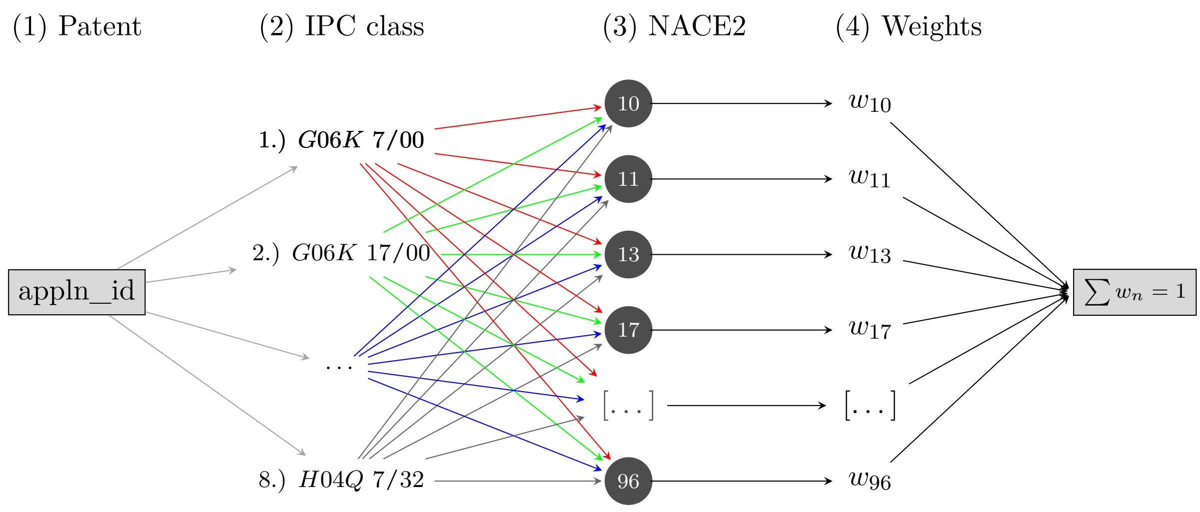
energy generation. Emission reducing technologies include those improving the fuel-efficiency of vehicles or the input/output efficiency of power plants. Finally, negative emission technologies comprise, for example, carbon capture and storage through biological or chemical separation.

We assign green patents to countries based on the country of the patent owner. Thus, patents filed by Siemens AG are counted towards German innovation, but patents filed by a Spanish subsidiary of Siemens are counted in Spain. The year of first filing is used as the application date of the patent. In order to attribute patents to sectors, we follow the procedure developed by Dorner and Harhoff (2018), who exploit a large dataset of linked inventor-employee data to create detailed and fine-grained concordance tables of patent technology classes (4-digit International Patent Classification (IPC) class) and industry sectors (2-digit NACE codes).

Every green (according to the Y02 classification) patent is assigned to 2-digit industries based on its 4-digit IPC codes. As many patents have multiple IPC codes and the link between technology and industry classes is $n : m$, we weigh each patent such that i) it is counted in all applicable industries and ii) the overall weight of every green patent is one.

The procedure of assigning green patents to industries is illustrated in Figure 2. For a given patent we collect all relevant IPC classes (step (2) in figure 2); use the Dorner and Harhoff (2018) mapping to identify the corresponding NACE2 codes and their weights (3); and adjust the weights (4) such that the sum of a patents' weights across all industries is equal to one.

Figure 2: Mapping of IPC classes into NACE2 sectors based on Dorner and Harhoff (2018)



A limitation of this approach is that we need to assume that the concordance of technology classes and industry sectors, which Dorner and Harhoff (2018) created based on German patents and establishments, also holds in other countries. It seems plausible that the relation of technology classes and industries is predominantly determined by technological considerations and limitations - particularly since we are looking at 'high-tech' patents - rather than country specificities. Nonetheless, this extrapolation might induce a degree of measurement error to our outcome variable. While this could make estimation noisier, it should not – assuming that the measurement error is unsystematic – result in biased estimates.

4.2 Environmental taxes

We use data from the Environmental taxes database from EuroStat. An environmentally related tax is defined as a tax on a physical unit of something that has a proven, specific negative impact on the environment. We collect data on environmentally related taxes for all European countries (including Iceland, Liechtenstein and Norway), unfortunately such data do not exist for other countries. Tax revenues are allocated to NACE2 sectors and available for the 1995-2018 period.

Additionally, all variables for environmentally related tax revenues are classified into energy, transport, pollution and resource taxes. Energy taxes include all taxes on energy production and cover tax revenues from emission trading systems, the mineral oil tax and emission taxes of CO2 and SO2. Therefore revenues of emission permits are part of this category. Transport taxes include taxes on the ownership of motor vehicles, e.g. transport equipment and services. Pollution taxes are measured or estimated values of emissions to water or air, management of solid waste and noise. Resource taxes include all taxes on the extraction or use of natural resources (e.g. deforestation).

4.3 R&D subsidies and tax deductions

The International Energy Agency database for government funding of energy-related R&D includes all relevant research subsidies in the field of energy. We can split those budgets in subgroups pertaining to R&D in nuclear, renewables, energy efficiency, hydrogen and other R&D. Nuclear and hydrogen include R&D in nuclear and hydrogen technologies, respectively. Renewable subsidies include public investments predominantly regarding solar, wind, and biofuels. Energy efficiency captures all activities which increase output with less or equal energy input. Other R&D is the residual category and comprises, among other areas, investments in fossil fuel research. Subsidies are allocated to countries and years.[10]

[10] We also experimented with the OECD's GBARD dataset, containing governmental R&D expenditures at the country/year level. The GBARD data are more comprehensive in the sense that they are not limited to energy-related R&D subsidies. However, the GBARD data contain only rather broad categories (e.g. university-funded research) and do not allow for a split into green-tech categories. While we also find positive effects with the GBARD data, we opted to use the IEA's database as it contains more interesting sub-categories.

