OECD Environment Working Papers No. 189

The effect of climate policy on innovation and economic performance along the supply chain: A firm- and sector-level analysis

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https://dx.doi.org/10.1787/3569283a-en

OECD

Organisation for Economic Co-operation and Development

ENV/WKP(2022)1

Unclassified **English - Or. English**

26 August 2022

ENVIRONMENT DIRECTORATE

Cancels & replaces the same document of 9 February 2022

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Environment Working Paper No. 189

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Authorised for publication by Rodolfo Lacy, Director, Environment Directorate.

Keywords: Low carbon innovation, Policy evaluation, Porter Hypothesis, Firm performance

JEL Codes: Q55, Q58, O38, L25

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JT03501409

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Abstract

The effect of climate policy on innovation and economic performance along the supply chain: a firm- and sector-level analysis

The paper empirically assesses the effect of climate policy stringency on innovation and economic performance, both directly on regulated sectors and indirectly through supply chain relationships. The analysis is based on a combination of global firm-level and sector-level data combined with input-output tables and data on embodied CO_2 emissions in international trade, covering 19 countries and the period from 1990 to 2015. First, the paper shows that climate policies are effective at inducing innovation in low-carbon technologies in the directly regulated sectors. The analysis does not find evidence that climate policies induce significant innovation along the supply chain, based on country-sector level supply-chain links. To the extent that effects of past policies can predict impacts of future policies, relying on indirect effects by regulating up- or downstream sectors might not induce large additional innovation. Second, the paper finds no evidence that climate policies – through the channel of clean innovation – either harm or improve the economic performance of directly regulated firms, in terms of productivity and value added, supporting the evidence that past climate policies have not been major burdens on firms' competitiveness, and suggests that clean innovation activity may enable firms to compensate for the potential costs implied by new climate policies.

Keywords: Low carbon innovation, Policy evaluation, Porter Hypothesis, Firm performance

JEL codes: Q55, Q58, O38, L25.

Résumé

Les effets directs et indirects des politiques climatiques sur l'innovation et la performance économique: une analyse au niveau des entreprises et des secteurs

L'article évalue empiriquement l'effet de la sévérité des politiques climatiques sur l'innovation et la performance économique, à la fois directement sur les secteurs réglementés et indirectement à travers les relations de la chaîne d'approvisionnement. L'analyse repose sur une base de données internationale au niveau des entreprises et des secteurs combinés avec des données d'entrées-sorties et avec des données sur les émissions de CO_2 incorporées dans le commerce international, couvrant 19 pays et la période allant de 1990 à 2015. Tout d'abord, le document montre que les politiques climatiques sont efficaces pour encourager l'innovation dans les technologies à faible émissions de carbone dans les secteurs directement réglementés. En revanche, l'analyse ne trouve pas d'effet significatif des politiques climatiques sur l'innovation des secteurs indirectement réglementés via les chaînes d'approvisionnement. En considérant que les effets des politiques passées peuvent prédire les impacts des politiques futures, l'article suggère que réglementer les secteurs en amont ou en aval pourrait ne pas induire d'innovations supplémentaires. Deuxièmement, l'article ne trouve aucun effet significatif des politiques climatiques - via l'innovation verte - sur les performances économiques des entreprises directement réglementées, en termes de productivité et de valeur ajoutée, ce qui confirme que les politiques climatiques passées n'ont pas négativement affecté la compétitivité des entreprises, et suggère que l'innovation verte permet aux entreprises de compenser les coûts impliqués par les nouvelles réglementations climatiques.

Mots clés : Innovation à faible intensité carbonique, évaluation des politiques, hypothèse de Porter, performance des entreprises.

Classification JEL : Q55, Q58, O38, L25.

Acknowledgements

This working paper is an output of the OECD Environment Policy Committee (EPOC) and its Working Party on Integrating Environmental and Economic Policies (WPIEEP). It is authored by Antoine Dechezleprêtre and Tobias Kruse. The work was conducted under the overall supervision of Shardul Agrawala, Head of the Environment and Economy Integration Division of the OECD's Environment Directorate.

The authors are grateful to WPIEEP delegates for helpful comments on earlier drafts of this paper. The authors thank Shardul Agrawala, Walid Oueslati, and Damien Dussaux for their useful comments and discussions. Illias Mousse Iye provided editorial assistance.

This document has been produced with the financial assistance of the European Union. The views expressed herein do not necessarily reflect the official views of the OECD or of the governments of its member countries and can in no way be taken to reflect the official opinion of the European Union. The responsibility for the content of this publication lies with the authors.

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Chapter 1. Introduction

To limit average temperature increases to well below 2 degrees, in line with the targets of the Paris Agreement, global greenhouse gas emissions need to be reduced drastically over the next decades and reach net zero by the middle of the century. Current commitments to reduce emissions fall short of these targets. Reducing emissions drastically over the next decades requires widespread adoption of low-carbon technologies and infrastructure (Rogelji et al., 2018[1]; OECD, 2018[2]).

