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## The impact of environmental regulation on clean innovation: are there crowding out effects?

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**Abstract**

We examine the extent to which environmental regulation affects innovation and which policy types provide the strongest incentives to innovate. Using a local projection framework, we estimate the regulatory impact on patenting activity over a five-year horizon. As a proxy for environmental policy exposure, we estimate firm-level greenhouse gas emissions using a machine learning algorithm. At the country-level, policy tightening is largely associated with no statistically significant change in environmental technology innovation. At the firm-level, however, environmental policy tightening leads to higher innovation activity in technologies mitigating climate change, while the effect on innovation in other technologies is muted. This suggests that environmental regulation does not lead to a crowding-out of non-clean innovations. The policy type matters, as increasing the stringency of technology support policies and non-market based policies leads to increases in clean technology patenting, while we do not find a statistically significant impact of market-based policies.

**Keywords:** Environmental regulation, Innovation, Emissions, Porter hypothesis, Euro Area
**JEL Codes:** O44, Q52, Q58

## Non-technical summary

Concerns about the impacts of climate change have led to a progressive tightening of environmental regulation at the EU level as well as nationally. This trend is likely to continue going forward as governments gradually translate their climate neutrality targets into legislation. Policy-makers have a broad range of tools at their disposal, including carbon taxes, performance standards and research and development (R&D) subsidies for environmentally friendly technologies. All these regulatory instruments are intended to reshape the economy by incentivising or mandating changes in firms' behaviour. While these policies often achieve their primary goal and reduce pollution, they also impose limits on the way firms can operate, which can increase costs, at least temporarily, due to necessary adjustments. The inevitability of a trade-off between sustainability and competitiveness has been, however, questioned by Porter and Van der Linde (1995), who argued that under certain conditions more stringent environmental regulations could increase innovation and consequently the competitiveness of firms. Through this mechanism, the short-term adjustment costs could be compensated or even exceeded by benefits. While this proposition, known as the Porter hypothesis, is theoretically attractive, it needs to be empirically tested on a representative sample of firms to inform reliable policy recommendations.

This paper tests the Porter hypothesis at the country and also at the firm level. We use country-level data from 15 euro area states and firm-level information for more than three million companies from six euro area countries over the period 2003 to 2019. We combine this information with the OECD Environmental Policy Stringency (EPS) indicator that allows us to compare the stringency of different types of environmental policies across countries and time. In addition, we estimate the greenhouse gas emissions of firms using a machine learning algorithm (XGBoost), to overcome the paucity of such information in available datasets, allowing us to distinguish between low and high polluters within this large sample of firms. This distinction is key to our empirical strategy as highly polluting firms can be expected to be more exposed to environmental regulations and, therefore, face higher costs. We estimate the impact of changes in environmental policies on innovation using a local projection approach, which allows us to examine the impact over different horizons (up to five years ahead), while still controlling for many other factors driving innovation. Furthermore, we explore whether the impacts of different policy types differ and investigate whether there are differences in firms' responses depending on their characteristics.

At the country level, we largely observe no significant impact of environmental policy tightening on clean innovation (captured by patent filing), with the exception of technology support policies, where we observe a minor decline three years after the policy shock. Firm or sectoral differences could, however, obscure the regulatory impact in this setting. Our firm-level analysis reveals that highly polluting firms that are more exposed to environmental regulation tend to patent more in clean technology classes, while patenting in other technology classes remains largely unchanged. The only exception are green subsidies, which appear to have a spillover effect on innovation in non-clean technology classes. Non-market based policies such as standards and technology support policies such as R&D subsidies and feed-in tariffs have a relatively more pronounced effect on clean technology patenting compared market-based instruments (e.g. taxes or cap-and-trade policies), with the magnitude of the impact at its peak three years after the policy shock. In related work (Benatti et al., 2023), we examine the effect of environmental policy tightening on productivity growth and largely find negative effects for high-polluting firms in the five years after the policy shock. It is possible, however, that the positive impact on certain types of innovation translates into productivity gains only beyond the 5-year horizon, which we were able to empirically examine.

The current study suggests that decisive environmental policy action is essential for increasing clean technology innovation, which in turn is vital for delivering greenhouse gas reductions at a lower cost in the future. The combined results from this study and Benatti et al. (2023) suggest that technology support measures possibly offer a 'no regret' policy pathway, which incentivises clean technology innovation, while limiting possible short-term productivity losses.

# 1 Introduction

The EU climate-neutrality target by 2050 sets a clear direction for the future and calls for a wide-ranging transformation of the economy. In addition to the EU Emissions Trading Scheme (ETS), the flagship policy for greenhouse gas emission abatement at the EU level, a growing number of EU governments are establishing their own 'net-zero' targets (Rogelj et al., 2021) and adopting increasingly stringent policies to deliver on their climate and broader sustainability ambitions at the national level. The implemented policies run the entire gamut of command-and-control instruments (such as mandatory standards), market-based tools (such as carbon pricing and auctions) and technology support measures (such as R&D subsidies and renewable energy feed-in tariffs). Changes in these policies are likely to trigger a substantial re-allocation of resources between sectors, especially when combined with stimulus packages adopted in the wake of the COVID-19 crisis, which were also dedicated to supporting 'green' economic activities albeit to varying degrees (Aulie et al., 2023). While these regulatory actions may have important benefits in terms of mitigating environmental market failures and the physical risks related to climate change, they could also have unintended economic consequences and, if implemented sub-optimally, increase transition risk (Stock, 2022). The economic effects of environmental regulation are therefore of central interest to policy-makers both at the national and EU levels.

Regulation is traditionally seen as a hindrance to economic activity, at least in the short to medium term, as it raises costs without increasing output and restricts the set of production technologies and outputs. In contrast to this view, the Porter hypothesis (Porter, 1991; Porter and Van der Linde, 1995) suggests that, under certain conditions, environmental policies can spur innovation and by doing so enhance productivity, which can offset or even outweigh the costs of the regulation. The body of existing empirical evidence evaluating the Porter hypothesis is large but results remain inconclusive, with some studies positing that it holds while others finding evidence of the opposite. The majority of relevant studies are either focused on single countries or industries and therefore suffer from limited external validity or are carried out at the industry or country levels, which obscures the impact of firm heterogeneity. Potential endogeneity issues are also rarely addressed in a robust manner. Moreover, few studies explicitly examine whether innovation gains in some technology classes may be offset by losses in others.

Since innovation is key to enabling pollution reduction without sacrificing economic growth, this paper focuses on the impact of environmental regulation on innovation. We contribute to the literature by probing the link between environmental policy stringency and innovation both at the country and the firm levels and explore innovation as a potential channel driving the observed productivity effects described in Benatti et al. (2024). We use local projections (Jordà, 2005) to estimate impulse responses of innovation to a shock in environmental regulation. This framework allows us to describe the dynamic effects of changes in regulation at different time horizons, an aspect that has been overlooked thus far (Ambec et al., 2020). In addition, we assess the dynamic impact of environmental regulation tightening on countries' and firms' innovative output in clean technologies as well as in non-clean technology classes, enabling us to evaluate possible crowding-out of the latter by the former.

While our country-level analysis does not reveal significant effects of tighter environmental regulation on the share of green innovation, at the firm level we find that tighter environmental policies lead to increased innovation efforts in clean technologies. Importantly, technology support and non-market based policy instruments tend to have a stronger impact on clean innovation than market based policies. These effects occur to be statistically significant with a lag of two to three years after the policy tightening. At the same time, there is no statistically significant impact of stricter regulation on other innovations, with the exception of positive effects of technology support policies. Thus, we do not observe a crowding out of other technologies due to more green innovation. We also show that these effects are mainly driven by the intensive margin, i.e. firms with patenting experience increase their efforts without new firms starting to patent.

Apart from new insights with respect to the dynamic effects of different types of regulation on innovation, and the trade-off between clean and non-clean innovation, we also contribute to the existing literature by leveraging a large new multi-country firm-level data set and by improving identification with firm specific estimates of regulatory exposure. We gathered data on more than three million individual firms, combining balance sheet information with patent data, which allows us to differentiate between 'green', 'non-green' and 'dirty' innovations, and with estimated firm-specific greenhouse gas emissions. Our identification strategy is based on the assumption that environmental policy is likely to affect firms heterogeneously depending on their exposure to regulation, with firm-level emissions used as a proxy for this exposure. A similar approach has been applied by Albrizio et al. (2017), albeit on an industry- rather than firm-level, which failed to account for the large within industry heterogeneity of emission intensities (Lyubich et al., 2018). Scarcity of firm-level emission data, especially for smaller firms, would normally preclude the deployment of this approach at firm level. We overcame this problem by estimating the firms' position in the emission distribution using a Boosted Trees machine learning model based on balance sheet data and firm characteristics.

The remainder of the paper is structured as follows: section 2 reviews the literature, section 3 explains the hypothesis that we want to test, section 4 details the data used, section 5 describes the empirical models used and justifies our claim to causality, section 6 discusses the aggregate and firm-level results and finally, section 7 concludes.

## 2 Literature Review

Porter and Van der Linde offered primarily anecdotal case study evidence to support their hypothesis (Porter, 1991; Porter and Van der Linde, 1995). However, these ideas have since inspired a large body of empirical literature addressing each of its theoretical offshoots. The 'weak' Porter hypothesis, which we examine in this paper, holds that optimally designed environmental regulation can spur innovation. In comparison, the 'strong' version goes further to propose that increases in environmental regulation can increase firms' competitiveness and improve other business outcomes. The 'narrow' version, which we also examine, suggests that flexible, market-based regulation performs better at incentivising certain kinds of innovation than more prescriptive forms of regulation (Jaffe and Palmer, 1997).

A number of possible sources of endogeneity complicate the identification of a causal link between regulation and economic outcomes including innovation. Albrizio et al. (2017) in particular highlight that simultaneity or reverse causality issues may arise if good environmental performance in certain industries facilitates adoption of more stringent environmental policies or if poor performers are able to successfully lobby against more stringent policies. We review the most relevant literature with a particular focus on the identification strategy chosen by the authors. We also elaborate falsifiable hypotheses based on the ideas of Porter and Van der Linde (1995) and other literature, both theoretical and empirical.

The studies that test the weak version of the Porter hypothesis largely find a positive relationship between stricter regulation and green innovation, but to varying degrees (Ambec et al., 2020; Cohen and Tubb, 2018; Kozluk and Zipperer, 2015). This is in contrast to the literature regarding the strong version of the Porter hypothesis which is even inconclusive regarding the direction and the significance of the effect. Existing studies vary widely in terms of the environmental policy stringency measure they use, the dependent variable used to capture innovation efforts as well as the empirical strategies and underlying data. A seminal paper by Jaffe and Palmer (1997) uses pollution abatement costs to proxy environmental policy stringency and R&D expenditures as well as the number of successful patent applications as the dependent variable. They find a positive link with R&D expenditures but no statistically significant effect on the number of patents.

An important subset of studies examines the impacts on innovation and/or clean innovation of specific individual environmental policies. These tend to be able to use difference-in-differences or regression discontinuity designs and therefore their causal identification is more robust. This includes, for instance, Calel and Dechezleprêtre (2016), who use a matched difference-in-differences design to examine the effect of the EU Emission Trading Scheme (EU ETS), exploiting the inclusion threshold which is defined in terms of the size of an individual installation. They show that EU ETS increased innovation activity in low-carbon technologies among participating companies but argue that the effect of the policy on innovation is weak overall. Howell (2017) offers well-identified insights regarding the impacts of R&D funding, using data about firms applying for support from the US Small Business Innovation Research (SBIR) programme. Dechezleprêtre et al. (2023) use a size-based inclusion threshold to assess the impact of a UK R&D tax incentive on innovation, relying on a regression discontinuity design. They find a positive impact of R&D tax credits on innovation but do not specifically examine clean innovation.

While the studies of specific policies offer valuable insights and offer a more straightforward path to causal identification of the impact of a specific policy instrument on innovation, the robust causal claim often comes at the expense of external validity. These studies provide little information about the global impact of environmental policy at large and the possible economy-wide costs and transition risk that it may introduce. Hence, there is also a broad literature with an aggregate perspective using country or industry data that analyses the effects of environmental regulation on different measures of innovation (Brunnermeier and Cohen, 2003; Popp, 2006; Johnstone et al., 2010b, 2012; Eugster, 2021). Lanoie et al. (2011), Rubashkina et al. (2015) and Martínez-Zarzoso et al. (2019) even test the entire Porter hypothesis chain. However, due to aggregation, problems in the timing, or no exogenous variation, the causal link between the policy variables and the innovation outcomes is usually not established in a robust manner.

Our empirical approach tries to combine the best of both appraoches by using aggregate policy measures in the multi-country study similar to Aghion et al. (2016), which estimates the impact of fuel taxes on clean and dirty innovation. Given our aim to study the impact of regulation also on firms without a patenting history, we opted however for relying on estimated emissions instead of the history of patent filing as exposure measure. By using granular firm data and following the identification approach by Rajan and Zingales (1998), we argue for the causality of the positive effects of (specific) environmental policies on green innovations.

Another key issue is the role of different types of policies and their design attributes. Johnstone et al. (2010a) find that stability and flexibility have distinct effects on innovation beyond that of policy stringency, capturing these traits using survey data. Arimura et al. (2007) consider the differences between technology standards, performance standards, input tax and pollution taxes in their effect on R&D budgets of manufacturing facilities in 7 OECD countries and find that the most prescriptive policy, technology standards, have the strongest effect. Popp (2003) shows that switching from a command-and-control instrument to permit trading to control sulphur dioxide emissions, in the wake of the Clean Air Act passage, reduced innovation activity. More recently Fabrizi et al. (2018) and Eugster (2021) used the disaggregated EPS index to investigate the impact of different policy types. The former study investigates the joint role of research networks and environmental stringency as a driver of green patents and finds that market-based instruments in conjunction with participation in European research networks lead to increased production of green patents. Eugster (2021) only examines clean energy patents and carries out his analysis only at the country level but finds a positive relationship between both non-market and market-based policies and clean innovation. In the absence of a plausible source of exogenous variation, the effects he finds are, however, not necessarily causal.

Ambec et al. (2020) raise an important point about the lag structure of the relationship between policy changes and innovation. In their meta-synthesis, they argue that previous studies often failed to pick up the effect of regulation on innovation due to inappropriate representation of the innovation cycle in their use of lags. Although Brunnermeier and Cohen (2003) find a positive relationship between lagged compliance costs and innovation and Lanoie et al. (2008) find a positive relationship between lagged regulatory stringency and productivity, most previous studies have relied on contemporaneous comparisons. The choice of an empirical model needs be informed by the fact that innovations may take several years to develop, and capital expenditures are often delayed for a few years through normal budgetary cycles and building lags. The local projection framework of Jordà (2005) is well suited to addressing this issue, though it has only been deployed in two recent IMF working papers by Eugster (2021) and Bettarelli et al. (2023). None of these two perform their analysis at the firm level and merely focus on innovation within the energy sector.

## 3 Hypotheses

The Porter hypothesis as it is originally stated merely posits that regulation, if well-designed, may incentivise innovation and lead to competitiveness gains that more than offset the cost of the regulation and not that is certainly will. It is therefore, in itself, not falsifiable. In this section, we explicitly state falsifiable hypotheses we are testing, inspired by the Porter Hypothesis and other follow-on contributions to the literature.

**Hypothesis 1:** Environmental regulation will incentivise clean technology innovation.

According to Porter and Van der Linde (1995) regulation may "trigger innovation [broadly defined] that may partially or more than fully offset the costs of complying with them". The intuitive notion that regulation, which changes the relative costs of factors of production relative to others, may induce innovation to reduce the use of those factors that have become relatively more expensive, dates back to Hicks (1963). But what are the forces that go against the weak version of the Porter hypothesis? Gans (2012) highlights the fact that environmental policy may, at least in the short to medium term, reduce output, which in turn would reduce the incentive to invest in innovation. Innovation in clean technologies faces additional hurdles compared to innovation in other technology classes. In an equilibrium, innovators will invest where the returns to innovative capital are the highest, however, the economics literature on innovation underlines that innovation is path dependent, meaning that companies tend to innovate in the technological areas in which they already have a substantial knowledge stock Aghion et al. (2016). As Calel and Dechezleprêtre (2016) highlight, based on empirical work, innovation in green technologies is far from the only possible response to environmental regulation. For instance, the Acid Rain program in the US, which regulates sulphur emissions from industrial plants, has been extensively studied and the results suggest nearly half of the emissions reductions were achieved by installing scrubber technology and the remainder by switching to coal with a lower sulfur content (Joskow et al., 1998). Moreover, Martin and Verhoeven (2022) recently found that the private value of clean innovations is more dispersed, thereby making investment into clean technology innovation more risky. Under financial constraints, therefore, firms may be less likely to invest into clean technologies, relative to dirty.

**Hypothesis 2:** Market-based policy instruments are more effective in incentivising clean innovation.

The general equilibrium model of Gans (2012) underscores that tightening climate regulation may not have an equal effect on all environmentally friendly technologies and that policy design is of key importance. Dechezleprêtre and Sato (2017) highlight that while the theoretical literature mostly argues that market-based regulation provides a stronger incentive to innovate compared to command-and-control (e.g. Parry et al., 2003), empirical literature mostly appears to show the opposite (e.g. Popp, 2003). Given that market-based instruments often leave more flexibility with respect to how pollution reductions are attained, it is possible that at a certain fixed level of stringency, these instruments yield better innovation performance as these may give the firm a bigger scope for optimising investment, and therefore would be less likely to reduce output. On the other hand, giving greater flexibility to firms may be less likely to induce innovation if firms opt for fuel switching, which may be a lower-risk option, or if the policy does not give enough certainty to make the long-term investment in innovation.