Data on R&D tax deductability are collected from the 'Implied tax subsidy rates on R&D expenditures' database from the OECD and include all OECD and eleven non-member countries between 2000-2016. In the regressions, we use the tax subsidy rate (1 minus B-index, which is a measure of the required before-tax income to spend USD 1 on R&D). This measure captures the relative support for private sector investment in R&D delivered through the tax system and is available at the country/year level.

4.4 Environmental regulation and stringency

We collect data on environmentally related, regulatory policies from the International Energy Agency and map around 6,000 different regulations into NACE2 sectors and countries. To this end, we exploit three classifications, which are available in the IEA database: policy types, sectors and technologies.

Based on a regulation's policy type, we classify policies as either market based (MB, 41% of all regulations) or non-market-based (NMB, 35% of all regulations).[11] NMB regulations are characterized by specific state-imposed targets, limits or performance standards, which must be reached by producers or consumers within a certain time period. MB regulations are characterized by using market-based mechanisms to reduce CO2 emissions.

We record only regulations which are currently in effect in a given country, industry and year. Thus, if a regulation expires, the associated dummy switches back to zero. Similar to our approach of mapping patents to industries, the 'sectors' (e.g. transport) and 'technologies' (e.g. passenger vehicles) field of a regulation allow us to assign regulation to industry sectors. In around 75% of cases, the sectors could be directly mapped to the corresponding NACE2 industries, while in around 20% of cases we used our best judgment to find the most appropriate NACE2. Around 5% of policies could not be reliably allocated and were dropped from the data. This procedure enables us to identify the prevalence of each policy type within clusters of country, sector and year.

However, while this approach allows us to infer the existence of environmental regulation at a fine-grained level, it does not take into account how strict this regulation is. For example, we would not expect a non-binding standard to affect innovation (or other outcomes) in an industry. Thus, in order to account for the intensity of regulation, we need a measure of the stringency of environmental regulation (Brunel and Levinson, 2020).

[11] We drop regulations that cannot be reliably and exclusively assigned to either group, e.g. by having features of both. In a previous draft we included these 'hybrid' regulations finding mostly insignificant effects on green innovation.

The Environmental Policy Stringency index (Kruse et al., 2022) is provided by the OECD and measures the stringency of environmental policies across countries and years. The index is based on a selection of environmental policy instruments related to climate and air pollution, and is aggregated into composite indexes for 29 countries from 1990 to 2020. The EPS is provided as an economy wide measure of policy stringency and can be subdivided into MB and NMB instrument stringency (Fabrizi et al., 2018).

In the regressions, we interact the indicator variables for environmental regulation (overall, market based and non-market based) with the corresponding EPS indexes. We thus do not separately identify the impact of the quality (stringency) and quantity (count) of sectoral regulations, but rather derive a compound measure comprising both elements. This seems reasonable, as effective regulation needs to be both in place and binding in order to affect green patenting.

Thus, in sum, we measure the stringency of regulation either overall or differentiating MB and NMB regulations which is important from a policy standpoint. Additionally, this approach achieves better comparability of regulation across countries and yields variation at the country, industry and year level which is crucial to identify coefficients.

4.5 Control variables

Control variables include a CO2 emission index (sourced from the OECD), gas prices, the knowledge stock and value-added at the industry level. We use natural gas prices from the IEA energy prices and tax statistics database. In the regressions we use two-year lags due to temporal lags between price changes and patent applications. Natural gas prices are based on average prices for industry and/or households. As fuel prices increase the cost of using carbon technologies, they are expected to increase green patent applications. To control for the knowledge stock within a given country and sector, we apply the perpetual inventory method with starting year 1995:

$$KS_{cst} = P_{cst} + (1 - \delta) * KS_{cst-1} \tag{1}$$

where KS_{cst} and P_{cst} denote the knowledge stock of patents and the flow of new patent applications in country c, sector s and year t. We discount patents with a rate of $\delta = .20$ by year as in Aghion et al. (2016).

Sectoral value-added is sourced from Eurostat and intended to control for size effects at the country/sector/year level. As, for example, environmental tax revenues scale with the economic activity in a sector, it is important to control for the tax base in order to distinguish size effects from policy effectiveness.

4.6 Summary statistics

Table 2 presents descriptive statistics on the main variables, while detailed definitions are provided in Table 1. The share of green over total patents is lower in the USA and Canada (6.9%) than in EU countries (8.6%). Environmental taxes on a country/NACE2/year level are more than 120 mio. € on average, the bulk of which is comprised of energy taxes.[12] While transport taxes (nearly 15% of environmental tax revenues) are important, resource taxes are of lesser importance.

In 9.3% of European country/NACE2/year observations, there is at least one active regulation (12.4% in North America). The average regulatory stringency, the interaction of a dummy for active regulation in an industry and the EPS index, is around 0.25 and quite similar in both regions.[13] The most prevalent type of regulation is NMB.

The average R&D tax deduction rate is around 11% and very similar for Europe and North America. Countries spend around €200 mio. yearly on green research subsidies in the average industry.[14] Natural gas prices are twice as high in Europe as in North America. The CO2 emission index is around 15% higher in North America than in Europe.

Figure 3 provides time series plots on our main variables. The share of green patents increases strongly between 2000 and 2010 and starts to decrease after 2010/2011. Maybe surprisingly, only the regulatory stringency of active regulations displays a consistent upward trend in the last two decades for both country groupings.[15] R&D subsidies as a share of GDP show disparate developments with a spike in both regions around 2010/2011 and a decline thereafter. Environmental taxes as a share of GDP display a decline in Europe after 2005, and stagnate at around 1.3% of GDP after 2010.[16] Thus, the summary statistics paint a somewhat sobering picture of the evolution and state of climate change policies. While the prevalence and stringency of active regulations increased, the GDP adjusted amount of environmental taxes and subsidies stagnated or declined over the last two decades.

[12] The largest part of energy taxes, in turn, is comprised of the mineral oil tax.

[13] The EPS index itself takes on values between zero (not binding regulation) and 6 (very stringent regulation). The average value of the index is 2.91.

[14] The absolute number is much larger for North America, because of industry size effects. On a per-capita basis, however, subsidies are quite comparable across regions, with Europe subsidizing green research at around 12 € p.c. versus 14 € p.c. in the USA/Canada.