Innovation in clean technologies is necessary to achieve the required emission reductions at the lowest cost and make the low-carbon transition compatible with sustained economic growth (Acemoglu et al., 2012[3]; OECD, 2018[2]; OECD, 2018[4]). Vast investments into low-carbon research and development – including improvements in existing technologies as well as the development of radically new technologies – are therefore required. Patent filings in low-carbon technologies[1] – one indicator of clean innovation activity – have however declined over the past years, raising concerns that innovation in cleaner technologies is slowing down at the time when they are needed the most (Dechezleprêtre, 2016[5]).[2] This may suggest that innovators see low-carbon technologies as not sufficiently profitable within the current policy environment. Similar trends in patent filings are also observed for broader groups of environmental technologies, beyond low-carbon, while the number of patent filings across all technologies continues to increase. Accelerating innovation in low-carbon technologies may therefore require additional policy support. Environmental policies can set standards and provide incentives (for instance through energy pricing) to increase innovation in clean technologies (Acemoglu et al., 2012[3]; OECD, 2018[6]). However, such policies are often difficult to implement due to concerns that they may harm the productivity of firms or destroy jobs. As a response to the COVID-19 pandemic, green stimulus packages that align economic recovery with climate objectives may offer an opportunity to jumpstart low-carbon innovation again. Stimulus packages can be designed to shift investment towards technologies that can accelerate the transition and increase economic growth (OECD, 2020[7]; Agrawala, Dussaux and Monti, 2020[8]).

However, an important question from a policy perspective is whether forcing firms to innovate in low-carbon technologies through environmental regulation is harmful to economic performance. The conventional view is that rational firms invest in profitable opportunities and that any additional effort required to comply with public policies comes at additional costs and diverts resources away from more profitable investments, resulting in weaker economic performance. Research and development efforts directed at cleaner technologies as a response to stricter environmental policies could thus *crowd out* R&D investments in productivity-enhancing technologies. These arguments are often used to oppose more stringent environmental regulation. This claim has been challenged over the past decades following the paper by Porter and van der Linde (1995[9]) who argued that well-designed environmental policy can actually *improve* firms' economic performance through innovation. Environmental regulation may help managers overcome behavioural biases and draw their attention to inefficiencies or new opportunities in

[1] This paper uses the terms 'low-carbon' and 'clean' technologies as synonyms. In this paper, they are equivalent to the Y02 patent classification of the European Patent Office as described in more detail in Section Chapter 3.

[2] Low-carbon patents are one possible measure of clean innovation that cover patentable technologies. One advantage of patent data is that globally comprehensive data – including all patents filed in any of the major patent offices – is maintained and regularly updated by the European Patent Office. Alternatives can for instance be R&D investments in clean technologies. To the best of our knowledge cross-country panel data at the firm level is however not available for clean R&D investments.

production processes. Environmental policy can thereby help firms reduce input costs of energy or raw materials through process innovations, or facilitate access to new markets through the development of new products (Lanoie et al., 2011[10]; Dechezleprêtre et al., 2019[11]).

The vast majority of existing papers that analyse the Porter Hypothesis focus on the effect of environmental regulation on innovation. This part of the causality chain helps assessing if environmental policies are successful at inducing innovation. Most papers do not assess additionally the impacts of clean innovation on the economic performance of firms, which is nevertheless important to address concerns that environmental regulation may reduce competitiveness. The economic performance of a firm may be negatively affected if low-carbon innovation requires resources that could be used more profitably in other parts of the firm. Better knowledge of the economic impacts of policies through innovation can therefore improve policy design by anticipating and helping to manage any economic effects from policies.

Another limitation of the existing literature, which this project aims to tackle, is that most of the existing work on the Porter Hypothesis focuses on the effect of environmental policy on directly regulated firms or sectors. It is however plausible that firms along the supply chain of regulated entities (both upstream and downstream) are also indirectly exposed to the regulation and respond by innovating. For example, a steel producer may respond to strengthened environmental regulation in the automobile sector when automobile firms demand lighter steel as inputs to comply with stricter fuel efficiency standards. The steel producer may therefore increase its innovation in low-carbon technologies to meet the demand from the automobile manufacturers – even though there is no change in direct regulation for the steel producer. Ignoring such effects may therefore underestimate the effect of environmental policy on clean innovation.