**Hypothesis 3:** Innovation in clean technologies will not crowd-out other types of innovation.

Less attention has been paid in the literature to the question of whether clean technology innovations, induced by environmental regulation, replace other types of innovation or whether they are additional. This is an important consideration to policy-makers who may typically be interested in increasing innovation and productivity across the entire economy. Calel and Dechezleprêtre (2016) find that the EU Emissions Trading Scheme increased innovation overall in firms covered by the regulation and find no evidence of substitution. Popp and Newell (2012) on the other hand find, that alternative energy patenting has crowded out other types of patenting at the firm level. In a similar vein, the results of Aghion et al. (2016) show that 'clean' car innovations replace 'dirty' can innovations (i.e. those related to the combustion engine) at the firm level in response to fuel price increases.

# 4 Data

Our analysis combines a variety of data sources to describe the effects of changes in environmental regulation on innovation. These include aggregate indicators from the OECD to describe macroeconomic changes and environmental policies as well as granular firm and emission data from ORBIS, iBACH and Urgentem. Urgentem is a source of firm-level emission data, which is key to our identification strategy, however, its coverage remains small. We therefore used a machine learning algorithm to generate synthetic data where emissions were not reported on the basis of balance sheet data, as described in more detail below. Our innovation data comes from the Orbis Intellectual Property databse. Our data set spans the period from 2003 to 2019 and includes 15 EA countries for the aggregate analysis and firms from six EA countries for our firm-level analysis. The resulting data set covers three million firms with multiple years of information each, resulting in more than 22 million firm-year observations from the covered six EA countries. This represents about one-quarter of all firms with employees operating in the analysed sectors.[1]

## 4.1 Environmental policy stringency

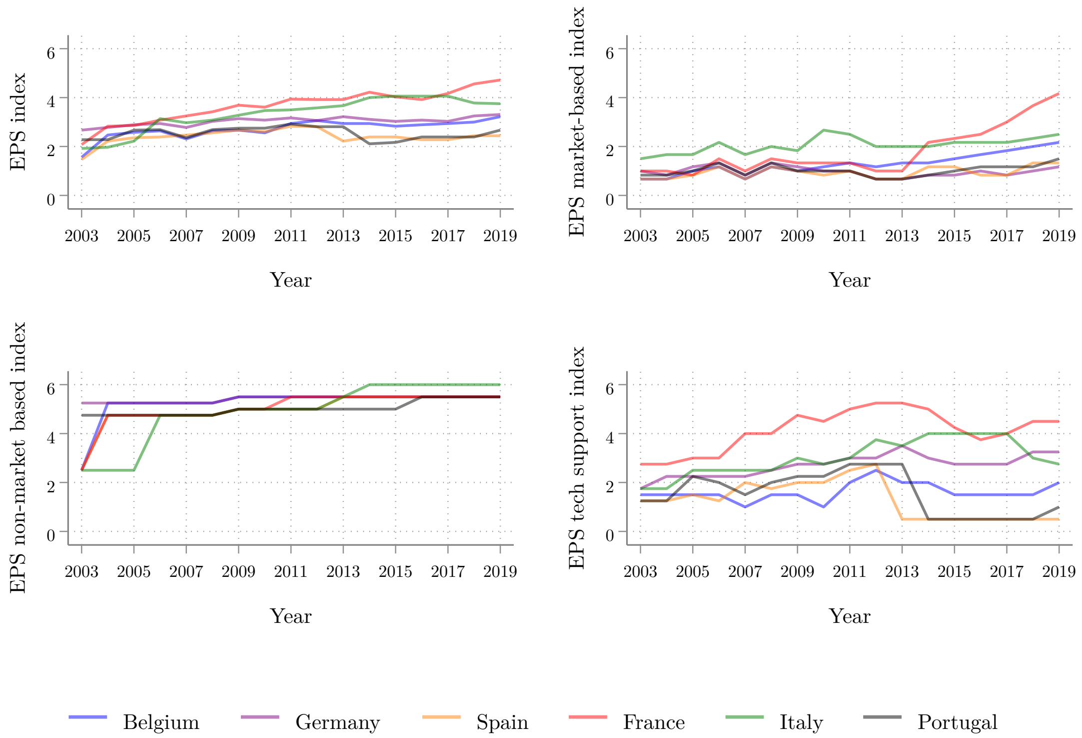
In order to capture the development of environmental regulation, we use the index of environmental policy stringency (EPS) developed by the OECD (Botta and Koźluk, 2014), which has undergone a substantial update in 2022 (Kruse et al., 2022). The current version of the EPS index covers 34 OECD countries over the period 1990–2020 and summarises environmental policy stringency across selected regulatory instrument categories. The indicator consists of three components: a market-based, a non-market based and a technology support sub-indicator. The market-based component groups instruments which assign an explicit price to environmental externalities (taxes: $CO_2$, $SO_X$, $NO_X$, and diesel fuel; trading schemes: $CO_2$, renewable energy certificates and energy efficiency certificates). The non-market component clusters performance standards (emission limit values for $SO_X$, $NO_X$ and PM, limits on sulfur content in diesel). Finally, technology-support policies capture green R&D subsidies (per GDP) and adoption support measures like feed-in-tariffs. All indicators range from 0 to 6, with 6 being associated with the most stringent environmental policies and 0 with the least.[2] Figure 1 provides an overview of the evolution of the EPS index as well as the three sub-indices in the countries relevant

[1] Austria, Belgium*, Estonia, Finland, France*, Germany*, Greece, Ireland, Italy*, Luxembourg, the Netherlands, Portugal*, Slovakia, Slovenia and Spain* - * indicates availability of firm-level data

[2] Stringent environmental policies imply high taxes, low emission limits and high subsidies, all with the aim to reduce emissions.

for the firm-level analysis. While we observe a trend towards more stringent policies, there is substantial heterogeneity across countries and sub-indicators. While previous studies used this index in their analysis (Albrizio et al., 2017; Fabrizi et al., 2018), the present study is the first to be able to leverage this measure after the major update.

Figure 1: EPS index




Note: Development of the EPS index and its sub-indicators (market, non-market and technology support) between 2003 and 2019. Range between 0 and 6, 6 represents the most stringent policies among OECD countries since 1990.

The objective behind the EPS index is to proxy for the exposure of the entire economy to environmental regulation, although environmental regulations are often sector specific. Botta and Koźluk (2014) focus on regulations of the energy and transport sector curbing greenhouse gas emissions and air pollution. These two sectors are important in all countries, tend to be characterised by high pollution intensity and tend to be regulated over an extended time period. By capturing regulations of upstream activities that impact other sectors indirectly, Botta and Koźluk (2014) argue that policy stringency measured by the EPS index is a reliable proxy for the overall aim to reduce negative emission externalities. Comparing the EPS indicator to other environmental policy stringency indices, like the economy-wide stringency indicator of World Economic Forums Executive Opinion Survey, supports this argument.

Similarly to Albrizio et al. (2017) and De Santis et al. (2021), our study uses the change in the EPS indicator rather than the level. The reason is that new investments into abatement technology are more likely to be spurred by a substantial change in regulatory stringency. When focusing solely on a single country, the presence of a fixed level of environmental regulations, in terms of the difference in relative prices of inputs, will not by itself motivate firms to alter their production methods. Furthermore, EPS (sub-indicator) levels are partly non-stationary, while first differences are stationary, thus facilitating empirical analysis. Since the Porter hypothesis concerns the effects of more stringent policies, we specifically focus on positive changes of the indicator to remove potential asymmetric effects of policy softening. In particular, we consider the annual changes of the overall index and its sub-indicators and replace all negative changes with zero.[3]

As a robustness exercise, we use a binary variable as our treatment which takes the value one if the increase in stringency is among the largest 25% of changes within a country (we henceforth refer to this specification as 'large regulatory change'). Thereby, we remove all negative and small changes and focus on the salient regulatory changes where reactions by firms are expected to be more pronounced. Figure 2 shows the number and temporal distribution of these large reform shocks for each sub-indicator in each of the six countries in our data set.[4] We also test for serial correlation of the positive and large changes in the EPS indicators using the bias-corrected Born and Breitung (2016) Q(p)-test. We find no serial dependency, except for positive changes in the technology support sub-indicator, which might stem from the serial correlation of GDP used as denominator to R&D subsidies. Hence, we argue that the changes in EPS indicators can be interpreted as independent shocks.

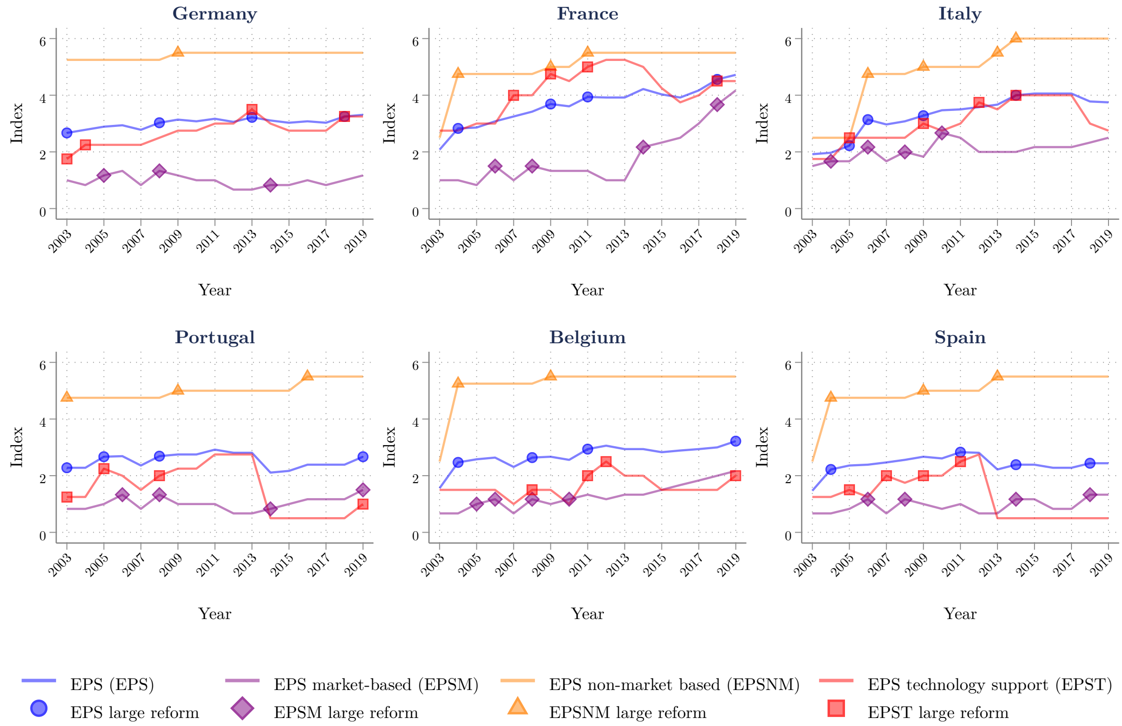
### 4.2 Firm-level data

We are using the Bureau Van Dijk's ORBIS and the European Committee of Central Balance Sheet Data Offices' BACH (Bank for the Accounts of Companies Harmonised) data sets, which report balance sheet and profit-and-loss data for both listed and unlisted companies (BACH, 2015). A well-known concern regarding these firm-level datasets is the lack of representative-

[3] Less than a fifth of the changes are negative (24% market, 0% non-market, 19% tech support) and these are spread across all countries.

[4] At EU level (affecting all six countries), major market policy reforms are the introduction of the ETS (2005) and large changes in certificate prices (2006, 2018). An EU-wide non-market regulation to limit sulphur came into place in 2009. Country specific reforms are, among others, higher solar energy subsidies in Germany (2004), Portugal, Italy (2005) and France (2006-2012), NOx and PM emission limit reductions in Portugal (2003), Belgium, Spain and France (2004) or the introduction of $CO_2$ taxes in Spain and France (2014).

Figure 2: Large EPS changes




Note: Occurrences of large changes in the EPS sub-indicators in the six countries used in the firm-level analysis. A change is considered large if it is among the top 25% of the country's EPS change distribution.

ness for some sectors and countries. In order to counter some of these issues, we use historical vintages of ORBIS and organise the data to improve the representativeness and reduce the sampling bias, as explained in Kalemli-Ozcan et al. (2015).[5] Additionally, for the five countries where iBACH data is available - France, Spain, Italy, Portugal and Belgium - the ORBIS and iBACH data sets are merged to improve coverage. Whenever a duplicate firm is observed, we keep the one from ORBIS. Data for Germany is retrieved only from ORBIS. We do not weight the data as the number of firms per country-sector-size-year cell is only available from 2009 onwards in the structural business statistics from Eurostat and Bajgar et al. (2020) report that weighting does not solve potential representativeness issues. By restricting the sample to the best-covered European countries, imputing value added and focusing on firms above 10 employees the Orbis data are broadly representative (Bajgar et al., 2020). By including iBACH data, we improve the coverage of small firms.

For the construction of our data set, we closely follow Kalemli-Ozcan et al. (2015) and Gopinath et al. (2017) and pursue a standard cleaning procedure. In particular, we keep only unconsol-

[5]Kalemli-Ozcan et al. (2015) argue that following their guidelines, there is no need to re-weigh the data to obtain nationally representative firm-level data sets.

idated accounts and remove sole proprietorships.[6] We restrict our analysis to non-financial and non-governmental sectors, and remove firms in the mining, energy and real estate sectors (NACE Rev. 2 codes C to N except D, K and L). In addition, we remove firm-year observations with less than one employee, negative value added and inconsistent balance sheet or income statement relations, including those with negative asset holdings. Furthermore, we keep only firms with at least two consecutive years of reporting to be able to create growth rates. Finally, all balance sheet variables are trimmed at the 1st and 99th percentiles to limit the influence of outliers. Summary statistics for the most relevant variables are shown in Table A1.

### 4.3 Patent data

Patent data are a widely used to measure innovation efforts within firms. Alongside with the number of new products, patents are an output-based measure as opposed to R&D spending, which gauges input into the innovation process. Albino et al. (2014) showed, however, that the two tend to be closely correlated. The pros and cons of using patents as a proxy for innovation are widely discussed in the literature (e.g. Calel and Dechezleprêtre, 2016; Eugster, 2021). Importantly, they are known to be strongly linked to economically important innovations (Dernis and Khan, 2004; Trajtenberg, 1990). The main benefit, in the context of this study, is that the detailed technological taxonomy in which patent documents are classified, the International Patent Classification (IPC) scheme and the Cooperative Patent Classification (CPC) scheme that extends it, allow us to distinguish between innovations on the basis of their climate change mitigation characteristics (Aghion et al., 2020) and, contrary to input indicators like R&D investments are also available for small and medium-sized firms (Aghion et al., 2023).

We use the Orbis Intellectual Property (IP) database to source information about the patenting activities of the firms within our data set. Similarly to the EPO Worldwide Patent Statistical Database (PATSTAT), Orbis IP has a comprehensive coverage, containing information about 138 million patents and, crucially, the data can be linked to other firm information within the Orbis database, allowing us to achieve the highest possible match between the two data sets and to construct firm-level innovation portfolios for the surveyed period. The database includes information about the inventor, filing dates, citations, patent families, technological categories, among other things. We opt for the most parsimonious way of identifying green patents and take advantage of the so-called 'Y02' tag developed by the OECD and EPO to identify innova-

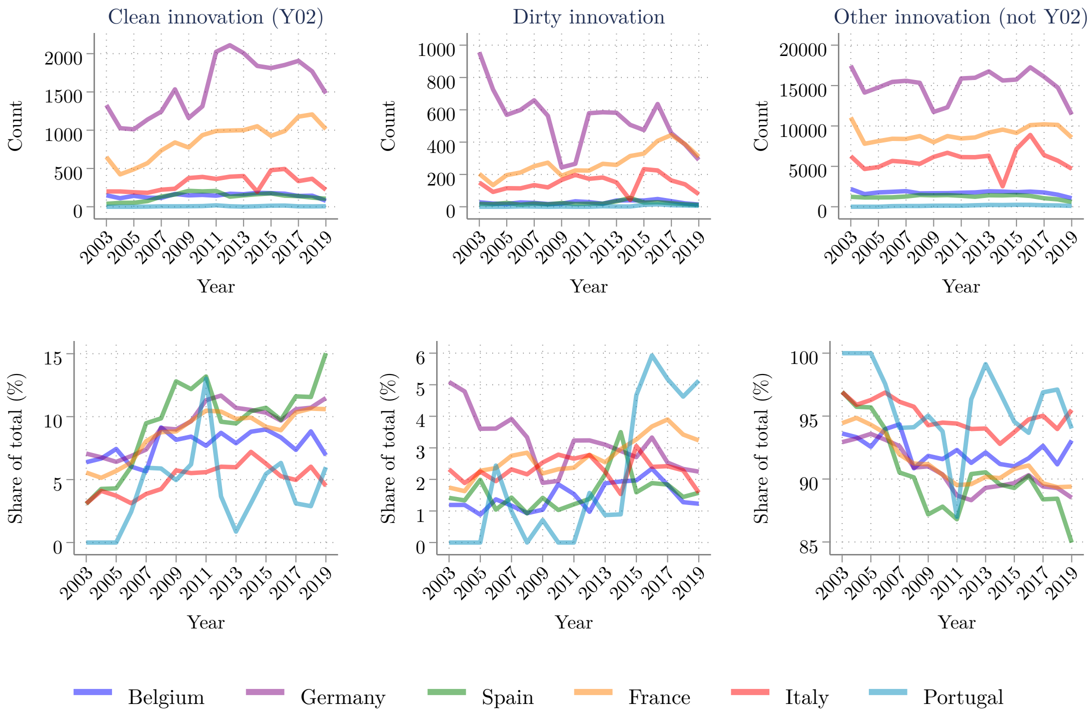
[6] The inclusion of consolidated accounts would combine the financials of subsidiaries across different countries and industries and thus complicate comparisons across countries and sectors.

tions that contribute to climate change mitigation. This approach to identifying green patents is widely considered to be the most reliable (e.g. Aghion et al., 2022). The CPC class symbols of patents considered are shown in Table A3. Other contributions to the clean innovation literature (e.g. Bolton et al., 2022) seek to differentiate between truly 'clean' technologies that contribute to the green transition as opposed to 'brown' technologies that merely contribute to efficiency improvements. However, for answering our research questions, a robust definition of green and non-green, as well as dirty technologies alone was sufficient. It is worth noting that the CPC class symbol codes that we use largely overlap with those identified in Haščič and Migotto (2015) and therefore also of Cohen et al. (2020), although our selection is more focused on climate change mitigation and adaptation.