[15] Separate plots of the occurrence of regulation and the EPS index reveal that regulatory stringency increased in both dimensions, the number of active regulations and their stringency.

[16] Unfortunately, we lack data on sectoral environmental taxes in the USA and Canada.

Table 1: Variable description

Variable	Definition	Source*	Unit	Level
	Dependent variable			
Y02 patents	We use the PATSTAT global spring 2020 version from the European Patent Office including worldwide patents. For the allocation of patents to sectors, see section 4.1.	EPO	weighted count	$c/s/t$
	Independent variables			
Environmental taxes	Environmental tax revenues separated by NACE2 code for each country and year. We use all available observations until 2016 of all European countries, incl. Iceland, Liechtenstein and Norway. Environmental taxes are classified into three main categories: Energy, Transport and Resource taxes.	EuroStat	mio. €	$c/s/t$
Environmental regulations	Environmental regulations for each country, sector and year worldwide. Using the IEA policy database and counting each regulation by start and end date. In the regressions we first compute a dummy if a given country, sector and year has a market-based or non-market-based regulation.	IEA	weighted count	$c/s/t$
Environmental Policy Stringency Index	The Environmental Policy Stringency Index (EPS) is an international comparable measure for each country. It measures an explicit or implicit price on pollution or environmentally harmful behavior. We use sub-index groups for market-based instruments (taxes and certificates, e.g. CO_2 trading schemes, CO_2 taxes, fuel taxes) and non-market based instruments (performance standards, e.g. emission limit values) based on Kruse et al. (2022). The EPS is defined between zero and six.	OECD EPS data	index	c/t
R&D subsidies	The IEA database for government funding of energy R&D includes all relevant funding in the field of energy across multiple countries and years. Separated in Nuclear, Renewables, Energy Efficiency & oth., Hydrogen, and others.	IEA	mio. €	c/t
R&D tax deductions	This variable is defined as a tax subsidy rate. The tax subsidy rate is calculated as 1 minus B-index, which is a measure of needed before-tax income to break even on USD 1 of R&D outlays.	OECD	%	c/t
	Control variables			
CO2 emissions	CO2 fuel combustion emissions expressed as an index, where the reference year 1990 is set to 100.	OECD	%	c/t
Natural gas price	Natural gas prices exclusive taxes.	IEA	$/MWh	c/t
Knowledge stock	Discounted sum of all patents (base 1995) with a yearly depreciation rate δ of .20 (perpetual inventory method).	EPO	count	$c/s/t$
Value Added	Gross Value Added is defined as output value at basic prices less intermediate consumption valued at purchasers' prices.	Eurostat	mio. €	$c/s/t$

Notes: c: country; s: sector; t: year; Source: IEA policy database https://iea.org/policies; Environmental tax database: https://appsso.eurostat.ec.europa.eu/nui/show.do?-dataset=env_ac_taxind2&lang=en; Environmental policy stringency index: https://www.oecd-ilibrary.org/environment/data/oecd-environment-statistics/environmental-policy-stringency-index_2bc0bb80-en. Value added: https://ec.europa.eu/eurostat/databrowser/view/teina400_r2/default/table?lang=en.

Table 2: Descriptive statistics

		EU			North America		
		Mean	SD	Obs.	Mean	SD	Obs.
1. Patents							
Number of Y02 patents	count	18.622	94.207	18,673	133.167	447.493	3,439
Number of total patents	count	208.178	928.729	18,673	1,976.905	6,396.542	3,439
Share of Y02 patents	share	0.086	0.032	18,673	0.069	0.015	3,439
2. Environmental related taxes							
Total environmental taxes	mio. €	121.155	310.313	18,673	*n.a.*	*n.a.*	0
Energy taxes	mio. €	101.361	274.168	18,594	*n.a.*	*n.a.*	0
Resource taxes	mio. €	2.396	27.292	18,599	*n.a.*	*n.a.*	0
Transport taxes	mio. €	17.874	64.157	18,614	*n.a.*	*n.a.*	0
3. Environmental regulations							
Sectoral regulation	count	0.523	2.403	18,673	2.310	11.119	3,439
Total NACE2 reg.	share	0.093	0.290	18,673	0.124	0.330	3,439
Regulatory stringency	index	0.269	0.872	18,673	0.251	0.734	3,439
Market-based str.	index	0.118	0.478	18,673	0.059	0.192	3,439
Non-market-based str.	index	0.378	1.326	18,673	0.426	1.310	3,439
4. R&D subsidies							
R&D tax deductions	rate	11.179	13.385	18,673	11.156	12.000	3,439
Total budget R&D	mio. €	202.679	283.231	18,673	2,419.547	2,274.549	3,439
Nuclear	mio. €	52.861	133.483	18,673	374.377	318.908	3,439
Renewables	mio. €	48.670	59.529	18,673	352.107	460.012	3,439
Energy eff. & oth. R&D	mio. €	64.655	70.612	18,673	559.063	591.178	3,439
Hydrogen	mio. €	6.858	11.617	18,673	83.766	117.296	3,439
Other R&D	mio. €	29.477	45.182	18,673	1,050.235	984.059	3,439
Control variables							
Natural gas price	$/MWh	37.394	13.764	18,673	16.041	6.390	3,439
Knowledge stock	count	1,103.545	5,001.576	18,673	10305.751	33141.014	3,439
CO2 emission	index	96.715	21.234	18,673	117.896	7.139	3,439
Value added	mio. €	8,372.213	15343.838	14,692	*n.a.*	*n.a.*	0

Notes: Data are reported at the country/sector/year level; no tax and value added data are available for US and CA (North America). Countries included in EU: AT, BE, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HU, IE, IT, LU, NL, PL, PT, SE.

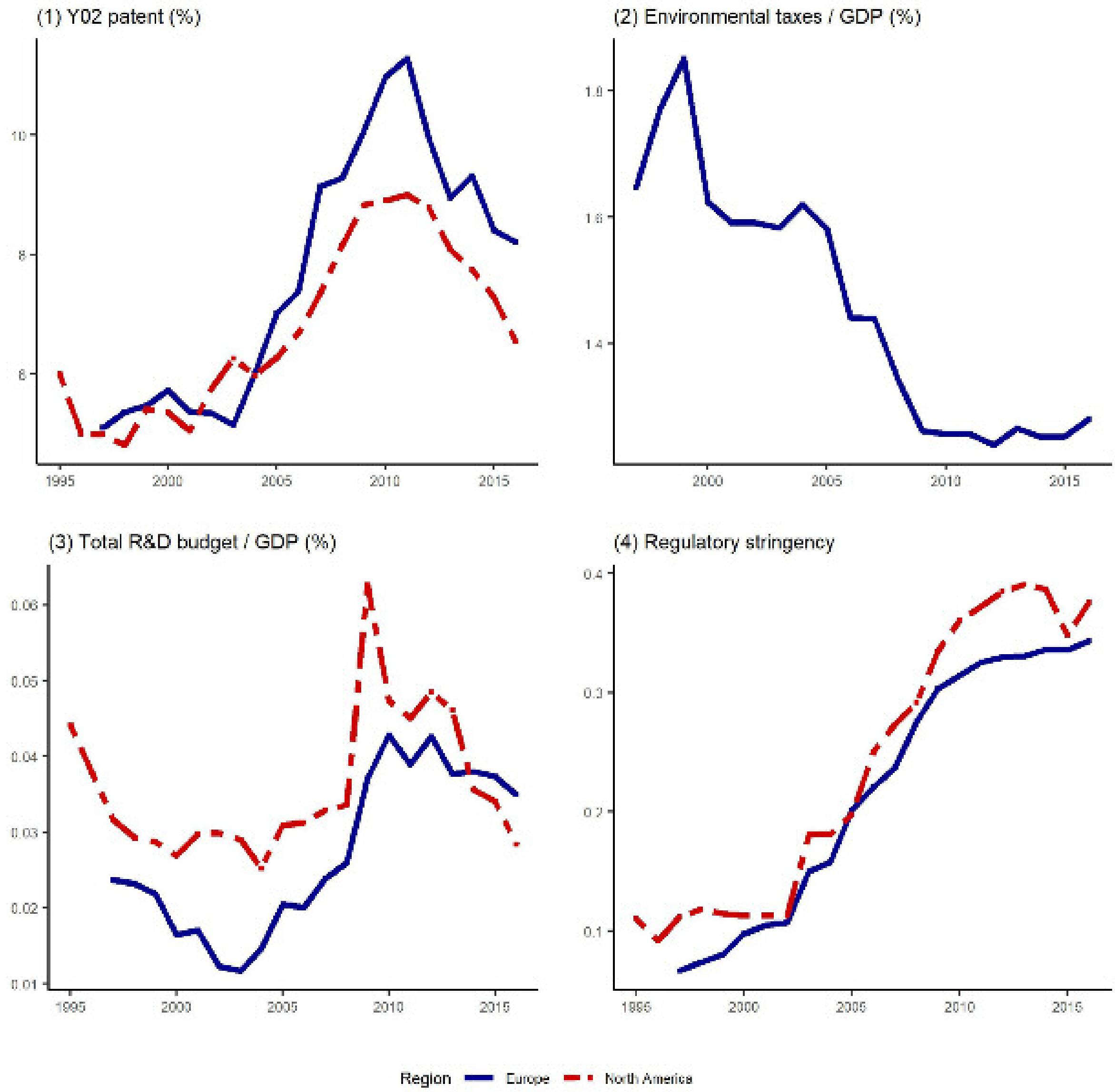
5 Empirical strategy

We estimate the impact of environmental policies on green innovation in a panel dataset at the country/sector/year level of observation using the following estimation equation:

$$ln(Y02)_{cst} = \alpha_{st} + \tau ln(Tax_{cst}) + \rho Reg_{cst} + \sigma ln(Sub_{ct}) + \gamma \mathbf{X}_{ct} + \varepsilon_{cst}. \quad (2)$$

The dependent variable is the natural logarithm of the weighted count of Y02 patents, allocated to country c and NACE2 s, in year t. All regressions include fixed-effects at the sector/year level (α_{st}). Thus, sectoral trends and shocks in patenting across countries are accounted for.

Figure 3: Main variables over time



Notes: (1) Share of Y02 patents over total patents by region and year; (2) Environmental taxes over GDP in Europe, no data available for US and Canada; (3) Total R&D budget over GDP by region; (4) Environmental regulation stringency by region (see section 4.4).

The main variables of interest on the right hand side are (i) the log of environmental tax revenues ($ln(Tax_{cst})$), in total as well as classified into three subcategories (energy taxes including pollution taxes, resource taxes and transport taxes); (ii) the presence and stringency of environmental regulation in a sector, country and year (Reg_{cst}), overall or distinguishing MB and NMB regulation; and (iii) R&D subsidies (Sub_{ct}), which we capture on the one hand by the log of state-level R&D budgets devoted to green energy innovation (direct subsidies), in total as well as classified into nuclear, renewables, and energy efficiency & others, hydrogen and other

R&D; and on the other hand by the R&D tax subsidy rate (indirect subsidies), i.e. the share of R&D costs companies can recoup through the tax system.

Additional control variables are collected in $\mathbf{X}_{ct}$; it includes a CO2 emission index, the log of the two year lagged price of natural gas, and the log of the knowledge stock (which varies at the country/sector/year level). In all regressions we also control for the log value added of an industry, proxying for industry size. Thus our regressions measure the effects of e.g. taxes and subsidies relative to economic activity in the industry and an increase in taxes or subsidies therefore indicates a rise in the stringency of policy. ε_{cst} is a heteroskedasticity-robust error term, allowing for error correlation within the 86 NACE2 clusters contained in the data.[17]

The identification of the causal impact of environmental policies on green innovation relies on two pillars. On the one hand we rely on panel econometrics, using a comprehensive set of fixed effects and control variables. The fixed-effects at the sector/year level account for differential exogenous (green) technological trajectories across sectors and over time, while the country/sector/year-specific knowledge stock controls for the level of innovative activity. Thereby, these variables make innovative sectors more comparable to low-tech sectors. Additionally, the inclusion of value added makes large and small industries more comparable. We hope to capture other factors driving green innovation through the set of control variables described above (e.g. gas prices and emissions).