Following common practice in the innovation literature, we aggregate filed patents to a patent family level, which groups patents that correspond to a single innovation and assign these to the year of the earliest patent filing within that patent family. We then aggregate patent families by firm and year. Figure 3 shows the evolution of clean, dirty and non-clean innovation in the surveyed period both in terms of innovation (patent family) counts and in terms of shares in the six countries that are included in our firm-level data set. Each patent has multiple technology classifications attached to it at the most detailed level, we count any patent family that has a Y02 class symbol attached to it as a 'green' innovation. To identify dirty innovation, we use the list of CPC class symbols elaborated by Dechezleprêtre et al. (2014). A detailed list of all CPC codes at the sub-group and main class level, both green and dirty, used in the analysis is included in the appendix.

For the country-level analysis, we rely on the OECD database of patents in environment-related technologies (OECD, 2023) instead of aggregating our firm-level innovation records to maximise the size of our sample. This database has more country-year combinations compared to our firm-level patenting data. When a patent was invented by several inventors from different countries, the respective fractional contribution of each country is taken into account. This is done in order to eliminate multiple counting of such patents. The OECD environmnent-related statistics are constructed with data extracted from the world-wide patent database PATSTAT, produced by the European Patent Office, and using algorithms developed by the OECD. To find patents in environment-related technologies, detailed search strategies have been developed drawing on more than 200,000 classification symbols. While the 'Y02' scheme is used to a large degree and is explicitly built on this scheme, this patent dataset encompasses a broader spectrum of environmental technologies related to environmental pollution and water scarcity as well as climate change mitigation. A detailed description of the search algorithms used to identify environment-related technologies is included in (Haščič and Migotto, 2015), showing that many 'Y02' tags are nested within this classification.

Figure 3: Innovation data




Note: Counts (first row) and shares (second row) of clean (Y02) innovations, dirty innovations and other innovations (not clean) within the sample

A number of caveats must be noted when interpreting results using patent data. Not all technological fields are equally likely to patent, and legal regimes differ across countries, so especially raw counts of patents are not directly comparable. Patents have a skewed value distribution with many having no industrial application and therefore have limited societal value while others are very valuable (Aghion et al., 2023). Many innovations are not patented at all because they are not legally patentable or because the intellectual property regime within a particular country favours other types of intellectual property protection such as industrial secrecy. That is also the reason why only 1.34% of our three million firms reported a patent at least once (we report results separately for this subset of firms). The authors of the hypothesis themselves note that innovation is not just technological change and can take various forms, including "a product's or service's design, the segments it serves, how it is produced, how it is marketed and how it is supported" (Porter and Van der Linde, 1995, p.98). This would potentially suggest that our results substantially underestimate the regulatory effect. However, there is no reason to assume that the clean vs. non-clean technology innovation trade-off (or lack thereof) is affected.

### 4.4 Emission estimation

One of the novel features of this paper is the estimation of $CO_2$ equivalent emissions for all firm in our sample using machine learning. Unfortunately, the availability of firms' emission data is very limited and biased towards large firms. However, financial and non-financial information can be used to infer $CO_2$ equivalent emissions. This effectively fills the data gap for firms which do not report emissions in order to support the analysis. Moreover, this synthetic data set can be used to monitor the exposures of the markets to polluting firms in an extensive number of other applications. The algorithm relies on emissions data provided by commercial providers for a sample of large listed firms, associated with the balance sheet information of those companies. The relevant quantities can then be predicted for non-reporting firms by applying the observed statistical relationships between the $CO_2$ equivalents emitted, the sector, the country and their financial information.

More specifically, we use Urgentem data on Scope 1 and Scope 2 $CO_2$ equivalent emissions[7] and link these with ORBIS/iBACH information to produce a sample of 35,000 firms. In order to simplify potential non-linearities in the relationship between emissions and financial information, we opted for creating ten emission quantity classes (bins) based on the distribution in our sample. Once the model is fitted on the Orbis data set, the meaning of the bins should be treated as arbitrary categories. This allows us to rely on a wide classification set between high-polluters and low-polluters which gives us the possibility to test different definitions in the analysis. It also simplifies the calibration of the model. We use emissions rather than emissions intensity classes because most regulations and disclosure requirements relate to absolute levels of emissions and not to intensity. For the estimation of the data generation model we use a machine learning algorithm called Extreme Gradient Boosting (XGBoost), which is one of the most successful models used in machine learning in the past years, based on ensembled trees (Chen and Guestrin, 2016; Rokach, 2016). The model selects the regressors (via lasso algorithm) and finds the best non-linear patterns (tree) to estimate the dependent variable, then it

[7] The data capture direct emissions due to own production and indirect emissions due to purchased energy. $CO_2$ equivalents are used to compare and aggregate the emissions from various greenhouse gases: carbon dioxide ($CO_2$), methane ($CH_4$), nitrous oxide ($N_2O$), hydrofluorocarbons (HFCs), perfluorocarbons (PCFs), sulphur hexafluoride ($SF_6$) and nitrogen trifluoride ($NF_3$).

averages them.

The confusion matrix below (Figure 4) shows how well XGBoost is able to estimate $CO_2$ emissions based on ORBIS/iBACH data for firms never seen by the model before. Since most observations in the confusion matrix are at or close to the main diagonal, it shows that actual and estimated emission bins are closely related and our algorithm performs well. As we only need to to split firms into high and low polluters for our empirical approach, the estimation accuracy is sufficient for our purpose. The bar plot in Figure 5 depicts the mean of the absolute SHAP (SHapley Additive exPlanations) values for each regressor. The SHAP value captures how much a single regressor affected the prediction of an observation and this is summarised by taking the average over the sample (Lundberg and Lee, 2017). Employment, turnover, tangible and intangible fixed assets as well as the (4-digit NACE) sector are the most important variables to determine $CO_2$ emissions of a firm. It is difficult to asses ex-post the accuracy of classifications done on millions of firms that do not report $CO_2$ but the relationships between sector, size and emissions follows our expectations.

Figure 4: Confusion matrix

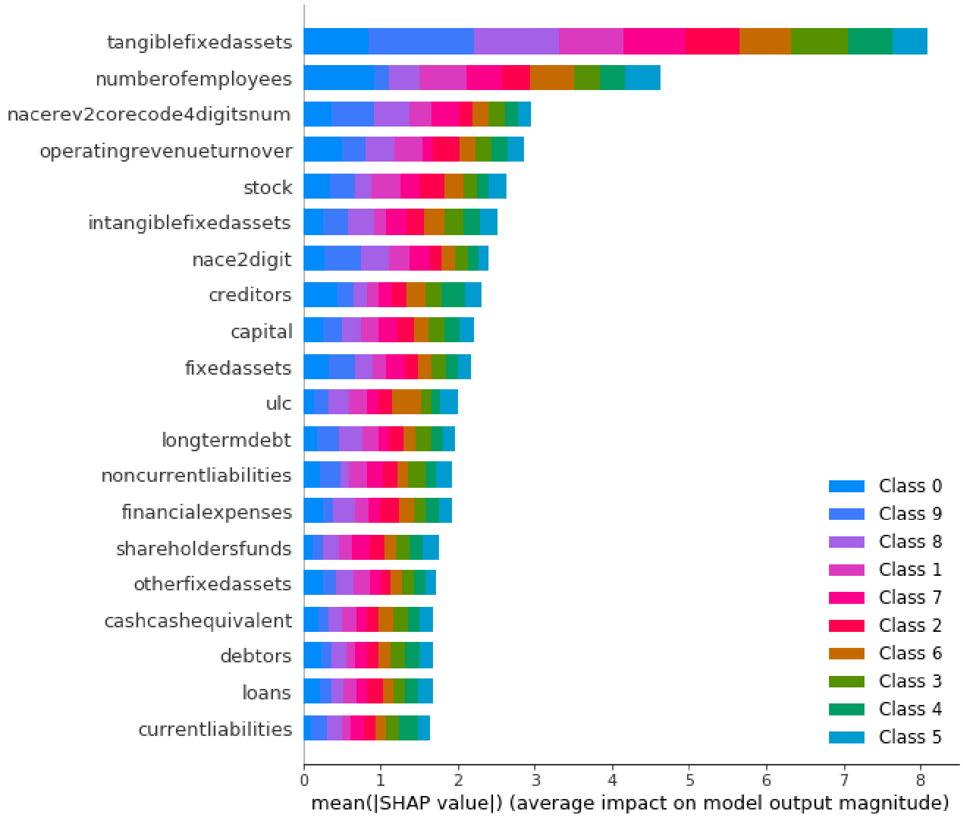
| | Re 1 2 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| A | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 0 | 168 | 88 | 30 | 31 | 18 | 8 | 5 | 7 | 6 | 3 |
| 1 | 56 | 117 | 54 | 22 | 21 | 13 | 10 | 3 | | 2 |
| 2 | 29 | 68 | 87 | 44 | 28 | 42 | 17 | 7 | 11 | |
| 3 | 11 | 28 | 57 | 65 | 62 | 49 | 28 | 7 | 10 | 1 |
| 4 | 13 | 14 | 51 | 55 | 72 | 53 | 28 | 27 | 26 | 9 |
| 5 | 6 | 21 | 21 | 45 | 47 | 72 | 35 | 29 | 22 | 9 |
| 6 | 8 | 10 | 15 | 20 | 39 | 57 | 61 | 64 | 21 | 5 |
| 7 | 4 | 2 | 5 | 9 | 25 | 32 | 72 | 96 | 69 | 29 |
| 8 | 2 | 6 | 4 | 6 | 7 | 13 | 38 | 39 | 99 | 42 |
| 9 | 3 | 1 | 1 | 2 | 4 | 6 | 4 | 27 | 58 | 202 |

Note: Each row of the matrix represents the instances in an actual class while each column represents the instances in a predicted class. The matrix shows to which extent the algorithm "confuses" two classes. A large accumulation at the main diagonal show the fit of the estimation.

## 5 Empirical Strategy

Determining the causal impact of a regulatory reforms over time poses various challenges, as mentioned in the literature review. To summarise, policy reforms create a dependency with business cycle dynamics and their impact could be heterogeneous reflecting macroeconomic or firm-specific conditions. Furthermore, policy and innovation changes could be jointly determined by many, sometimes unobserved, variables. Secondly, as Brunel and Levinson (2020)

Figure 5: Importance of balance sheet variables - SHAP values




Note: Importance of variables in the machine learning algorithm, measured by the mean of the absolute SHAP value, starting with the most important and going to the least important.

highlight, there is the problem of simultaneity, since environmental reforms might affect innovation but also the innovative performance of firms can influence the appetite of policy-makers to implement reforms. Thirdly, in a cross-country analysis we have to deal with different industrial compositions across countries. Inferences can be incorrect, because even identical laws have different effects when the average firm faces different environmental costs across countries. Hence, in this section, we explain how we estimate the regulatory effects and how we deal with these concerns.

## 5.1 Identification

Our identification strategy relies on the assumption that environmental policy reforms affect country and firm innovation growth differently depending on their a priori exposure to the regulation. A higher amount of $CO_2$ equivalent is expected to be a suitable proxy for the level of environmental reform exposure. The associated costs and the need for adjustment after a regulatory change should be higher for polluting countries and firms and hence, the impact of environmental policies on innovation is expected to be larger compared to their non-polluting peers. We test this hypothesis to evaluate the underlying mechanism that explains the intended direction and excludes reversed causality (from innovation to regulatory changes), after controlling for a broad set of control variables and granular fixed effects. This approach was popularised by Rajan and Zingales (1998) who use financial dependence as the exposure variable to analyse the role of financial development on growth. Since then it has been used often to analyse the impact of national policies on industries or firms. Albrizio et al. (2017), for instance, use the industry-level pollution intensity to analyse the impact of environmental reforms on productivity.

In our empirical setting this approach implies that the EPS index is interacted with a pollution intensity indicator for countries in the aggregate analysis, and with emission indicators of individual firms in the firm-level analysis. Beside the assumption that different technologies lead to variations in emissions and hence to different adjustment needs, the identification is based on the assumption that the exposure variable (emissions) is exogenous to regulatory changes. Hence, it is crucial for this approach to use pre-determined (lagged) emission indicators that are unlikely to be affected by current changes in environmental regulation. In addition, we tested whether an increase in regulatory stringency affects the probability of being a high-polluting firm and we find no significant impact. Table A4 shows the effects of positive EPS changes on the emission indicator (logit regression) and the ten emission bins (linear regression). Highly polluting firms may reduce their emissions, but remain among high-polluters up to five years after the reform. In a similar vein, most high polluting countries remain in this group over the whole period, despite the fact that they introduced environmental policies. This supports our identification approach.

### 5.2 Local projections

Since we expect that effects of regulatory changes occur with some delay, we apply an econometric approach that allows to capture effects at different horizons. Local projections (LP), introduced by Jordà (2005), calculate impulse responses directly by estimating regressions at each period of interest rather than extrapolating into increasingly distant horizons. This technique is based on sequential regressions of the endogenous variable shifted forward in time onto its lags. Cette et al. (2020, p.7) describe the method as the "differences between two forecasts - the first corresponding to a situation with the shock and the second to the same situation without this shock." Compared to vector autoregressions, LP are less prone to misspecifications (Li et al., 2022) and more flexible regarding the analysis of non-linear and state-dependent impacts, while still able to deal with endogeneity issues (Bordon et al., 2018). The approach has been recently widely applied in the study of the economic impacts of structural reforms (Bordon et al., 2018) and fiscal consolidation measures Jordà and Taylor (2016); Owyang et al. (2013).

At the country level, the dependent variable in our empirical model is the cumulative difference in the share of environmentally related innovations, between year $h$ after the reform and the pre-reform year.[8] The main regressor ($\Delta EPS_{i,t}^{j}$) is the positive change in the EPS index or the positive change in one of its sub-indicators $j$. We interact the policy index with a dummy ($CO2$) indicating if the country or firm was among the top most polluting ones of its peer group in the year before the reform. By using the change in the EPS index between $t-1$ and $t$, we limit the problem of simultaneity as it is unlikely that future patent filing changes affect past regulatory changes. More specifically, the baseline model for our aggregate analysis follows the specification below:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = \alpha_{1,i}^{h} + \alpha_{2,t}^{h} + \beta_1^h CO2_{i,t-1} + \beta_2^h \Delta EPS_{i,t}^{j} + \beta_3^h (\Delta EPS_{i,t}^{j} * CO2_{i,t-1}) \\ + \gamma_1^h X_{i,t} + \varepsilon_{i,t+h} \qquad h = 0, 1, ..., 5 \end{aligned} \tag{1}$$

where $y_{i,t+h}$ is percentage of environmentally related technologies of country $i$ in year $t$ (as measured by the OECD); $h$ represents years after the reform. $\varepsilon_{i,t+h}$ captures the idiosyncratic error. $X$ collects all country controls including the cyclical position of the country's economy, labour market regulation, startup costs, governmental R&D expenditure and the level of economic development, following Albrizio et al. (2014) if the variables are available. Table A2 in the Appendix contains details on the variables. The last four controls are included as first lags (before the reform) so that they can be interpreted exogenously and not as an outcome of the environmental policy change. The cyclical position of the country measured by the output gap controls for business cycle dependencies of productivity growth and new regulations. The employment protection legislation indicator and startup costs approximate supply side policies within the labour and product markets. Governmental R&D expenditure controls for another potential omitted variable bias as it influences both firm innovation as well as decisions on green subsidies.

[8] We have only few zero observations at country level given the size of the countries and dynamics in the recent years. Hence, no further transformation is necessary.

We use country fixed effects ($\alpha_i$) to capture the different institutional settings across countries, as well as other differences that are potentially relevant to innovation activity. In addition, we include time dummies ($\alpha_t$) to capture developments specific to a year but common to all countries or firms like the ECB's monetary policy or the occurrence of the global financial crisis. Regarding the concern of industrial composition differences across countries, we add the industry share as control variable at the aggregate level and see no changes in the baseline results. This will not be necessary in our firm-level analysis as it is not subject to the industrial composition problem by looking at each firms response separately. However, at the country level, differences in emissions emerge only from between-country differences, which is the same level of variation as the change in environmental policy stringency. The country-level analysis is therefore correlative.