On the other hand, we employ an IV strategy, instrumenting environmental taxes, direct R&D subsidies and regulatory stringency, since these policies are likely to be endogenously determined in the political decision making process and not randomly assigned.[18] There might be many reasons for endogenously determined environmental policies. For example, if the economy is strong it may be easier for politicians to pass new regulations, finance new subsidies or even impose a carbon tax. Conversely, it may be tough to pass legislation if the economy is not doing well.[19] Thus, the timing of new environmental taxes, regulations, and R&D subsidies is not random and could bias the estimated coefficients. We therefore need to find instruments which (1) affect environmental taxes, regulations, and R&D subsidies (i.e. are not weak instruments)

[17] We do not estimate count models (e.g. Poisson or negative binomial), because our unit of observation is an industry in a country in a year and we log the sum of weigthed green patents at this level. Thus, the dependent variable is neither a count, nor does it suffer from zero inflation. However, the data are heteroskedastic, right-skewed, and have a variance that increases with the mean. We tackle these problems by taking logs, introducing a comprehensive set of fixed effects as well as heteroskedasticity-robust, clustered error terms.

[18] We do not instrument for indirect R&D subsidies (the R&D tax subsidy rate), since they apply to all R&D and can arguably be viewed as exogenous to green patenting activity. Empirically, R&D tax subsidy rates are very stable, in some countries they have not changed for decades. More importantly, they apply to all sorts of R&D activity (not only environmental R&D) and do not react much to the current political debate on climate change.

[19] As an example, see the (eventual) passage of the Inflation Reduction Act in the US in 2022 containing predominantly subsidies and regulations to combat climate change.

and (2) do not directly affect green patenting activity in an industry but only indirectly via the applied policies (i.e. the exclusion restriction should be fulfilled).

We propose that this is achieved by the use of Hausman-style instruments, where the state of environmental policy in a country, sector and year is instrumented via the policies in the same sector and year in other countries (excluding the focal one). Specifically, to instrument for an environmental policy in country c and sector i (we measure policy trends at the one-digit NACE level) and year t, we calculate the average taxes/regulations/subsidies in sector i and year t in other countries, $-c$. To abstract from size effects and ensure comparability across countries, we construct the instruments for taxes and subsidies on a log per-capita basis. While our instruments are generally calculated using all other available countries, our main results (table 3) excludes North American countries, as environmental tax data are not available. Thus, the instruments for European countries are calculated from other European countries.

Overall, we instrument sectoral policies using general trends in these sectors in other countries. As our main concern for endogeneity are within-country specificities – such as e.g. the election of a government that is particularly for or against certain policies –, an approach using general, sectoral trends in other jurisdictions seems appropriate to eliminate any feedback between a countries' political situation and its environmental policies.

6 Results

6.1 Main results

This section presents our main results on how environmental policies impact green patenting. Table 3 contains the estimation results for equation 2. Column (1) presents the results for the main categories of environmental taxes, regulatory stringency and R&D subsidies in an OLS specification (i.e. disregarding the potential endogeneity of policies), while the other columns use the IV approach described above. Column (3) distinguishes between different types of environmental taxes, while column (4) also looks at the sub-categories of regulatory stringency. Column (5) additionally distinguishes sub-categories of R&D subsidies. The first-stage regressions (three of which are reported in table A1 in the appendix, while the rest is omitted for brevity) for columns (2)-(5) show that the IV approach works as desired: the endogenous policies are significantly related to the Hausman-instruments and the corresponding F-values indicate that instruments are not weak. Tests for underidentification and weak identification conducted on the first stage regressions strongly reject the null hypothesis.

Before we turn to the main results, a few words about the coefficients on control variables are in order. As in Aghion et al. (2016), the lagged price of natural gas positively affects green patenting. The log stock of knowledge in an industry obtains coefficients of around 0.8-0.9, indicating a strong effect of the overall patent stock on green patenting (Scotchmer, 1991; Aghion et al., 2016). While the overall CO2 emission index has a negative effect on green patenting, the coefficients of (log) value added remain insignificant.

It is interesting to compare the results obtained from OLS estimation with those from an IV approach (columns (1) and (2)): while the coefficients of tax breaks and most control variables are nearly identical, those of taxes, subsidies and regulation change substantially when instrumenting. Thus there is evidence that some policies are indeed endogenous. With an IV approach, environmental taxes significantly direct innovation towards green patenting. The coefficient indicates that doubling the environmental taxes in an industry on average increases green patenting activity by around 6.7%. Column (3) reveals that energy and resource taxes, as well as – to a lesser extent – transport taxes, are responsible for the positive effect.

Environmental regulatory stringency also has the potential to direct technological change towards green. Doubling the strictness of regulation in an industry is associated with a 16.4% increase in green patenting. Columns (4) and (5) convey that market based regulations are (predominantly) responsible for this significantly positive effect.

State subsidization of R&D in green technologies – both direct R&D subsidies and indirect tax benefits – significantly increases the number of green patents. Doubling direct state R&D subsidies leads to a 9% increase in green patent applications. From column (4) it is apparent that subsidies for renewable energy technolgies are the main drivers of this effect. The coefficients of R&D subsidies for energy efficiency and other R&D are significantly negative. This likely indicates substitution effects between green technologies and fossil fuels. Reducing R&D costs for companies indirectly via more generous tax deductions of R&D costs also increases green patenting. An increase of the R&D subsidy rate by 1 percentage point increases green patent applications by 0.3%.

6.2 Geography and Time

Table 4 differentiates effects by geographic region as well as by time period. Specifically, we compare policies in North America (comprising the US and Canada) with the EU (see table 2 for a list of included countries) and also policy effects up to and after 2010. Since we lack data on environmental taxes in North America, we focus on regulation and R&D subsidies in the regional regression.

Table 3: Effects of environmental policy instruments on green innovation

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV
1. Taxes					
Env. taxes	0.011***	0.067***			
	(0.004)	(0.007)			
Energy taxes			0.040***	0.040***	0.021***
			(0.008)	(0.008)	(0.008)
Resource taxes			0.020***	0.022***	0.015***
			(0.002)	(0.002)	(0.002)
Transport taxes			0.005*	0.005	0.013***
			(0.003)	(0.003)	(0.003)
2. Regulation					
Regulatory stringency	0.045***	0.164***	0.174***		
	(0.008)	(0.031)	(0.032)		
Non-market-based				0.039**	0.027
				(0.018)	(0.018)
Market-based				0.215***	0.146***
				(0.028)	(0.022)
3. R&D					
Total budget	0.140***	0.090***	0.072***	0.071***	
	(0.007)	(0.008)	(0.008)	(0.008)	
Nuclear					0.033***
					(0.004)
Renewables					0.280***
					(0.009)
Energy eff. & oth.					-0.072***
					(0.007)
Hydrogen					0.004
					(0.003)
Other R&D					-0.044***
					(0.006)
R&D tax deductions	0.003***	0.003***	0.002***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables					
Gas price	0.221***	0.280***	0.293***	0.293***	0.203***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.029)
Knowledge stock	0.881***	0.889***	0.917***	0.918***	0.768***
	(0.009)	(0.011)	(0.011)	(0.011)	(0.012)
CO2 emission index	-0.002***	-0.002***	-0.003***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Value added	0.012	-0.013*	-0.011	-0.011	-0.011
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)
Observations	20883	20883	20783	20783	20448
R^2	0.95	0.81	0.81	0.81	0.82
Kleibergen-Paap LM		74.56	76.86	86.40	88.07

Notes: NACE2-clustered standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is the log of Y02 patents allocated to a country/industry/year cluster, all tax and R&D subsidy variables are logged as well. All regressions include fixed-effects at the NACE2/year level (1720 regressors) and contain observations on 86 NACE2 sectors across 22 countries.

Table 4: Effects of policy instruments on green innovation by region

	By region		By period	
Region				
North Am. × Regulatory stringency	0.246**	(0.117)		
North Am. × Total budget	0.084***	(0.014)		
North Am. × R&D tax deductions	0.001	(0.001)		
EU × Regulatory stringency	0.219**	(0.086)		
EU × Total budget	0.096***	(0.011)		
EU × R&D tax deductions	-0.003***	(0.001)		
Period				
pre-2010 × Regulatory stringency			-0.062	(0.064)
pre-2010 × Total budget			0.068***	(0.011)
pre-2010 × Env. taxes			0.080***	(0.014)
pre-2010 × R&D tax deductions			0.002***	(0.001)
post-2010 × Regulatory stringency			0.278**	(0.107)
post-2010 × Total budget			0.115***	(0.018)
post-2010 × Env. taxes			0.034**	(0.016)
post-2010 × R&D tax deductions			0.003***	(0.001)
Control variables				
Gas price	0.144***	(0.017)	0.277***	(0.033)
Knowledge stock	0.924***	(0.013)	0.897***	(0.019)
CO2 emission index	0.005***	(0.000)	-0.002***	(0.000)
Value added	0.014	(0.012)	-0.011	(0.015)
Observations	22112		20883	
R^2	0.88		0.81	
Kleibergen-Paap LM	7.16		6.60	

Notes: NACE2-clustered standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is the log of Y02 patents allocated to a country/industry/year cluster, all tax and R&D subsidy variables are logged as well. All regressions include fixed-effects at the NACE2/year level (1720 regressors) and contain observations on 86 NACE2 sectors across 22 countries.

The impact of environmental regulatory stringency is strong and homogeneous across regions. European Union countries and USA/Canada display rather similar coefficients. The effects of direct R&D subsidies are positive as well across country subgroups with comparable coefficients. Indirect R&D subsidies remain insignificant in North America, while exhibiting a negative effect in the EU. Thus, there appear to be no strong heterogeneities across regions and no substantial differences to the main results, with the exceptions of R&D tax breaks being insignificant or negative in this specification.

When evaluating the impact of environmental policies in different time periods, we generally find larger effects in the post-2010 period: while regulatory stringency has no significant effect before 2010, it significantly directs innovation after. The impact of R&D subsidies and tax breaks is positively significant in both periods, but substantially increases in size after 2010. Only the coefficient on environmental taxes decreases, but remains significant.

Thus while heterogeneity across regions appears to be limited, we find that environmental policies have had a more substantial impact in recent years.

6.3 Policy interaction effects

Most countries use more than one policy to tackle environmental problems. For example, the use of combustible fuels is subject to taxation as well as regulation in many countries. Other examples include the EU ETS pricing emissions from electricity generation and emission standards for coal or gas plants or portfolio standards for renewables. In this section we try to answer a question that is of first-order policy relevance: how do different environmental policy instruments interact, when used in conjunction?

Table 5 presents results when including a full set of interaction terms between the three policy types. We consider all policies (except R&D tax deductions) to be potentially endogenous and construct instruments for interactions analogously to the main policies. Table 5 reports the F-values of underidentification tests, but omits first-stage regressions (all of which have F-values of more than 100).

There is a clear tendency of substitutive effects to dominate if policies are applied in conjunction. The largest substitutive effects are obtained for the regulation and R&D subsidy interaction term. Thus, the marginal effects of R&D subsidies diminish significantly if there is also regulation in place tackling the same problem (and vice versa). While the interaction effect of taxation and R&D subsidies is significantly negative, its magnitude in absolute terms is much lower than the interaction between regulation and R&D subsidies. Thus, it appears that carbon taxes/pricing entails less crowding out than regulation with respect to the effects of R&D subsidies.

One would expect substitutive effects if there are increasing costs of abatement and/or diminishing returns to innovation. For example, if carbon emissions are reduced in the automobile sector via fleet regulations, the marginal effect of an R&D subsidy is lower since additional reductions in emissions via innovation are harder to achieve.