The dependent variables in our firm-level model (2) are the cumulative relative changes in the number of innovations (patent families), between year $h$ after the reform and the pre-reform year. The definition of innovations and how we aggregate them at the firm-year level is detailed in the section 4.3. We apply the inverse hyperbolic sine (or arcsinh) transformation to innovation counts[9] because it allows us to retain zero-valued observations, which are very common in our data set, and because, similarly to a log transformation, it reduces the influence of outliers in highly skewed distributions.[10] A common alternative to this approach when analysing innovation outcomes is using a specification $log(1 + no.of patents)$, used for instance in Aghion et al. (2023). We also run the analysis with this specification of the dependent variable and obtained similar results (see Table A7).

$$\begin{aligned} arcsinh(y_{f,t+h}) - arcsinh(y_{f,t-1}) = \alpha^h_{1,t} + \alpha^h_{2,s} + \alpha^h_{3,f} + \beta^h_1 CO2_{f,t-1} + \beta^h_2 \Delta EPS^j_{i,t} + \\ \beta^h_3(\Delta EPS^j_{i,t} * CO2_{f,t-1}) + \gamma^h_1 X_{i,t} + \gamma^h_2 Z_{f,t} + \varepsilon_{f,t+h} \qquad h = 0, 1, ..., 5 \end{aligned} \tag{2}$$

In addition to the macro indicators from the aggregate analysis, we add lagged firm characteristics $Z$ (before the reform) as control variables: age, size, return-on-assets and firm patent stock in the pre-sample period (1990-2002). Again, details are provided in the appendix. The specification also includes firm-specific $CO2_{f,t-1}$ equivalent emissions estimated as decile bin within the emission distribution. These are interacted with our EPS indicators that capture the environmental policy stringency. Exposure at the firm or industry level exploits within-country

[9] $arcsinh(y) = ln(x + \sqrt{x^2 + 1})$

[10] The inverse hyperbolic sine function has been gaining popularity as an alternative to the natural logarithmic transformation which is not defined at zero or negative values (Bellemare and Wichman, 2020; Norton, 2022). However, it has also been criticised for its scale dependence (Chen and Roth, 2022). Since the scale of patents is less controversial than that of prices or weights, and the regulatory effects come mainly from the intensive margin, we consider the arcsinh transformation to be suitable approach in our analysis.

variation to argue in favour of exogeneity in contrast to the country level analysis.

In the firm-level analysis, we replace country FE with more granular sector and firm FE ($\alpha_s$, $\alpha_f$) to control for unobserved heterogeneity across sectors and firms. The combination of sector, firm and time FE with a broad set of controls substantially reduces any potential omitted variable bias. In order to control for potential anticipation effects of new policies, we additionally include next year's EPS change in the firm-level specification, assuming perfect foresight. As this is a strong assumption and the inclusion reduces the magnitude of our estimated effects only slightly, we decided not to include it in the baseline specification. The standard errors are clustered on country or firm-level respectively to allow for fully flexible time series dependence in the errors within each block.[11]

A limitation of our empirical approach is that the measurement of the timing of events, in particular the implementation dates of policies, is imperfect. The lags between policy change and the economic effect of interest, in our case captured by the the filing of a patent, are likely to differ by firm and depend on policy type. For instance, market-based instruments such as taxes and cap-and-trade schemes may trigger a gradual readjustment, allowing a firm to invest in research and development, while mandates and bans call for a more immediate reaction on the part of the firm. These differences may cloud inference. The majority of studies exploring the relationship between environmental regulation and innovation focus on a specific regulation, which has a precise implementation date that often helps to reinforce the causal identification as elaborated in section 2. This comes, however, at the expense of external validity which is crucial for policy-makers.

We believe that there is a value in contributing to the body of knowledge regarding the economic impact of environmental policies using firm-level data also through multi-country and multi-sector studies. The type of insights our study can generate are relevant to EU-level policy-makers, who are interested in the economic impacts of environmental policy beyond specific instruments and regulated sectors. The present study reflects the real life context, in which firms are affected, directly or indirectly, by an often overlapping mix of policies at any particular time. As such, it enhances our understanding of transition risks and possible regulatory responses to it. Although we consider the trade-off between precise causal inference and external

[11] Given the national EPS indices and national institutions in charge of collecting the firm data, clustering SE at the country level would also be appropriate in the firm-level specification. Due to the low number of clusters (6) and the more relevant correlation among firm observations, we decided to use firm clusters.

validity acceptable, we seek to strip away possible sources of bias through additional analyses and multiple robustness checks. Beside the use of a broad set of macro and firm controls as well as firm, sector and year fixed effects, we apply a serially uncorrelated measure of policy changes. In addition to the anticipation effect test outlined above, we analyse large changes in the EPS index, which are defined as such if they are among the top 25% of the country's EPS change distribution. These large regulatory change events have a distinct timing (as shown in figure 2). All these variations lead to robust results on the relationship between environmental regulation and green innovation, as presented in the following section.

# 6 Results

In this section, we present the impact of changes in the environmental policy stringency on the number of innovations in clean and non-clean technology classes. First, we describe the results at the aggregate level for a pooled sample of 15 countries. We then use firm-level data to control for potential sources of endogeneity. In analysing the aggregate country data, we consider the full firm population, including entry and exit, the relative importance of effects across firms weighted by their size, as well as the patenting activities of public sector organisations and universities. This analysis may, however, suffer from aggregation and endogeneity bias. The firm-level analysis can address these problems, but has limitations in terms of population representativeness and tracking firm entry and exit dynamics. Additional results, which include for instance the regression results for dirty technologies and the baseline results only for the subset of firms that ever patent during the surveyed period, are in the Appendix.

## 6.1 Country-level results

Figure 6 shows the impulse response functions (IRF) at the country level, using the change in the share of environment-related technology patents as dependent variable. The green lines show the mean responses to a one percentage point increase in policy stringency over the five year horizon and the grey bands depict the respective confidence intervals around the point estimations (68% and 90%). In the left column of Figure 6 we show the clean innovation responses of the countries with the lowest greenhouse gas (GHG) emissions per capita (bottom 50% of the sample). We contrast them to the responses of the high polluting countries (top 50%) in the right column.[12] The results are largely not statistically significant, with the exception of a very small effect at year 2 for the non-market based policy component and at year 3 for the technology support component in the low polluting countries.

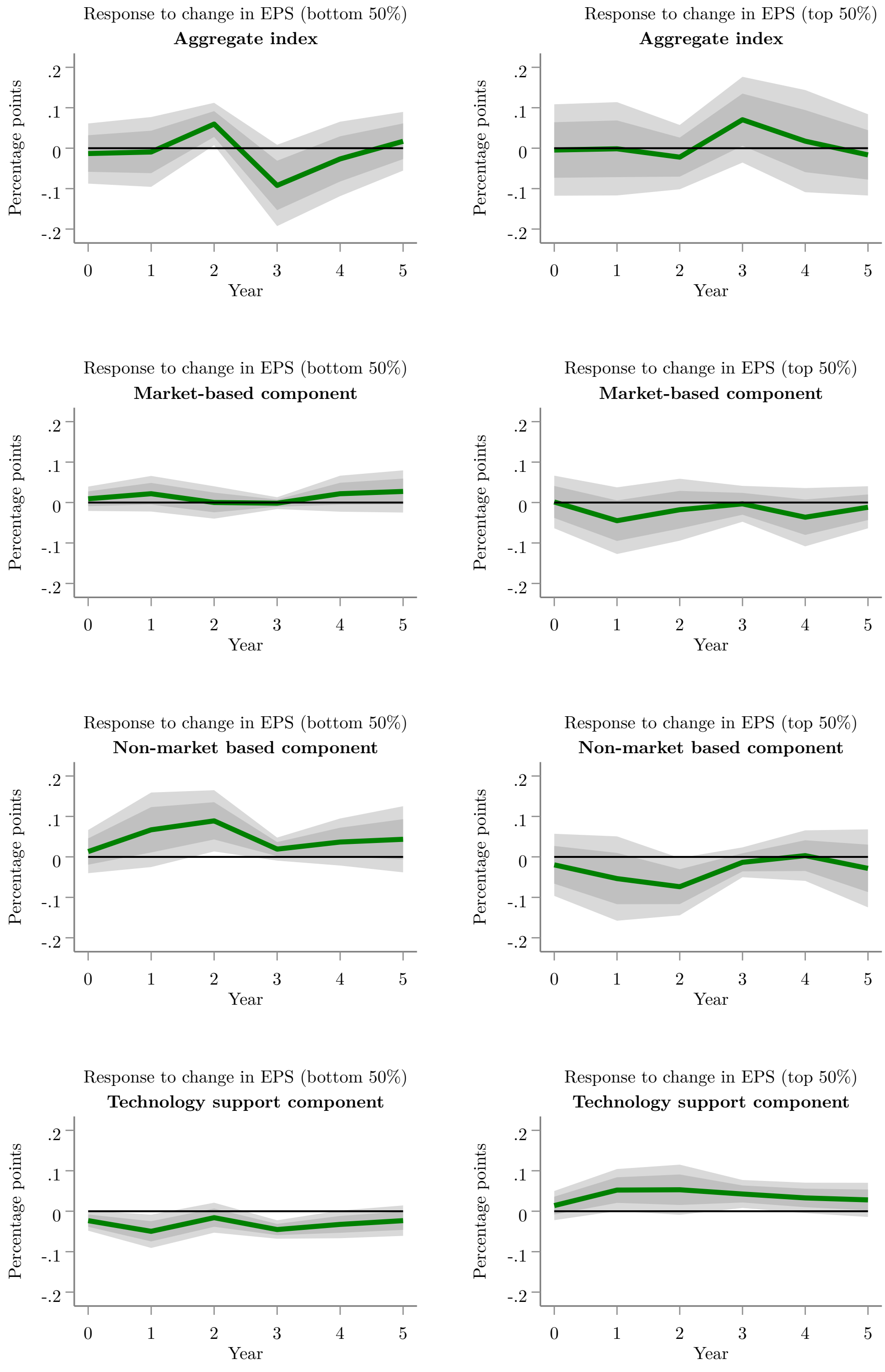
We repeat the exercise with different specifications of regulatory shock, for instance, instead of a time-series of positive changes in the EPS index, we use a dummy that equals one if a salient change takes place that is among the largest 25% of changes in a country within our period of observation, however, the results are still not statistically significant. There is substantial heterogeneity among countries and their responses seem depend on their pollution intensity. Nonetheless, aggregate responses mask heterogeneous patterns across firms operating in a given country and sector as indicated by the large confidence bands. Moreover, there are still some remaining concerns about potential endogeneity at the aggregate level. For these reasons, the next section replicates the analysis at the firm-level.

### 6.2 Firm-level results

Figure 7 shows the response *differences* of high versus low polluting firms on patented clean (left column; green line) and non-clean (right column, blue line) innovations to a one percentage point increase in the EPS indicator and its sub-indicators. The grey areas represent the corresponding confidence intervals (68% and 90%). We compare the responses of firms that are assigned to the top four bins by our machine learning algorithm to those assigned to the bottom six emission bins by our machine learning algorithm (as described in section 4.4). We decided for this unequal split as there are fewer high-polluters than there are firms in the low-polluter group. In the specifications at firm level, we make use of the granularity of the firm-level data to control for sector and firm fixed effects so that we capture a broad set of reasons for different innovation growth rates and reduce the omitted variable bias to a minimum. The effects on low-polluting firms' patenting behaviour confirm the validity of our identification approach, and hence the direction of the estimated effects. We find no regulatory impact on low-polluting firms and significantly different effects on high-polluting firms as shown in the Appendix (Figures A2-A4). The inverse sine is approximately equal to $log(2y_i)$ or $log(2) + log(y_i)$, and so it can be interpreted in the same way as a standard logarithmic dependent variable. We already approximated the elasticity interpretation in the charts for convenience. The values of the estimated regression coefficients are depicted in Table A5 and Table A6.

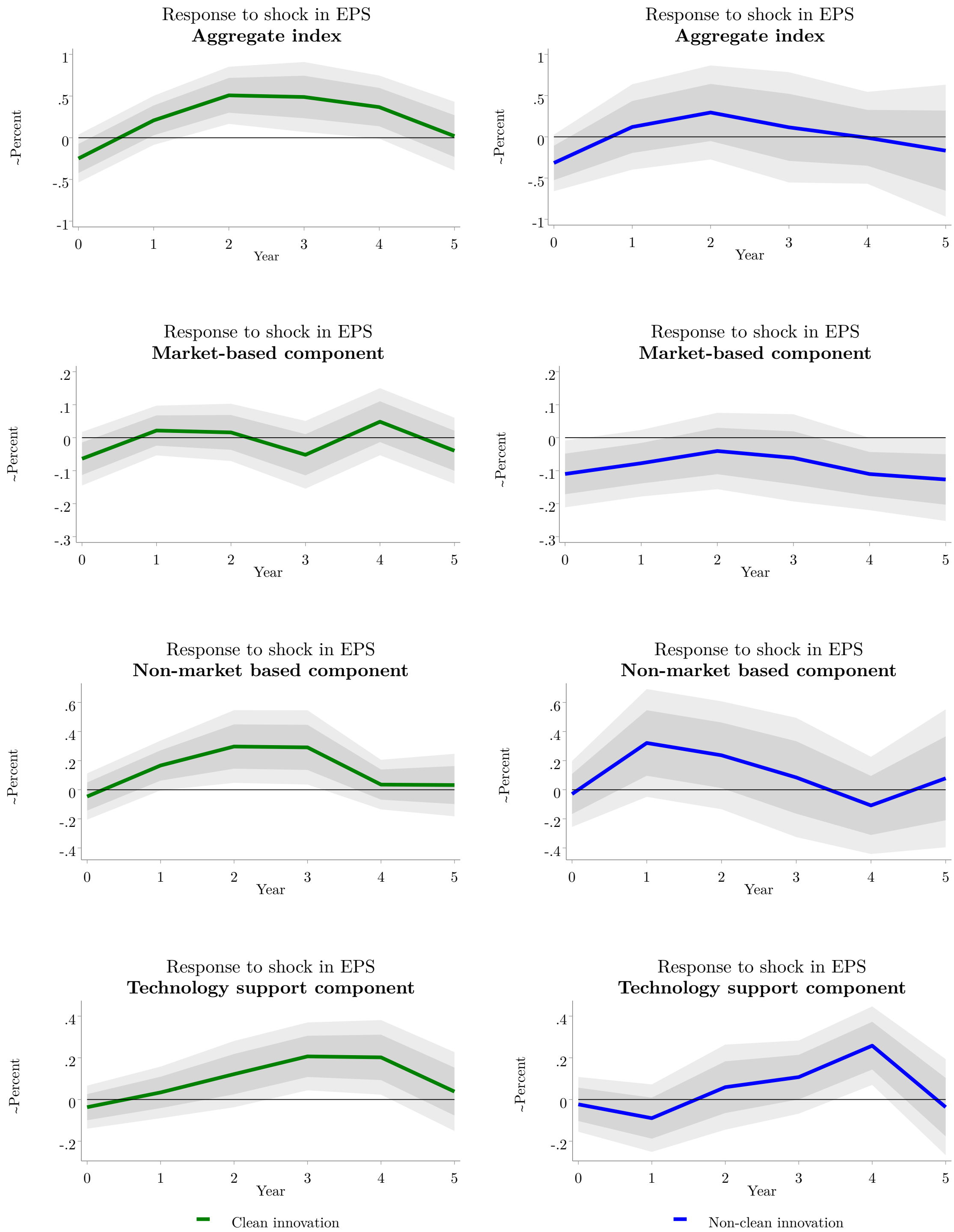
[12] Belgium, Germany, Estonia, Finland, Ireland, Luxembourg and the Netherlands are in all years among the countries with above median pollution intensity, Greece in 8 years, Austria in 3 years.

Figure 6: IRF - Environment-related patenting to EPS change (country level)




Note: Cumulative impulse responses of the environment-related patenting share to 1 pp EPS shocks (positive changes) over 5 years. Left column contains countries with low pollution intensity, right column contains the countries with high pollution intensity. Green line represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure 7: IRF - Clean/non-clean innovation to EPS change (firm level)




Note: Cumulative impulse responses of the relative change in clean and non-clean patent families to 1 pp EPS shocks (positive changes) over 5 years. Left column (green) - clean innovation, right column (blue) - non-clean innovation. Green/blue lines represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

A tightening in environmental regulation spurs a positive response in innovation efforts in clean technologies for high-polluting firms, in contrast to low-polluting firms. A one percentage point increase in the EPS leads to approximately 0.5% increase in the cumulative number of clean innovations with the effect at its strongest after three years. This aggregate effect is mainly driven by the positive innovation responses due to non-market and technology support policies. Therefore, we can confirm **hypothesis 1**, according to which environmental regulation tightening would be expected to yield a statistically significant effect on green innovation.

Moreover, we find no statistically significant (negative) impact on other types of innovation for the overall EPS indicator, as well as the marked and non-market based index components. Thus, we find support for **hypothesis 3**, which holds that in response to regulatory change, clean innovation will not necessarily crowd-out other types of innovation. In the case of technology support policies, we even report a small but significantly positive impact on innovations that are not clean. This suggests that there are potential spillovers to non-clean innovations after the expansion of this type of policies. This might stem from research in green technologies that lead to new developments in other fields or the deviating classifications of "green" technology.

In general, the patterns of the various policy sub-types are different from each other. While the market-based component produces almost no change in either clean innovations or non-clean innovation, the non-market based component produces statistically significant responses in clean innovation as does the technology support component, which includes R&D subsidies and feed-in-tariffs. Based on these results, we have to reject **hypothesis 2** that market-based regulation has a stronger effect in terms of incentivising green innovation, as neither high nor low-polluting firms intensify their patenting activities. The positive effects of the other policy types seems to have a different profile over time. The implementation of binding standards (non-market based component) directly mandate an adjustment and hence, produces a faster increase in innovation compared to the technology support component. However, in both cases it takes some time until new regulations lead to the filing of new innovations, which shows the importance of an empirical approach that allows for dynamic responses.