6.4 A comparison of policies

The question of the cost-effectiveness of different measures is of prime interest. Unfortunately, we are unable to directly calculate and compare the economic costs associated with individual policies. While R&D subsidies and environmental tax revenues per induced patent may give an impression on how large program costs per induced patent are, these are not the economic costs associated with these policies. For example, R&D subsidies must be financed by tax

Table 5: Interaction effects of policy instruments

	(1)	(2)	(3)	(4)	(5)
Env. taxes	0.067***	0.067***	0.230***	0.239***	0.245***
	(0.007)	(0.007)	(0.026)	(0.027)	(0.028)
Regulatory stringency	0.164***	0.536***	0.878***	0.888***	0.905***
	(0.031)	(0.103)	(0.127)	(0.128)	(0.130)
Total budget	0.090***	0.097***	0.161***	0.167***	0.121***
	(0.008)	(0.008)	(0.012)	(0.013)	(0.013)
R&D tax deductions	0.003***	0.003***	0.005***	0.007***	-0.002
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Regulation × Env. taxes		-0.038***	-0.039**	-0.037*	-0.034*
		(0.014)	(0.019)	(0.019)	(0.020)
Regulation × R&D subsidy		-0.214***	-0.330***	-0.337***	-0.348***
		(0.053)	(0.066)	(0.067)	(0.068)
Regulation × R&D tax deductions		-0.002	-0.007***	-0.007***	-0.006***
		(0.001)	(0.002)	(0.002)	(0.002)
Env. taxes × R&D subsidy			-0.044***	-0.045***	-0.045***
			(0.006)	(0.006)	(0.006)
Env. taxes × R&D tax deductions				-0.001**	-0.001***
				(0.000)	(0.000)
R&D subsidy × R&D tax deductions					0.002***
					(0.000)
Observations	20883	20883	20883	20883	20883
R^2	0.81	0.81	0.80	0.79	0.79
Kleibergen-Paap LM	74.56	80.47	185.00	187.47	185.67

Notes: NACE2-clustered standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is the log of Y02 patents allocated to a country/industry/year cluster, all tax and R&D subsidy variables are logged as well. All regressions include fixed-effects at the NACE2/year level (1720 regressors) and contain observations on 86 NACE2 sectors across 22 countries.

revenues and environmental taxes may be passed on to consumers via higher prices, introducing deadweight losses we cannot measure. We therefore resort to estimating standardized (beta) coefficients, indicating by how many percent the outcome changes, when a regressor changes by one standard deviation.[20] This achieves comparability in the increment of the policy analyzed (one standard deviation) judging from the history of such variation. Thus, if it is comparably difficult (e.g. due to political economy constraints) or costly (direct and indirect costs of a policy) to increase policy intensity by one historical standard deviation, we can compare the effectiveness in inducing green patenting of the three policies.

[20]The beta coefficients are obtained by first standardizing all variables to have a mean of 0 and a standard deviation of 1. Thus, the coefficients then reflect s.d.-changes in the dependent variables for a one-s.d. change in the in the respective independent variable. These values are then multiplied with the in-sample standard deviation of the dependent variable, log of green patents. Thus, the reported values indicate the expected % change in the outcome, for a one-s.d.-change in an independent variable.

Table 6 displays the results on standardized coefficients calculated from the estimates in Table 3. In addition to the main categories of environmental taxes, regulatory stringency and R&D subsidies, we display standardized coefficients for the respectively most effective sub-groups, energy taxes, market-based regulations and renewable subsidies, i.e. those with the largest positive marginal effects in Table 3. The three main instruments display a fairly even influence on green patents. A one standard deviation increase of environmental taxes, regulations and direct R&D subsidies increase green patents by between 14% and 18%.

This masks important heterogeneities across instruments. The single most important and effective instrument are R&D subsidies for renewables with a standardized coefficient of 0.444: a one s.d. increase in renewable R&D subsidies increases green patents by around 45%. Energy taxes and market based regulation follow next.

The theory channels discussed in section 3 can help to rationalize these findings. As outlined, two market failures lead to the excessive emission of greenhouse gases and the sub-optimal level of technical change towards green inventions, the environmental externality and the public goods nature of knowledge. The most direct mechanism to internalize the second externality is through R&D subsidies or direct state funding of green research. Accordingly, we find that this mechanism is most effective in inducing green patents. While environmental taxes and regulation tackle predominantly the first externality, they can only indirectly rectify the knowledge externality (via increasing the relative – explicit or implicit – prices of carbon on the market). Thus, while carbon taxes/pricing and regulation may be best suited to internalize the current environmental externality, R&D subsidies are most effective in inventing new green technologies needed in the future to combat climate change.[21]

Table 6: Beta coefficients in percentage

	Main	Subgroup	
Env regulations	0.145	0.072	(market-based)
Environmental taxes	0.179	0.054	(energy taxes)
R&D subsidies	0.137	0.444	(renewables)
R&D tax deductions	0.036	*n.a.*	

[21] This is consistent with the model in Aghion et al. (2016) stating that R&D subsidies push scientists toward undertaking clean innovation. This is the direct channel. A carbon tax reduces the market for the dirty input and increases the market for clean technologies. This indirectly also redirects innovation toward clean technologies. Our results indicate that the direct channel is more important than the indirect channel.

6.5 Robustness

We collect our robustness tests in Table 7. The four columns contain checks on (1) assigning patents by applicants, rather than inventors; (2) only counting patents that were ultimately granted; (3) collapsing the data by industry and (4) collapsing the data by country.

In column (1), we assign patents to countries based on the location of the applicant, rather than the location of the inventor. The resulting coefficients and significances are very similar to those reported in Table 3.

Column (2) only counts patents that were ultimately granted for the dependent variable. Most policy-related coefficients somewhat increase with this change in sampling strategy, but the direction and significance of the effects remain unchanged.

Finally, columns (3) and (4) contain more radical checks on our empirical approach, where we eliminate variation across countries and industries respectively. In column (3), we average NACE2 sectors across all countries, such that we are left with 86 'average' NACE2 groups and 1892 observations. In column (4), we calculate within-country means across all industries, leaving us with 263 observations of 22 countries. To address these changes in sample variation and statistical power, columns (3) and (4): i) report OLS, rather than IV, coefficients[22] and ii) use contemporary gas prices, rather than second lags, to avoid further loss of observations. All policy-related coefficients retain their positive sign and, in column (3), also their statistical significance. In column (4), where we look at country-averages over time, taxes and subsidies become insignificant, likely due to the low number of observations.