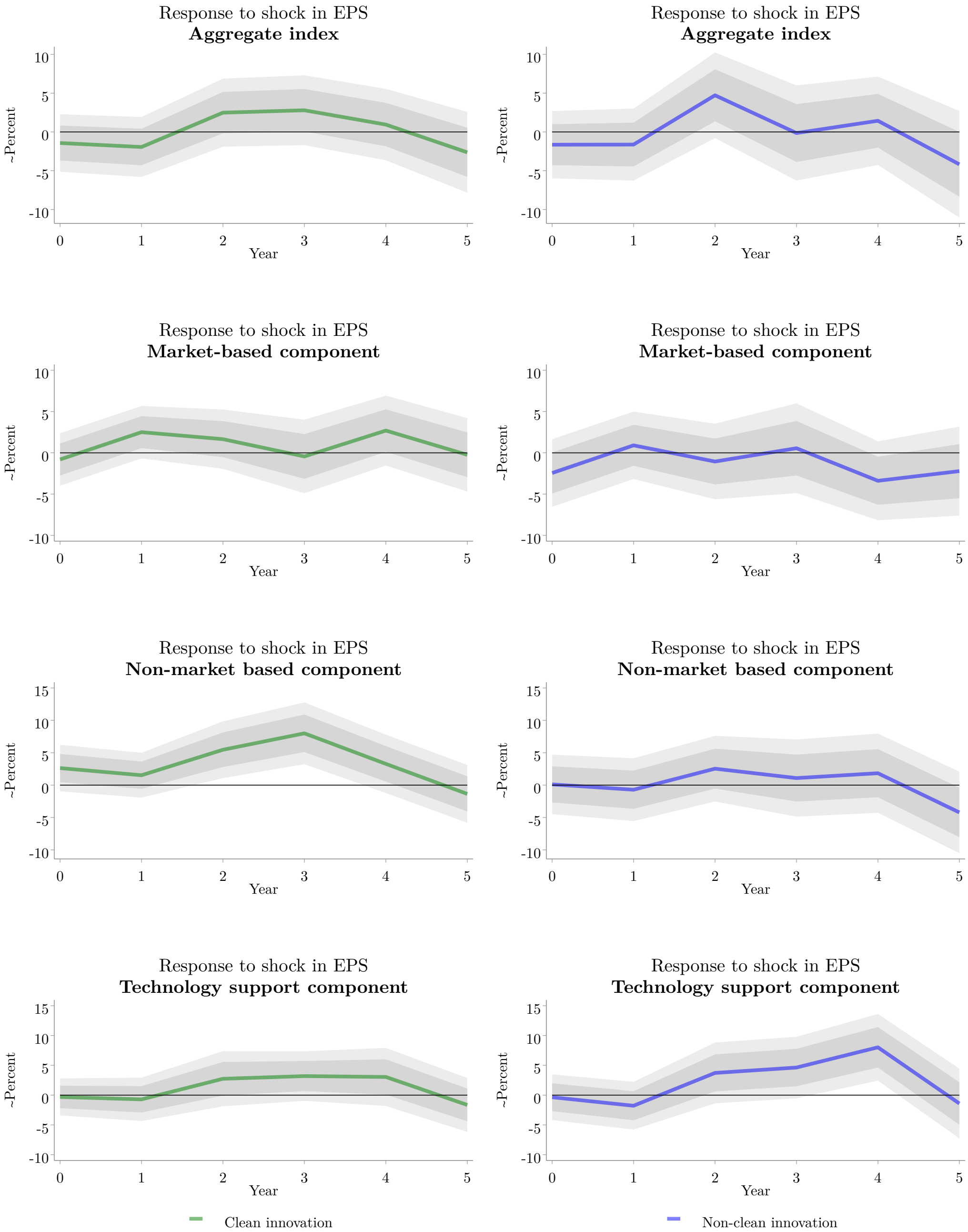
As there are many firms that do not file any patents and we want to know specifically which firms drive our results, we also examine whether the environmental regulation tightening mostly affects the extensive or the intensive margin. We use the pre-sample patent stock to determine which companies have previously never filed a patent and which have and rerun our firm-specific local projections. The corresponding regression tables are included in the Appendix (Tables A11 and A12). Our results appear to be mostly driven by the intensive margin, which is consistent with the findings of Dechezleprêtre et al. (2023). Similarly, we restrict our sample to firms that have filed for at least one patent in the surveyed period 2003-2019. The response tracks similar patterns to when we run the analysis on the entire sample, however, the effects are more pronounced in magnitude, which is consistent with expectations. The results are shown in the Appendix (Figures A6 and A7).

### 6.3 Robustness & discussion

As robustness checks, we carried out several additional exercises. First, we conducted the analysis with a 'large reform' indicator as described in section 4.1. We show the results in Figure 8. While for most of the EPS index sub-components the results are not statistically significant in this specification, for non-market based regulation the response in clean patenting of highly-polluting firms is still both significant and large. A large reform leads to an almost 10% increase in the number of clean innovations filed in the high-polluting group compared to the low-polluting group. We also test both reform specifications with cumulative changes in dirty (instead of non-clean) innovations as the response variable (see Figures A4 and A5 in the Appendix) but see no statistically significant response. The only exception is a minor short-term decline in dirty technology patenting for the large reform specification in the case of market-based instruments.

In as far as the EPS market-based index captures the signal from more flexible forms of regulation, our results challenge the "weak" and "narrow" version of the Porter hypothesis, as we find that market-based based regulation is associated with non-significant effects on green innovations and lower green innovation growth compared to increased stringency in technology-support and non-market based policies. The finding that non-market based regulation has a stronger effect on clean technology patenting would appear to be at odds with much of the established theory, but also highlights the concern that (at the current stringency level) market policies are not stringent enough. As Johnstone et al. (2010a) note, however, the distinction between market-based regulation and direct command-and-control is largely arbitrary and what matters more is specific policy attributes such as predictability, flexibility, incidence and depth. They emphasise that there is no precise mapping between the main policy types and these attributes.

Figure 8: IRF - Clean/non-clean innovation to large EPS change (firm level)




Note: Cumulative impulse responses of the relative change in clean and non-clean patent families to large EPS shocks (top 25%) over 5 years. Left column (green) - clean innovation, right column (blue) - non-clean innovation. Green/blue lines represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Given the comparable dataset and methodological approach, it is interesting to relate our results with those in our study on productivity growth (Benatti et al., 2024). There we found that market-based policies have a significantly negative impact on firm productivity over the whole projection horizon, but at a much lower level than the non-market based policies. This is in accordance with the "narrow" Porter hypothesis that states that market based measures are more productivity-friendly than non-market based measures. However, in contrast to the "strong" Porter hypothesis, the market-based tools still have negative productivity effects. This finding brings to the fore the necessary trade-offs in setting policy to address environmental externalities. While more flexible instruments, which enable firms to trade obligations, have the lowest cost in terms of sacrificing productivity, they tend to produce weaker clean innovation outcomes and vice-versa.

Finally, we also explore to which extent firms with different characteristics and capabilities deal with regulatory reforms. However, we detect no statistically significant differences between high and low polluting firms regarding their innovation response to more stringent policies based on their total factor productivity, age, size, equity ratio, cash holdings or patenting record (see Table A8 and A9. Also a decomposition according to different sectors (Table A10) does not show significant differences. This is a departure from our productivity study (Benatti et al., 2024), where we show that larger firms, firms with better access to financial markets and firms with more research experience face lower losses in terms of productivity. While heterogeneity among firms matter in terms of productivity responses due to vast differences among firms in the sample, the group of patenting firms are more homogeneous and additional differentiation matters less. At the same time, the relatively small sample of patenting firms makes it harder to clearly identify heterogeneities even if they exist.

# 7 Conclusion

Innovating in clean technologies is not only essential for achieving EU's climate neutrality targets but also for increasing or at least maintaining productivity in a world of ever increasing climate policy stringency. Our analysis offers insights into the nature of the impacts of environmental policy, and its main variants, on firms' innovating activity and in conjunction with the findings in Benatti et al. (2024) into economic impacts of environmental policy more broadly. Causal identification is inevitably challenging in this context, with reverse causality being of particular concern.

Our findings suggest consistency with the "weak" version of the Porter hypothesis, however, appear to contradict the "narrow" version. We showed that highly polluting firms tend to respond to environmental policy tightening by increasing their innovation efforts in clean technologies in an economically significant manner, especially in response to large changes in regulation. At the same time, we largely observe no statistically significant change to their innovation efforts in other, non-clean technology classes. This finding suggests that innovation in clean technologies, is not necessarily crowding out innovation elsewhere. The results also show that it takes some time to translate regulatory changes into newly filed patents as effects are only seen after two to three years. Our data further allows us to disentangle the relative effectiveness of different environmental policy types - market-based, non-market based and technology support. We find that technology support policy and non-market based policy instruments tend to have a stronger impact on clean innovation compared to market-based policy. Particularly in the case of large environmental policy stringency tightening shocks, non-market based policy induces a strong response in clean technology innovation, which peaks three years after the event. In as far as the implied flexibility of market-based policy instruments may come, at least to some degree, at the expense of certainty at the individual firm level, our findings are consistent with the notion that policy uncertainty has adverse effects on investments for the low-carbon economy (e.g. Noailly et al., 2022; Johnstone et al., 2010a).

Innovation is a key channel for productivity growth. In Benatti et al. (2024), we showed that environmental policy stringency increases have a negative impact on productivity in the time horizon we were able to explore, hence challenging the "strong" version of the Porter hypothesis. Amongst the various policy types, however, the impact of technology support policy was negative only during a short transition period after which it had a positive impact on productivity growth. It would appear, therefore, that technology support policies in the form of R&D subsidies offer may possibly offer a 'no-regret' option for inducing innovation in clean technologies while limiting the possibility of causing a productivity decrease in the regulated firms. While increasing stringency in non-market based environmental policy had a negative impact on productivity in the five year horizon we observed, it is possible that the clean innovation increase these policy instruments induce may offset or even reverse the productivity decline beyond that time horizon.

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# Appendix

## Descriptives

Table A1: Summary statistics - firm characteristics

| | Mean | SD | Min | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| **Belgium** | | | | | | |
| Firm age | 21.55 | 13.49 | 0 | 12.00 | 19.00 | 27.00 |
| Employees | 17.22 | 401.84 | 1.00 | 2.00 | 4.00 | 9.00 |
| Fixed intangible capital intensity | 77,022.96 | 7,918,942.88 | -1,524,679.40 | 0.00 | 298.00 | 3,027.50 |
| Return on assets | 14.63 | 15.51 | -115.33 | 6.08 | 12.56 | 21.21 |
| Emission bin estimation | 0 | 0.12 | 0 | 0 | 0 | 0 |
| Equity-assets ratio | 32.62 | 30.90 | -100.00 | 13.35 | 30.79 | 53.57 |
| **Germany** | | | | | | |
| Firm age | 30.06 | 25.97 | 0 | 16.00 | 23.00 | 35.00 |
| Employees | 58.52 | 908.50 | 1.00 | 4.00 | 13.00 | 35.00 |
| Fixed intangible capital intensity | 103,632.60 | 4,999,215.62 | -6,686,549.50 | 0.08 | 164.93 | 2,015.14 |
| Return on assets | 12.93 | 13.86 | -159.68 | 5.12 | 11.29 | 19.42 |
| Emission bin estimation | 0.02 | 0.26 | 0 | 0 | 0 | 0 |
| Equity-assets ratio | 35.93 | 35.03 | -100.00 | 11.73 | 34.15 | 62.07 |
| **Spain** | | | | | | |
| Firm age | 16.32 | 9.81 | 0.00 | 9.00 | 15.00 | 21.00 |
| Employees | 20.03 | 6,143.86 | 1.00 | 2.00 | 4.00 | 10.00 |
| Fixed intangible capital intensity | 59,485.85 | 6,564,793.65 | -78,982,696.00 | 0.00 | 965.28 | 7,050.15 |
| Return on assets | 20.65 | 75.48 | -169.95 | 1.85 | 6.70 | 14.64 |
| Emission bin estimation | 0 | 0.08 | 0 | 0 | 0 | 0 |
| Equity-assets ratio | 32.09 | 34.96 | -100.00 | 9.60 | 29.99 | 57.36 |
| **France** | | | | | | |
| Firm age | 18.09 | 13.00 | 0 | 9.00 | 15.00 | 24.00 |
| Employees | 29.40 | 599.24 | 1.00 | 2.00 | 5.00 | 12.00 |
| Fixed intangible capital intensity | 55,273.17 | 3,360,115.12 | -13,130,103.00 | 375.51 | 2,897.62 | 17,629.15 |
| Return on assets | 10.83 | 14.83 | -209.38 | 3.28 | 9.78 | 18.15 |
| Emission bin estimation | 0 | 0.11 | 0 | 0 | 0 | 0 |
| Equity-assets ratio | 33.90 | 28.47 | -100.00 | 16.97 | 34.46 | 53.29 |
| **Italy** | | | | | | |
| Firm age | 20.95 | 13.09 | 0 | 12.00 | 18.00 | 28.00 |
| Employees | 19.91 | 206.89 | 1.00 | 2.00 | 6.00 | 13.00 |
| Fixed intangible capital intensity | 33,542.88 | 864,838.29 | -9,985,670.00 | 238.24 | 1,841.73 | 9,274.91 |
| Return on assets | 33.20 | 83.89 | -97.69 | 4.15 | 8.67 | 17.89 |
| Emission bin estimation | 0 | 0.09 | 0 | 0 | 0 | 0 |
| Equity-assets ratio | 23.42 | 24.29 | -100.00 | 6.98 | 18.11 | 37.14 |
| **Portugal** | | | | | | |
| Firm age | 20.28 | 14.14 | 0 | 11.00 | 17.00 | 25.00 |
| Employees | 10.79 | 104.68 | 1.00 | 2.00 | 3.00 | 7.00 |
| Fixed intangible capital intensity | 16,436.09 | 760,404.23 | -12,038,928.00 | 0.00 | 0.00 | 175.74 |
| Return on assets | 6.52 | 23.79 | -706.16 | 0.96 | 6.67 | 15.05 |
| Emission bin estimation | 0.01 | 0.14 | 0 | 0 | 0 | 0 |
| Equity-assets ratio | 32.87 | 37.21 | -100.00 | 11.11 | 31.79 | 59.42 |

Table A2: Variable description

| Variable | Country | Firm | Description | Source |
|---|---|---|---|---|
| Clean patents | | ✓ | Patent families at firm-year level with the 'Y02' tag associated with technologies or applications for mitigation or adaptation against climate change | IP Orbis |
| Country-level clean patents | ✓ | | Percentage of patents in environment-related technologies, as a percentage based on fractional counts | OECD |
| Non-clean patents | | ✓ | Patent families at firm-year level which do not have the 'Y02' tag | IP Orbis |
| Dirty patents | | ✓ | Patent families at firm-year level which fall into one of the CPC symbol classes listed in Dechezleprêtre et al. (2014) | IP Orbis |
| Environmental policy stringency | ✓ | ✓ | EPS index, values between 0 and 6 (least to most stringent), aggregate or sub-indicator, growth rate | OECD |
| Emission indicator | ✓ | | Greenhouse gas emissions per capita, dummy variable equals one if country is among top (50 %) polluters | AMECO |
| Firm level emission indicator | | ✓ | Dummy variable equals one if firm is among top X emission equivalence bins according to XGBoost classification, based on Urgentem data | own calc |
| Output gap | ✓ | ✓ | Cyclical component of real GDP | AMECO |
| GDP per capita | ✓ | ✓ | GDP per capita | AMECO |
| Employment prot. | ✓ | ✓ | Strictness of employment protection legislation | OECD |
| Startup costs | ✓ | ✓ | Costs of starting a business for men as percentage of income per capita | World Bank |
| R&D spending | ✓ | ✓ | Research and Development investment as percentage of of GDP, measured in constant prices of 2015 and PPPs | OECD |
| Firm size | | ✓ | Number of employees, standardized | ORBIS/iBACH |
| Firm age | | ✓ | Years since formation of business, standardized | ORBIS/iBACH |
| Return-on-assets | | ✓ | Profit as percentage of assets, standardized | ORBIS/iBACH |
| Equity ratio | | ✓ | Equity per total assets, standardized | ORBIS/iBACH |
| Total factor productivity | ✓ | | Used for heterogeneity analyses; based on ORBIS/iBACH data, Petrison-Levin-Wooldridge approach (Ackerberg et al., 2015), growth rate | own calc |

Table A3: List of CPC codes

| | |
|---|---|
| **Clean patent classes** | |
| Y02B | Climate change mitigation technologies related to buildings including housing and appliances or related end-user applications |
| Y02C | Capture, storage, sequestration or disposal of greenhouse gases (GHG) |
| Y02D | ICT technologies aiming at their own energy reduction |
| Y02E | Climate change mitigation technologies in energy generation, transmission and distribution |
| Y02P | Climate change mitigation technologies in the production or processing of goods |
| Y02T | Climate change mitigation technologies related to transport |
| Y02W | Climate change mitigation technologies related to wastewater treatment or waste management |
| **Dirty patent classes** | |
| C10G1 | Production of liquid hydrocarbon mixtures from oil-shale, oil-sand, or non-melting solid carbonaceous or similar materials, e.g. wood, coal, oil-sand, or the like B03B |
| C10L1 | Fuel |
| C10J | Production of fuel gases by carburetting air or other gases |
| E02B | Hydraulic engineering |
| F01K | Steam engine plans; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles |
| F02C | Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants |
| F22 | Steam generation |
| F23 | Combustion apparatus; combustion processes |
| F24J | Production or use of heat not otherwise provided for |
| F27 | Furnaces; kilns; ovens; retorts |
| F28 | Heat exchange in general |
| F02B | Internal-combustion piston engines; combustion engines in genera |
| F02D | Controlling combustion engines |
| F02F | Cylinders, pistons, or casings for combustion engines; arrangement of sealing in combustion engines |
| F02M | Supplying combustion engines with combustibles mixtures or constituents thereof |
| F02N | Starting of combustion engines |
| F02P | Ignition (other than compression ignition) for internal-combustion engines |

Table A4: Emission regressions

| | Top 6 emission bin - dummy | | | | Emission bin (0-9) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\Delta EPS$ | 0.00916 | | | | -0.00002 | | | |
| | (0.00682) | | | | (0.00001) | | | |
| $\Delta marketEPS$ | | 0.00137 | | | | -0.000005** | | |
| | | (0.00193) | | | | (0.000002) | | |
| $\Delta non-marketEPS$ | | | 0.00649 | | | | 0.000007 | |
| | | | (0.00398) | | | | (0.000005) | |
| $\Delta techsupportEPS$ | | | | 0.00128 | | | | -0.00001*** |
| | | | | (0.00241) | | | | (0.000003) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time F.E. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector F.E. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm F.E. | No | No | No | No | Yes | Yes | Yes | Yes |
| $R^2$ adjusted | | | | | 0.71 | 0.71 | 0.71 | 0.71 |
| N | 6,167,610 | 6,167,610 | 6,167,610 | 6,167,610 | 6,286,273 | 6,286,273 | 6,286,273 | 6,286,273 |

Note: Local projections 3 year ahead, (1)-(4) logit regression with top 6 emission bin dummy as dependent variable, (5)-(8) linear regression with emission bins as dependent variable. Controls include: output gap, gdp/capita, EPL, gov R&D expendicture, startup costs, TFP frontier growth, distance to frontier, firm size, age and ROA. * $< 0.1$, ** $< 0.05$, *** $< 0.01$

## Main results - regression tables

Table A5: Baseline specification - the response of clean technology patenting to change in EPS

| | Dependent variable: cumulative of differences in arcsinh(# of clean innovations) | | | | | |
|---|---|---|---|---|---|---|
| | h=0 | h=1 | h=2 | h=3 | h=4 | h=5 |
| CO2 | 0.00301 | -0.0166 | -0.0277 | -0.0605** | -0.0620** | -0.0272 |
| | (0.0108) | (0.0141) | (0.0177) | (0.0187) | (0.0213) | (0.0229) |
| EPS shock | -0.00000165 | -0.00000547 | -0.00000817* | 0.0000132** | -0.00000384 | 0.00000337 |
| | (0.00000368) | (0.00000447) | (0.00000464) | (0.00000495) | (0.00000585) | (0.00000614) |
| CO2 * EPS shock | -0.00249 | 0.00208 | 0.00509** | 0.00489* | 0.00368 | 0.000198 |
| | (0.00174) | (0.00179) | (0.00208) | (0.00255) | (0.00230) | (0.00250) |
| Output gap | 0.00000941 | 0.0000139 | -0.00000870 | -0.0000232 | -0.0000234 | 0.00000556 |
| | (0.0000120) | (0.0000180) | (0.0000251) | (0.0000287) | (0.0000309) | (0.0000345) |
| GDP/capita | -0.00169* | -0.00440** | -0.00582** | -0.00696** | -0.00967** | -0.0151*** |
| | (0.000861) | (0.00138) | (0.00215) | (0.00271) | (0.00341) | (0.00427) |
| EPL index | 0.000615* | 0.000742* | 0.00141** | 0.000158 | -0.000895* | -0.00158** |
| | (0.000330) | (0.000384) | (0.000473) | (0.000510) | (0.000491) | (0.000531) |
| R&D spending | 0.000409** | 0.000713** | 0.000410 | 0.00111** | 0.00269*** | 0.00392*** |
| | (0.000207) | (0.000317) | (0.000422) | (0.000486) | (0.000579) | (0.000733) |
| Startup costs | -0.000375*** | -0.000528*** | -0.000394*** | -0.000542*** | -0.000814*** | -0.000987*** |
| | (0.0000667) | (0.0000956) | (0.000106) | (0.000126) | (0.000130) | (0.000136) |
| No. employees | 0.000190 | 0.000184 | 0.000341 | 0.000161 | 0.000467 | 0.000425 |
| | (0.000172) | (0.000277) | (0.000488) | (0.000453) | (0.000656) | (0.000724) |
| ROA | -0.00000110 | 0.0000214 | 0.000000254 | 0.00000164 | -0.0000164 | -0.00000865 |
| | (0.0000137) | (0.0000201) | (0.0000255) | (0.0000297) | (0.0000347) | (0.0000446) |
| Age | 0.0000892 | 0.000799 | 0.00198*** | 0.00196*** | 0.00223** | 0.00299*** |
| | (0.000372) | (0.000518) | (0.000425) | (0.000550) | (0.000680) | (0.000787) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 10,506,630 | 8,881,329 | 7,677,256 | 6,650,852 | 5,708,208 | 4,858,612 |

Note: Standard errors in parentheses. Local projections for h years ahead. $CO2$ indicator equals to one if a firm belongs to the top 4 bins of polluting firms. All controls are lagged except for output gap. Age, size and ROA are standardised. * p<0.10, ** p<0.05, *** p<0.01

Table A6: Baseline specification - the response of other (not clean) technology patenting to change in EPS

| | Dependent variable: cumulative of differences in arcsinh(# of not clean innovations) | | | | | |
|---|---|---|---|---|---|---|
| | h=0 | h=1 | h=2 | h=3 | h=4 | h=5 |
| CO2 | 0.00682 | -0.00708 | -0.0220 | -0.0454 | -0.0472 | -0.0304 |
| | (0.0149) | (0.0209) | (0.0260) | (0.0286) | (0.0302) | (0.0356) |
| EPS shock | 0.000274 | -0.00187 | 0.000521 | -0.00318 | -0.00274 | -0.00282 |
| | (0.000455) | (0.00178) | (0.000877) | (0.00333) | (0.00300) | (0.00310) |
| CO2 * EPS shock | -0.00316 | 0.00120 | 0.00295 | 0.00115 | -0.000116 | -0.00167 |
| | (0.00209) | (0.00315) | (0.00346) | (0.00406) | (0.00339) | (0.00486) |
| Output gap | 0.0000596* | 0.00000816 | 0.0000631 | 0.000181** | 0.000174* | 0.000522*** |
| | (0.0000350) | (0.0000502) | (0.0000713) | (0.0000827) | (0.0000918) | (0.000107) |
| GDP/capita | -0.00376 | -0.00108 | -0.0112* | -0.0299*** | -0.0352*** | -0.0444*** |
| | (0.00256) | (0.00391) | (0.00583) | (0.00746) | (0.00933) | (0.0115) |
| EPL index | 0.00504*** | 0.00962*** | 0.0106*** | 0.00724*** | -0.00127 | -0.00738*** |
| | (0.00105) | (0.00120) | (0.00147) | (0.00146) | (0.00137) | (0.00151) |
| R&D spending | 0.00505*** | 0.00885*** | 0.00701*** | 0.0114*** | 0.0141*** | 0.0101*** |
| | (0.000606) | (0.000889) | (0.00117) | (0.00133) | (0.00152) | (0.00182) |
| Startup costs | -0.00141*** | -0.00300*** | -0.000627** | -0.000419 | -0.00136*** | -0.00277*** |
| | (0.000167) | (0.000251) | (0.000305) | (0.000362) | (0.000365) | (0.000386) |
| No. employees | -0.000368 | -0.000967* | -0.00189 | -0.00214 | -0.00192 | -0.00151 |
| | (0.000233) | (0.000575) | (0.00122) | (0.00146) | (0.00140) | (0.00118) |
| ROA | 0.0000848** | 0.0000953 | 0.000131* | 0.000106 | -0.000171* | -0.000309** |
| | (0.0000411) | (0.0000599) | (0.0000742) | (0.0000844) | (0.0000968) | (0.000110) |
| Firm age | 0.00190** | 0.00172 | 0.00552*** | 0.00223 | 0.00000471 | 0.00880*** |
| | (0.000644) | (0.00105) | (0.00147) | (0.00173) | (0.00186) | (0.00242) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 10,506,630 | 8,881,329 | 7,677,256 | 6,650,852 | 5,708,208 | 4,858,612 |

Note: Standard errors in parentheses. Local projections for h years ahead. $CO2$ indicator equals to one if a firm belongs to the top 4 bins of polluting firms. All controls are lagged except for output gap. Age, size and ROA are standardised. * p<0.10, ** p<0.05, *** p<0.01

## Alternative specifications of the dependent variable

Table A7: Baseline specification - the response of clean technology patenting to change in EPS; alternative transformation of the dependent variable using ln(1+patent families)

| | Dependent variable: cumulative of differences in ln(1+patent families) | | | | | |
|---|---|---|---|---|---|---|
| | h=0 | h=1 | h=2 | h=3 | h=4 | h=5 |
| CO2 | 0.000953 | -0.0133 | -0.0237* | -0.0505*** | -0.0527** | -0.0247 |
| | (0.00851) | (0.0112) | (0.0141) | (0.0151) | (0.0173) | (0.0183) |
| EPS shock | -0.00000114 | -0.00000432 | -0.00000646* | 0.0000102** | -0.00000308 | 0.00000260 |
| | (0.00000287) | (0.00000349) | (0.00000362) | (0.00000387) | (0.00000458) | (0.00000480) |
| CO2*EPS shock | -0.00181 | 0.00175 | 0.00420** | 0.00424** | 0.00327* | 0.000444 |
| | (0.00137) | (0.00145) | (0.00167) | (0.00205) | (0.00187) | (0.00201) |
| Output gap | 0.00000843 | 0.0000121 | -0.00000510 | -0.0000167 | -0.0000158 | 0.00000685 |
| | (0.00000937) | (0.0000142) | (0.0000197) | (0.0000226) | (0.0000243) | (0.0000273) |
| GDP/capita | -0.00141** | -0.00358** | -0.00479** | -0.00577** | -0.00801** | -0.0123*** |
| | (0.000675) | (0.00109) | (0.00170) | (0.00216) | (0.00272) | (0.00340) |
| EPL index | 0.000490* | 0.000595** | 0.00111** | 0.000148 | -0.000716* | -0.00122** |
| | (0.000257) | (0.000300) | (0.000371) | (0.000401) | (0.000384) | (0.000418) |
| R&D spending | 0.000340** | 0.000581** | 0.000352 | 0.000911** | 0.00216*** | 0.00315*** |
| | (0.000163) | (0.000249) | (0.000333) | (0.000385) | (0.000460) | (0.000582) |
| Startup costs | -0.000299*** | -0.000422*** | -0.000320*** | -0.000439*** | -0.000648*** | -0.000787*** |
| | (0.0000524) | (0.0000751) | (0.0000836) | (0.0000999) | (0.000103) | (0.000108) |
| No. employees | 0.000150 | 0.000143 | 0.000266 | 0.000113 | 0.000363 | 0.000349 |
| | (0.000135) | (0.000218) | (0.000385) | (0.000360) | (0.000518) | (0.000582) |
| ROA | -0.000000782 | 0.0000173 | 0.000000318 | 0.00000142 | -0.0000128 | -0.00000606 |
| | (0.0000107) | (0.0000158) | (0.0000202) | (0.0000235) | (0.0000273) | (0.0000357) |
| Firm age | 0.0000829 | 0.000643 | 0.00157*** | 0.00159*** | 0.00182*** | 0.00242*** |
| | (0.000293) | (0.000409) | (0.000336) | (0.000438) | (0.000543) | (0.000631) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 10,506,630 | 8,881,329 | 7,677,256 | 6,650,852 | 5,708,208 | 4,858,612 |

Note: Standard errors in parentheses. Local projections for h years ahead. $CO2$ indicator equals to one if a firm belongs to the top 4 bins of polluting firms. All controls are lagged except for output gap. Age, size and ROA are standardised. * p<0.10, ** p<0.05, *** p<0.001

## Heterogeneity results

Table A8: Heterogeneity analysis; h=3

| | Dependent variable: cumulative of differences in arcsinh(# of clean innovations; h=3) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| CO2 | -0.0708*** | -0.0325* | -0.0694*** | -0.0719*** | -0.0951*** | -0.0657*** | -0.0500** |
| | (0.0200) | (0.0189) | (0.0192) | (0.0187) | (0.0198) | (0.0195) | (0.0235) |
| EPS shock | 0.0000108** | 0.0000143** | 0.0000108* | 0.0000116** | 0.0000111** | 0.0000127** | 0.00000875* |
| | (0.00000487) | (0.00000506) | (0.00000555) | (0.00000491) | (0.00000502) | (0.00000505) | (0.00000478) |
| CO2*EPS shock | 0.00645** | 0.00335 | 0.00519* | 0.00539** | 0.00470* | 0.00485* | 0.00161 |
| | (0.00279) | (0.00234) | (0.00282) | (0.00263) | (0.00248) | (0.00263) | (0.00303) |
| CO2*EPS shock*Employees | -0.0000890 | | | | | | |
| | (0.0000598) | | | | | | |
| CO2*EPS shock*Firm age | | 0.00123 | | | | | |
| | | (0.00145) | | | | | |
| CO2*EPS shock*TFP level | | | -0.00192 | | | | |
| | | | (0.00392) | | | | |
| CO2*EPS shock*Equity ratio | | | | -0.000175 | | | |
| | | | | (0.000107) | | | |
| CO2*EPS shock*Cumulative patents | | | | | -0.0000865 | | |
| | | | | | (0.000251) | | |
| CO2*EPS shock*Cash holdings | | | | | | 0.000271 | |
| | | | | | | (0.000700) | |
| CO2*EPS shock*ΔCash holdings | | | | | | | -0.00453 |
| | | | | | | | (0.00336) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Aggregate controls (Output gap, R&D, EPL) | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm characteristics (age, size, ROA) | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 6,650,852 | 6,650,852 | 6,286,273 | 6,645,044 | 6,650,852 | 6,258,264 | 6,374,162 |

Note: Standard errors in parentheses. $CO2$ indicator equals to one if a firm belongs to the top 4 bins of polluting firms. All controls are lagged except for output gap. Age, size and ROA are standardised. * p<0.10, ** p<0.05, *** p<0.01

Table A9: Heterogeneity analysis; h=5

| | Dependent variable: cumulative of differences in arcsinh(# of clean innovations; h=5) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| C02 | -0.0443* | -0.00998 | -0.0264 | -0.0477** | -0.136** | -0.0280 | -0.0131 |
| | (0.0245) | (0.0216) | (0.0227) | (0.0228) | (0.0454) | (0.0235) | (0.0285) |
| EPS shock | -0.00000123 | 0.00000432 | 0.00000241 | 0.00000117 | 0.0000719 | 0.00000378 | 0.000000363 |
| | (0.00000616) | (0.00000632) | (0.00000710) | (0.00000609) | (0.000108) | (0.00000626) | (0.00000604) |
| CO2*EPS shock | 0.00106 | 0.000187 | 0.000105 | 0.00119 | -0.000125 | 0.000283 | -0.00438 |
| | (0.00253) | (0.00266) | (0.00317) | (0.00259) | (0.00416) | (0.00264) | (0.00394) |
| CO2*EPS shock*Employees | -0.0000886 | | | | | | |
| | (0.0000606) | | | | | | |
| CO2*EPS shock*Firm age | | -0.0000139 | | | | | |
| | | (0.00121) | | | | | |
| CO2*EPS shock*TFP level | | | -0.00386 | | | | |
| | | | (0.00591) | | | | |
| CO2*EPS shock*Equity ratio | | | | -0.000242 | | | |
| | | | | (0.000149) | | | |
| CO2*EPS shock*Cumulative patents | | | | | 0.000342 | | |
| | | | | | (0.000220) | | |
| CO2*EPS shock*Cash holdings | | | | | | -0.000410 | |
| | | | | | | (0.000838) | |
| CO2*EPS shock*ΔCash holdings | | | | | | | -0.00619 |
| | | | | | | | (0.00458) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Aggregate controls (Output gap, R&D, EPL) | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm characteristics (age, size, ROA) | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 4,858,612 | 4,858,612 | 4,624,177 | 4,855,440 | 4,179,564 | 4,576,254 | 4,661,694 |

Note: Standard errors in parentheses. Local projections for h years ahead. $CO2$ indicator equals to one if a firm belongs to the top 6 bins of polluting firms. All controls are lagged except for output gap. Age, size and ROA are standardised. * p<0.10, ** p<0.05, *** p<0.01

## Sector interactions

Table A10: Sector interactions - clean innovations

| | Dependent variable: cumulative of differences in arcsinh(# of clean innovations) | | | | | |
|---|---|---|---|---|---|---|
| | h=0 | h=1 | h=2 | h=3 | h=4 | h=5 |
| $CO2_{t-1}$ | 0.00493 | 0.00945 | 0.00432 | -0.00916 | -0.00524 | -0.00436 |
| | (0.00971) | (0.0123) | (0.00914) | (0.00886) | (0.0118) | (0.00945) |
| EPS shock | 0.00000110 | 0.00000224 | 0.0000101** | 0.0000178*** | 0.0000131** | 0.00000599 |
| | (0.00000371) | (0.00000437) | (0.00000444) | (0.00000497) | (0.00000524) | (0.00000538) |
| $CO2_{t-1}$ × EPS shock | 0.00141 | 0.000661 | 0.00109 | 0.000380 | 0.00276 | 0.00271* |
| | (0.00177) | (0.00203) | (0.00120) | (0.00107) | (0.00179) | (0.00149) |
| $CO2_{t-1}$ × NACE F× EPS shock | -0.00141 | -0.000664 | -0.00109 | -0.000386 | -0.00276 | -0.00312** |
| | (0.00177) | (0.00203) | (0.00120) | (0.00107) | (0.00179) | (0.00155) |
| $CO2_{t-1}$ × NACE G × EPS shock | -0.000224 | -0.00103 | -0.00165 | 0.00102 | -0.00211 | -0.000880 |
| | (0.00213) | (0.00206) | (0.00143) | (0.00161) | (0.00189) | (0.00239) |
| $CO2_{t-1}$ × NACE H × EPS shock | -0.000908 | 0.00225 | -0.000897 | 0.000147 | -0.00107 | -0.00195 |
| | (0.00198) | (0.00354) | (0.00130) | (0.00123) | (0.00220) | (0.00169) |
| $CO2_{t-1}$ × NACE I × EPS shock | -0.00141 | -0.000657 | -0.00108 | -0.000374 | -0.00276 | -0.00271* |
| | (0.00177) | (0.00203) | (0.00120) | (0.00107) | (0.00179) | (0.00149) |
| $CO2_{t-1}$ × NACE J × EPS shock | -0.00142 | -0.000669 | -0.00109 | -0.000380 | -0.00276 | -0.00271* |
| | (0.00177) | (0.00203) | (0.00120) | (0.00107) | (0.00179) | (0.00149) |
| $CO2_{t-1}$ × NACE M × EPS shock | 0.00434 | 0.00940 | 0.00893 | -0.00102 | 0.0189 | 0.0152 |
| | (0.00584) | (0.0101) | (0.00964) | (0.00145) | (0.0201) | (0.0167) |
| $CO2_{t-1}$ × NACE N × EPS shock | -0.00142 | -0.000657 | -0.00109 | -0.000373 | -0.00275 | -0.00271* |
| | (0.00177) | (0.00203) | (0.00120) | (0.00107) | (0.00179) | (0.00149) |
| Aggregate controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,506,630 | 8,881,329 | 7,677,256 | 6,650,852 | 5,708,208 | 4,858,612 |