7 Conclusion

Although it is well-accepted among economists that the optimal policy to combat climate change is a combination of a (sufficiently high and potentially increasing) carbon tax and R&D subsidies, we see few real world examples of such a first-best approach. The reluctance to adopt such costly policies is likely owed to the dearth of empirical evidence on their effectiveness. This paper aims to fill this gap by providing empirical estimates of the effectiveness of environmental policies to direct innovation toward green technologies in a comprehensive dataset.

We construct a panel dataset, comprising detailed information on green patenting at the country/sector/year level of observation, and evaluate whether and how sectors react to three different environmental policies: carbon prices/taxes, environmental regulatory stringency, and

[22] In the aggregated estimation settings reported in columns (3) and (4) of Table 7, endogeneity concerns are less pertinent: while in the disaggregated main sample a country might react endogenously to, e.g., a comparative sectoral advantage, such a targeted response is not possible when looking at country-level or sector-level averages.

Table 7: Robustness tests

	(1)	(2)	(3)	(4)
1. Taxes				
Env. taxes	0.062***	0.094***	0.084***	0.136
	(0.007)	(0.008)	(0.030)	(0.130)
2. Regulation				
Regulatory stringency	0.131***	0.103***	0.169***	1.498***
	(0.029)	(0.038)	(0.028)	(0.375)
3. R&D				
Total budget	0.148***	0.161***	0.346***	0.025
	(0.008)	(0.009)	(0.033)	(0.034)
R&D tax deductions	0.001***	0.006***	0.018***	0.007**
	(0.000)	(0.000)	(0.002)	(0.003)
Control variables				
Gas price	0.642***	0.050	0.232***	0.233***
	(0.028)	(0.035)	(0.036)	(0.075)
Knowledge stock	0.861***	0.815***	0.783***	0.365**
	(0.012)	(0.014)	(0.155)	(0.162)
CO2 emission index	-0.001***	-0.005***	0.021***	0.003
	(0.000)	(0.000)	(0.002)	(0.003)
Value added	-0.023***	-0.021**	-0.628***	-0.811
	(0.008)	(0.009)	(0.115)	(0.521)
Observations	20873	20664	1892	263
R^2	0.79	0.76	0.99	0.97
Kleibergen-Paap LM	74.53	74.61		

Notes: NACE2-clustered standard errors in parentheses (except column (4), where SEs are clustered at the country level), * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is the log of Y02 patents allocated to a country/industry/year cluster, all tax and R&D subsidy variables are logged as well. All regressions include fixed-effects at the NACE2/year level (except columns (3) and (4), which contain NACE2- and country-level FEs, respectively). Column (1) assigns patents by applicant; column (2) counts only granted patents; columns (3) and (4) collapse the sample by industry and country, respectively (see text).

green R&D subsidies. Our main results are encouraging. All three policies direct innovation towards green patenting. Environmental taxes, environmental regulatory stringency and state subsidization of R&D of green technologies significantly increase the number of Y02 patents in affected countries and sectors.

From the point of view of policy, the questions of interaction effects between different policies and cost-effectiveness are of prime interest. Our results allow some guidance on both dimensions. Concerning policy interactions, we consistently find negative effects, i.e. there is a preponderance of substitutive effects among policies when applied in conjunction with each other. The largest substitutive effects are obtained for the regulation times R&D subsidy interaction term. Thus, the marginal effects of R&D subsidies diminish significantly if there is also regulation in place tackling the same problem (and vice versa). Contrariwise, it appears that carbon taxes/pricing entails less crowding out than regulation with respect to the effects of R&D

subsidies. These results are consistent with increasing costs of abatement and/or diminishing returns to innovation.

To address cost-effectiveness, we estimate standardized coefficients. Consistent with theory, we find that the single most effective policy is direct R&D subsidies for renewables: a one-standard-deviation increase in direct R&D subsidies for renewables induces the largest increases in green patents of around 45%. In comparison, both environmental taxes and environmental regulatory stringency achieve lower increases. Thus, while carbon taxation and possibly regulation may be best suited to internalize the current environmental externality, R&D subsidies can successfully help obtain the new green technologies needed in the future to combat climate change.

Our main result is that all three policy instruments are effective in directing technological change towards green innovation. Thus, if for some reason, e.g. due to political feasibility, it is not possible to implement the first-best policy combination – carbon taxes/prices in conjunction with R&D subsidies – that is no excuse for environmental idleness: regulation (in conjunction with R&D subsidies), if stringently applied, also directs technological change towards green. Moreover, environmental policies do not only have short-run effects but can spark longer-run green innovation. Thus, the long-run cost-benefit balance of these policies is more favourable than when only considering short-run costs and benefits. However, we were not yet able to compare the economic costs of policies, nor calculate the economy wide, general equilibrium impact of the policies under consideration. While our results are suggestive, future research should take further steps to identify which policies combat climate change at the lowest cost.

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Appendix

Table A1: First stage regressions for column (2) in table (3)

	Regulatory stringency	Env. taxes	R&D subsidies
Instrument Regulation	-21.268***	-4.105***	-2.885***
	(1.938)	(0.987)	(0.390)
Instrument Tax	-0.001	-7.964***	-0.080***
	(0.020)	(0.245)	(0.028)
Instrument R&D Budget	0.010	4.916***	-12.590***
	(0.047)	(0.167)	(0.054)
R&D tax deductions	0.000	-0.004***	0.011***
	(0.000)	(0.001)	(0.000)
Gas price	-0.000	-0.117**	-0.136***
	(0.015)	(0.050)	(0.013)
Knowledge stock	0.003	0.605***	0.619***
	(0.003)	(0.015)	(0.005)
CO2 emission index	-0.000	0.006***	-0.006***
	(0.000)	(0.000)	(0.000)
Value added	-0.005**	0.264***	0.126***
	(0.003)	(0.019)	(0.006)
Observations	20883	20883	20883
F	53.23	458.81	21727.28

Notes: Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01.