Note: Standard errors in parentheses. Local projections for h years ahead. $CO2$ indicator equals to one if a firm belongs to the top 4 bins of polluting firms. Aggregare controls (EPL index, R&D spending, output gap, startup costs, GDP/capita) are lagged except for output gap. Firm characteristics (age, size and ROA) are standardised. Simple interactions between the sector and the EPS shock as well as between the sector and the CO2 status were also included but not shown for brevity. Sectors are codified at section level; with C being the base category (C= Manufacturing; F= Construction; G= Wholesale and Retail; H= Transportation and Storage; I= Accommodation and Food Service Activities; J= Information and Communication; M= Professional, Scientific and Technical Activities; N= Administrative and Support Service Activities). * p<0.10, ** p<0.05, *** p<0.01

## Intensive/extensive margin

Table A11: Extensive margin - impulse response projections for firms with zero patent stock in the pre-period 1990-2002; clean innovations

| | Dependent variable: cumulative of differences in arcsinh(# of clean innovations) | | | | | |
|---|---|---|---|---|---|---|
| | h=0 | h=1 | h=2 | h=3 | h=4 | h=5 |
| CO2 | 0.00976 | 0.0171* | 0.0176 | 0.000262 | -0.0119 | -0.000958 |
| | (0.00605) | (0.00929) | (0.0112) | (0.00917) | (0.0147) | (0.0130) |
| EPS shock | -0.00000105 | -0.00000172 | -0.000000808 | 0.00000761** | 0.00000227 | 0.00000122 |
| | (0.00000182) | (0.00000229) | (0.00000253) | (0.00000251) | (0.00000319) | (0.00000324) |
| CO2*EPS shock | -0.000336 | 0.0000289 | 0.000953 | 0.00147 | 0.00218 | 0.00261 |
| | (0.00107) | (0.000665) | (0.00146) | (0.00168) | (0.00186) | (0.00265) |
| Output gap | -0.00000967* | -0.00000255 | -0.00000410 | -0.000000431 | -0.00000796 | -0.00000139 |
| | (0.00000556) | (0.00000796) | (0.0000112) | (0.0000130) | (0.0000148) | (0.0000154) |
| GDP/capita | 0.000429 | 0.000279 | 0.000118 | -0.00000909 | 0.000333 | 0.000174 |
| | (0.000378) | (0.000579) | (0.000865) | (0.00108) | (0.00134) | (0.00159) |
| EPL index | 0.000126 | 0.000204 | 0.000308 | -0.000307 | -0.000436 | -0.000207 |
| | (0.000200) | (0.000211) | (0.000262) | (0.000303) | (0.000265) | (0.000287) |
| R&D spending | 0.00000411 | 0.000329** | 0.000187 | 0.000261 | 0.000512** | 0.000693** |
| | (0.0000989) | (0.000144) | (0.000198) | (0.000227) | (0.000255) | (0.000306) |
| Startup costs | -0.0000770** | -0.000162*** | -0.0000681 | -0.0000692 | -0.000153** | -0.000229*** |
| | (0.0000303) | (0.0000399) | (0.0000488) | (0.0000596) | (0.0000595) | (0.0000618) |
| No. employees | -0.0000689 | -0.000146 | -0.000453 | -0.000507 | -0.000297 | -0.000391 |
| | (0.0000514) | (0.000172) | (0.000333) | (0.000501) | (0.000524) | (0.000291) |
| ROA | -0.00000216 | 0.00000671 | 0.00000271 | -0.0000105 | -0.0000166 | -0.00000932 |
| | (0.00000805) | (0.0000127) | (0.0000136) | (0.0000166) | (0.0000208) | (0.0000283) |
| Firm age | -0.0000951 | 0.000142 | 0.000472** | 0.000409 | 0.000175 | 0.000466 |
| | (0.000116) | (0.000117) | (0.000159) | (0.000269) | (0.000338) | (0.000292) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 10,260,487 | 8,663,533 | 7,482,234 | 6,476,685 | 5,553,757 | 4,722,853 |

Note: Standard errors in parentheses. Local projections for h years ahead. $CO2$ indicator equals to one if a firm belongs to the top 4 bins of polluting firms. All controls are lagged except for output gap. Age, size and ROA are standardised. * p<0.10, ** p<0.05, *** p<0.01

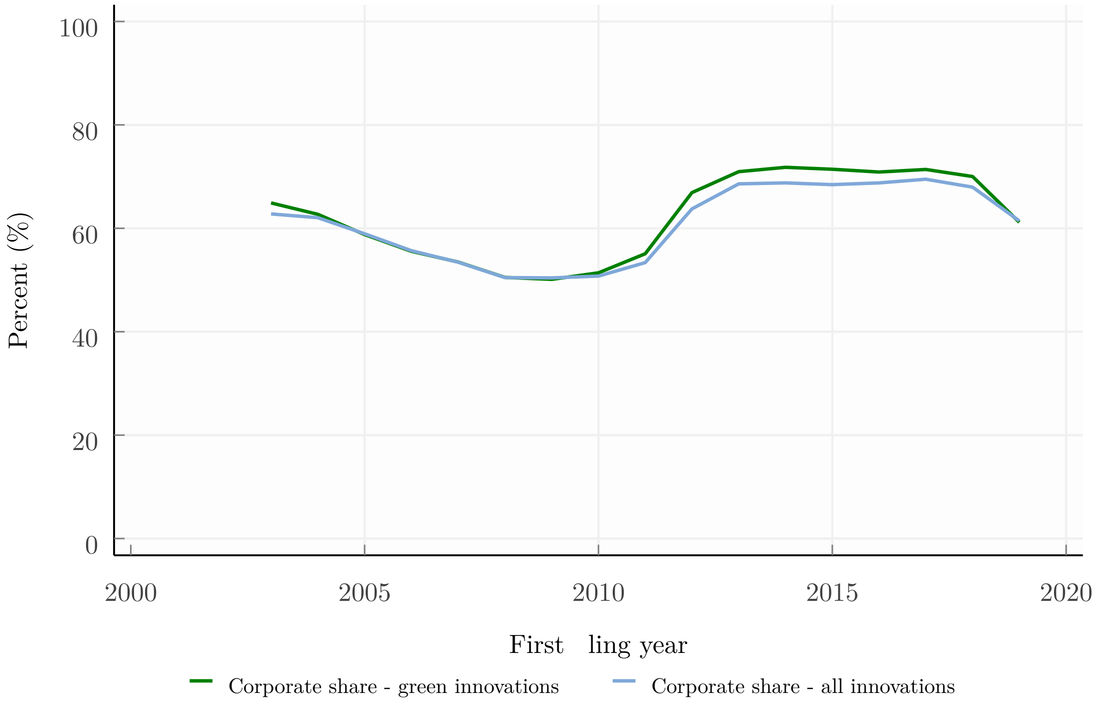
Table A12: Intensive margin - impulse response projections for firms with a patent stock in the pre-period 1990-2002 greater than zero; clean innovations

| | Dependent variable: cumulative of differences in arcsinh(# of clean innovations) | | | | | |
|---|---|---|---|---|---|---|
| | h=0 | h=1 | h=2 | h=3 | h=4 | h=5 |
| CO2 | -0.00889 | -0.0610** | -0.0829** | -0.135*** | -0.120** | -0.0550 |
| | (0.0238) | (0.0299) | (0.0373) | (0.0401) | (0.0436) | (0.0478) |
| EPS shock | 0.0000309 | 0.0000585 | -0.000122 | 0.0000572 | -0.000122 | -0.00000585 |
| | (0.000101) | (0.000109) | (0.000111) | (0.000114) | (0.000129) | (0.000132) |
| CO2*EPS shock | -0.00515 | 0.00406 | 0.00951** | 0.00790 | 0.00452 | -0.00266 |
| | (0.00349) | (0.00369) | (0.00409) | (0.00496) | (0.00435) | (0.00422) |
| Output gap | 0.000221 | -0.000157 | -0.000749 | -0.00142** | -0.00164** | -0.0000629 |
| | (0.000304) | (0.000462) | (0.000592) | (0.000676) | (0.000699) | (0.000783) |
| GDP/capita | -0.0524*** | -0.0835*** | -0.0840** | -0.106*** | -0.119** | -0.198*** |
| | (0.0155) | (0.0206) | (0.0265) | (0.0314) | (0.0377) | (0.0497) |
| EPL index | 0.0223 | 0.00632 | 0.00281 | 0.00404 | 0.0451 | 0.00186 |
| | (0.0152) | (0.0172) | (0.0195) | (0.0301) | (0.0360) | (0.0343) |
| R&D spending | 0.00489 | -0.00339 | -0.0126 | -0.0107 | 0.0168 | 0.0309 |
| | (0.00912) | (0.0151) | (0.0206) | (0.0256) | (0.0300) | (0.0338) |
| Startup costs | -0.00327 | -0.000238 | 0.00290 | 0.00424 | -0.00418 | -0.00527 |
| | (0.00251) | (0.00338) | (0.00358) | (0.00397) | (0.00488) | (0.00545) |
| No. employees | 0.000577 | 0.000534 | 0.000751 | 0.000410 | 0.000713 | 0.000648 |
| | (0.000592) | (0.000701) | (0.000935) | (0.000711) | (0.00102) | (0.00107) |
| ROA | 0.000255 | 0.00129 | 0.000358 | 0.00106 | 0.000572 | 0.000767 |
| | (0.000716) | (0.000911) | (0.00118) | (0.00127) | (0.00133) | (0.00156) |
| Firm age | -0.0131 | -0.0114 | -0.000585 | -0.00731 | -0.00966 | -0.000596 |
| | (0.00920) | (0.0122) | (0.00701) | (0.00816) | (0.00842) | (0.00865) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 246,143 | 217,796 | 195,022 | 174,167 | 154,451 | 135,759 |

Note: Standard errors in parentheses. Local projections for h years ahead. $CO2$ indicator equals to one if a firm belongs to the top 4 bins of polluting firms. All controls are lagged except for output gap. Age, size and ROA are standardised. * p<0.10, ** p<0.05, *** p<0.01

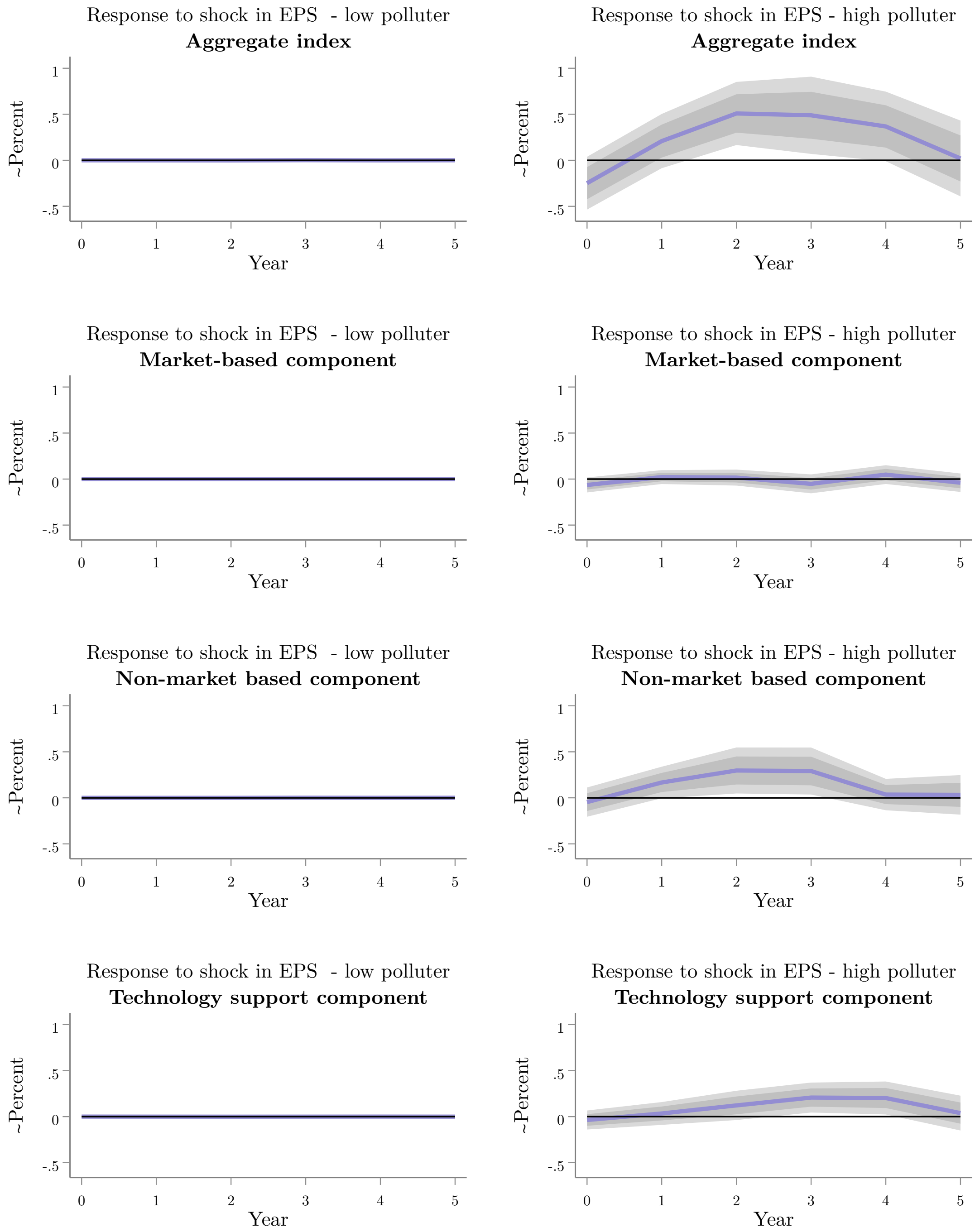
## Additional figures

Figure A1: Share of patents by corporate entities among all innovations and green innovations



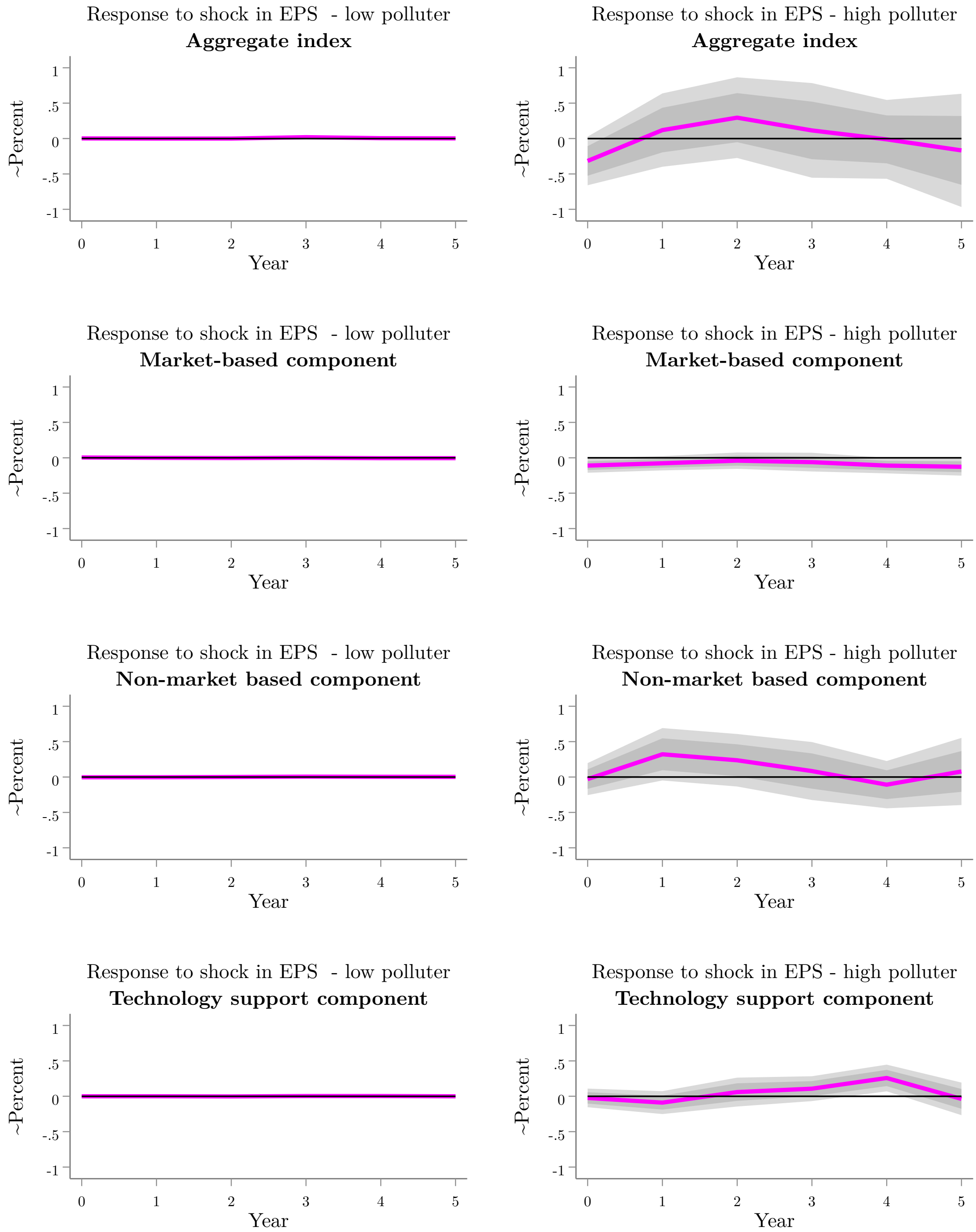

Note: We use the psn sector variable in PATSTAT version spring 2021. Where an applicant is classified as belonging to multiple sectors, only one of which is a corporation, we still classify the entity as corporate. More details about the variable can be found in the PATSTAT catalogue.

Figure A2: IRF - Clean innovation to EPS changes (high vs low polluters)



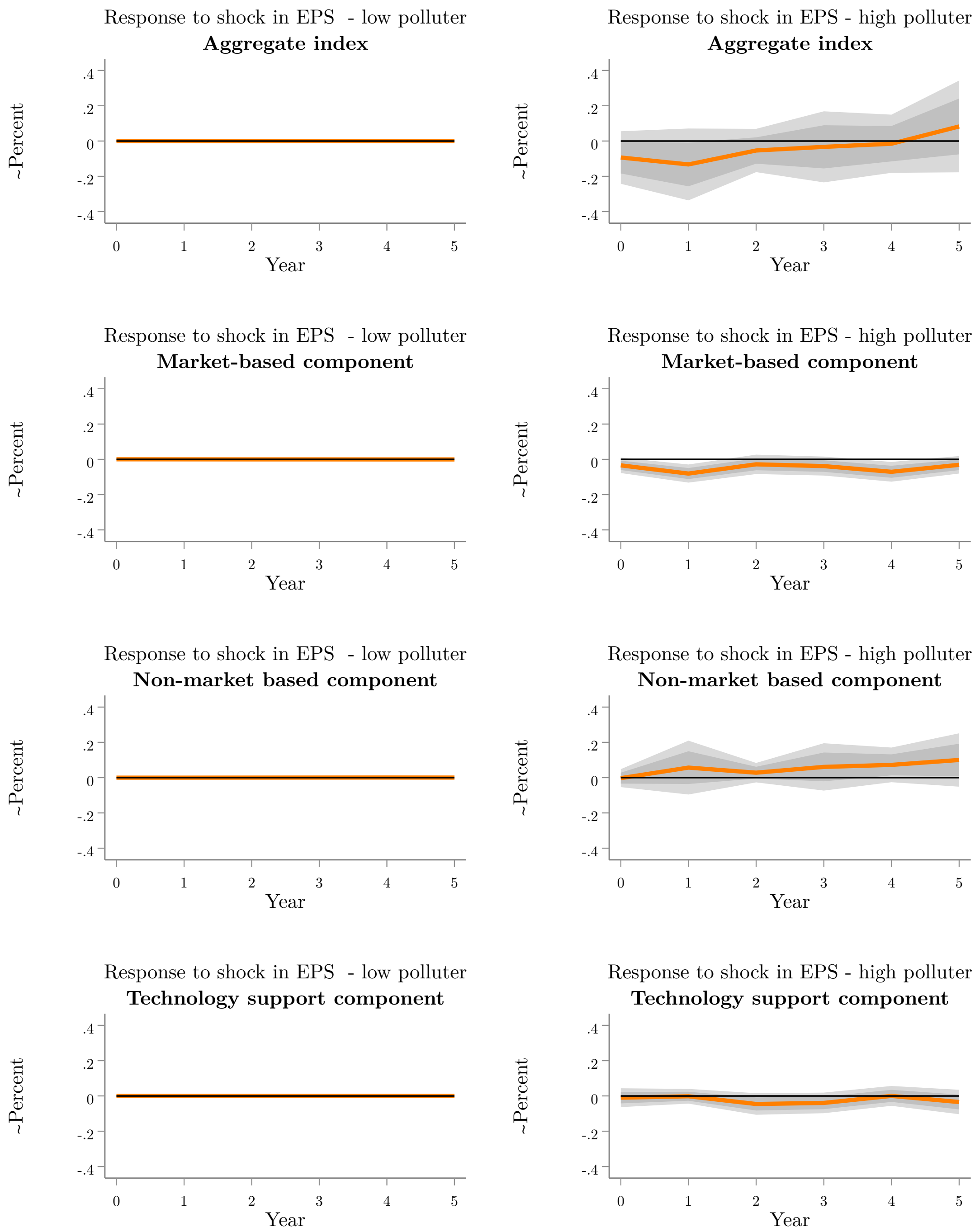

Note: Cumulative impulse responses of the relative change in clean patent families to a 1 pp EPS shock (only positive) over 5 years. Left column - low polluters (bottom 4 bins), right column - high polluters (top 6 bins). Solid lines represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure A3: IRF - Non-clean innovation to EPS changes (high vs low polluters)



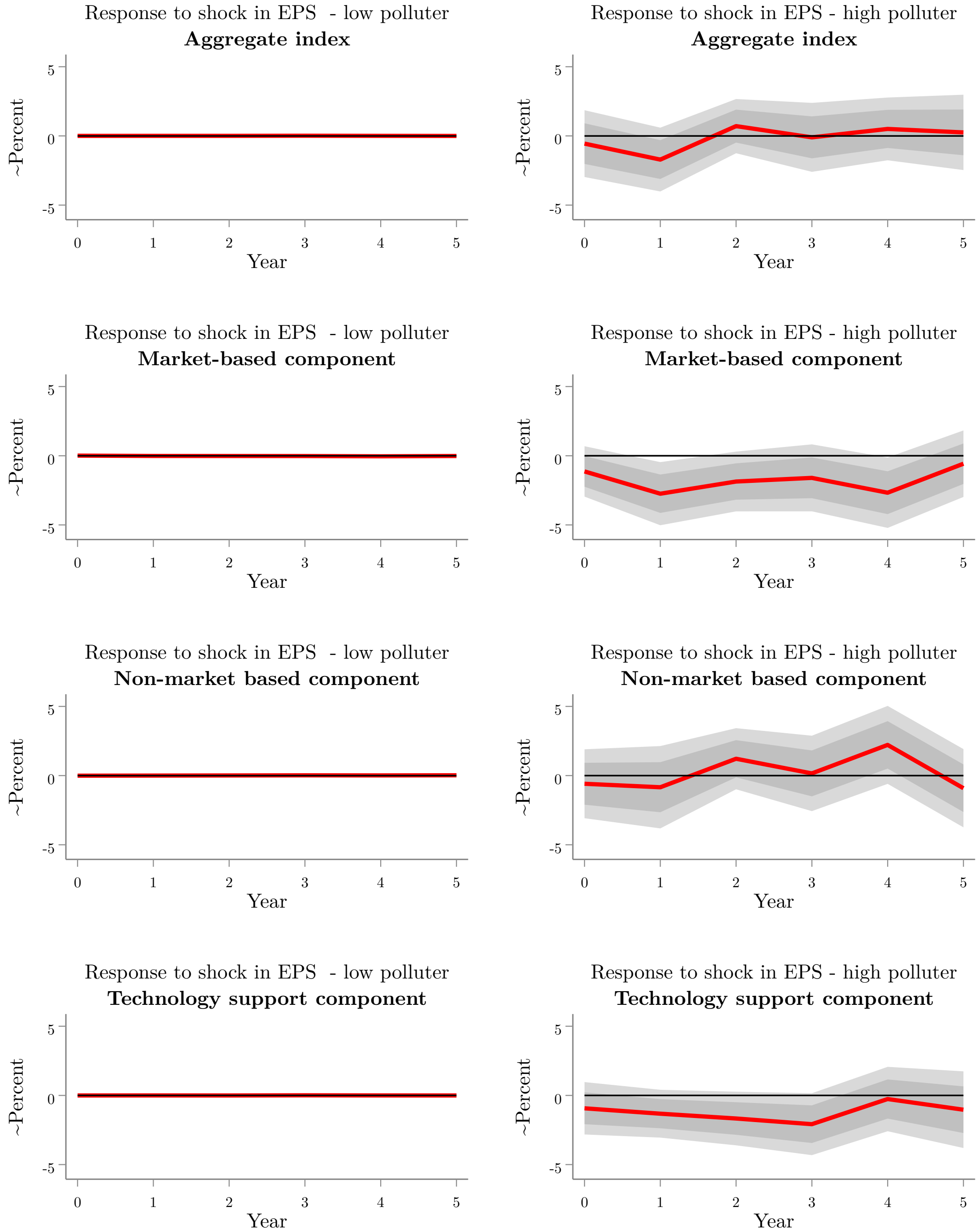

Note: Cumulative impulse responses of the relative change in non-clean patent families to a 1 pp EPS shock (only positive) over 5 years. Left column - low polluters (bottom 4 bins), right column - high polluters (top 6 bins). Solid lines represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure A4: IRF - Dirty innovation to EPS changes (high vs low polluters)



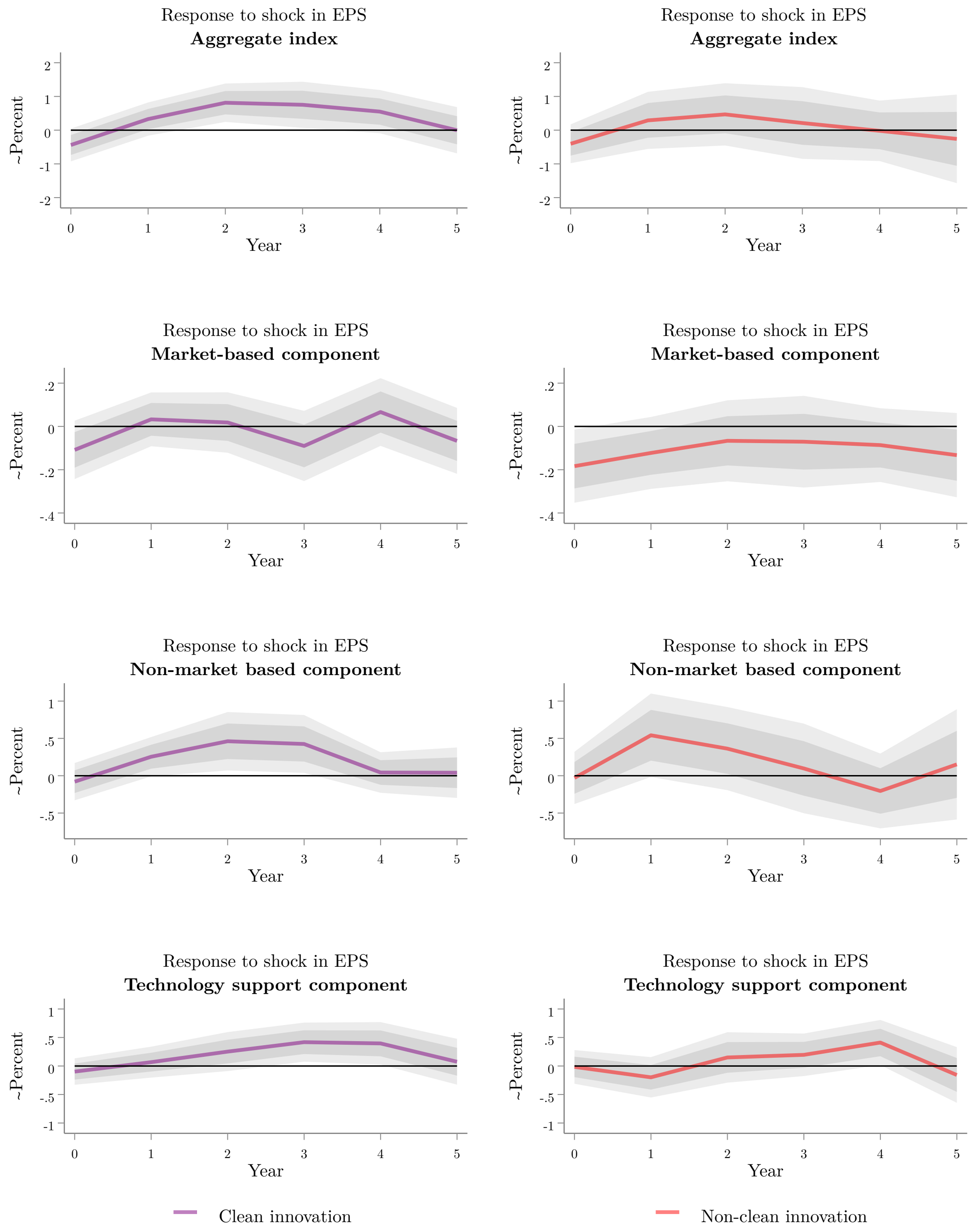

Note: Cumulative impulse responses of the relative change in dirty patent families to a 1 pp EPS shock (only positive) over 5 years. Left column - low polluters (bottom 4 bins), right column - high polluters (top 6 bins). Solid lines represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure A5: IRF - Dirty innovation to large EPS changes (high vs low polluters)



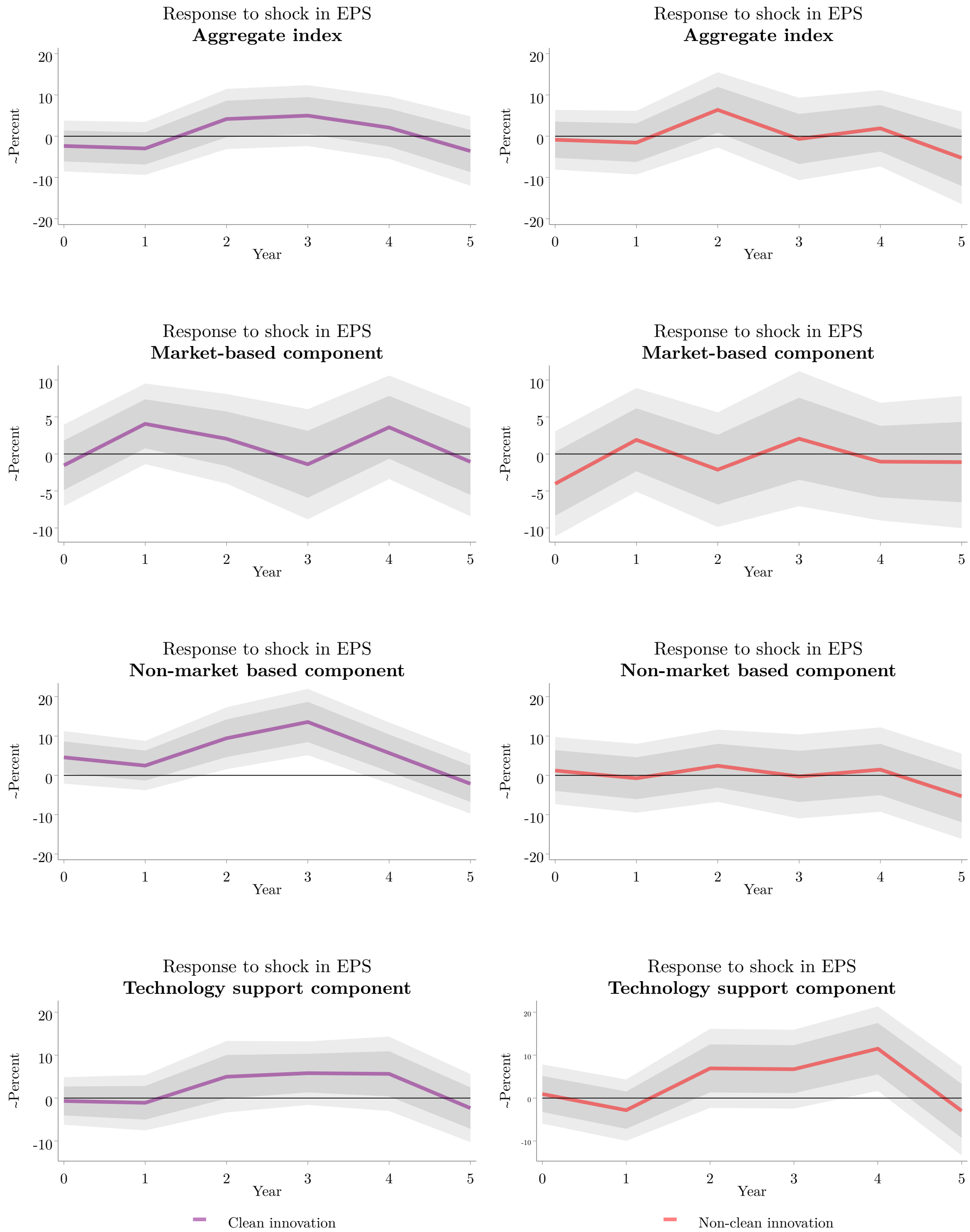

Note: Cumulative impulse responses of the relative change in dirty patent families to a large EPS shock (top 25%) over 5 years. Left column - low polluters (bottom 4 bins), right column - high polluters (top 6 bins). Solid lines represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure A6: IRF - Patenting on EPS changes (firm level, only patenters)




Note: Cumulative impulse responses of the relative change in clean and non-clean patent families to 1 pp EPS shocks (positive changes) over 5 years. Left column - clean innovation, right column - non-clean innovation. Violet/red lines represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

Figure A7: IRF - Patenting on large EPS changes (firm level, only patenters)




Note: Cumulative impulse responses of the relative change in clean and non-clean patent families to large EPS shocks (top 25%) over 5 years. Left column - clean innovation, right column - non-clean innovation. Violet/red lines represents mean responses, dark grey area 68% confidence bands, light grey area 90% confidence bands.

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