This paper estimates the effect of environmental policy on firms' clean innovation outcomes as well as on their economic performance, both directly on regulated sectors, and indirectly through supply chain relationships.[3] Combining input-output data together with indicators of environmental policy stringency at the country-sector level, we observe supply chain relationships and exposure to changes in environmental regulations in both up-, and downstream sectors. Since comprehensive firm-level information on supply chain relationships is not available, this paper relies on country-sector level supply-chain links, which might limit our ability to identify indirect effects. Our sample covers approximately 10,000 firms that patent in low-carbon technologies, covering 19 countries and the period from 1990 to 2015. Our analysis on energy price data covers 17 countries and the period from 1995 to 2015.[4]

First, the paper shows that environmental policies are effective at inducing innovation in low-carbon technologies in the directly regulated sectors. This paper does not find evidence that environmental policies induce innovation along the supply chain. To the extent that effects of past policies can predict impacts of future policies, relying on indirect effects by regulating up- or downstream sectors might not induce large additional innovation. Second, the paper finds no evidence that environmental policies – through the channel of clean innovation – either harm or improve the economic performance of directly regulated firms, in terms of productivity and value added. In line with the previous literature, this supports the existing evidence that past environmental policies have not been major burdens on firms' competitiveness (Dechezleprêtre

[3] For the purpose of this paper the terms "climate policy" and "environmental policy" are used interchangeably. The empirical part of the paper analyses the effect of energy prices and the OECD Environmental Policy Stringency (EPS) index, which includes a set of climate change and air pollution mitigation policies. The paper does not analyse the effects of policies regulating other important environmental domains including water, waste-management or biodiversity.

[4] Annex B presents the country coverage in our analysis for FEPI and EPS respectively.

et al., 2019[11]) and suggests that clean innovation activity may enable firms to compensate for the potential costs implied by new environmental regulations.

The remainder of the paper is structured as follows. Section Chapter 2. reviews the prior literature and outlines the contribution of this paper. Section Chapter 3. presents the empirical models to estimate the effect of environmental policy on innovation, and to estimate the effect of innovation on economic performance. Section Chapter 4. describes the data. Section Chapter 5. presents the results for the effect of environmental policy on clean innovation, and Section Chapter 6. shows the effects of clean innovation on economic performance. Section Chapter 7. provides some concluding remarks.

Chapter 2. Literature

2.1. The Porter Hypothesis

The paper by Porter and van der Linde (1995[9]) made an important contribution to a branch of research within the field of environmental economics and policy, which analyses the relationship between environmental regulation, innovation and economic performance (Jaffe, Newell and Stavins, 2002[12]). The theoretical framework has been expanded, and empirical work has since analysed different elements of the hypothesis. The Porter Hypothesis (PH) can take different forms according to the strength of the effect and the type of regulation (Jaffe and Palmer, 1997[13]). This paper provides insight on the two major components of the PH, which are illustrated in Figure 2.1. The 'weak' version of the PH states that environmental regulation will spur innovation, but it remains silent on the economic effects. Thus, firms respond to regulation through innovation that reduces their costs of compliance (i.e. the first causal link in Figure 2.1). This 'weak' version does not indicate if the innovation is good or bad for a firm's economic performance. The 'strong' version of the PH states that the regulation induces firms to find new products or processes that increase profits while complying with the regulation (the second causal link in Figure 2.1) (see also Lanoie et al., (2011[10])). According to this strong version, the benefits of the regulation more than offset its costs.[5]

Figure 2.1. Causal links involved in the Porter Hypothesis

Source: Authors' illustration.

A relatively large literature has assessed the effect of environmental regulation on innovation, i.e. testing the 'weak' version of the PH (see e.g. Popp (2019[14]); Popp, Newell and Jaffe (2010[15]); Ambec et al., (2013[16]) for reviews of the literature). Overall, the literature finds support for this hypothesis, suggesting that environmental regulation tends to induce innovation. However, papers in this branch of the literature do not establish whether the effects are beneficial or harmful for firms' economic performance. Concerns about the economic impacts of environmental policies remain a major concern for policy makers and can act as a barrier to the introduction or strengthening of policies. Indeed, the economic impacts of environmental policies are a key component of the political feasibility and public support for such policies.

Fewer studies have so far analysed the entire causality chain of the Porter Hypothesis, meaning the effect of environmental regulation on business performance through innovation, in other words combining both the 'weak' and the 'strong' version of the hypothesis. Rexhäuser and Rammer (2014[17]) use a 2009 cross-section of firms included in the German Community Innovation Survey (CIS). They find evidence that environmental innovations (both policy-induced and voluntary) can

[5] Furthermore, the 'narrow' version of the PH states that only certain types of regulation (e.g. flexible market instruments such as environmental taxation) will encourage innovation, whereas non-market based instruments (e.g. standards) will not (Jaffe and Palmer, 1997[13]).

provide positive profitability effects, but only if the innovation improves firms' resource efficiency. Other innovations, which do not improve firms' resource efficiency – such as end-of-pipe innovations – do not improve firms' economic performance. Such cross-sectional analysis however suffers from well-known empirical drawbacks arising from omitted variables.

Panel data analysis can at least partly overcome many of the limitations inherent in cross-sectional analysis by controlling for firm- and year fixed effects. Van Leeuwen and Mohnen (2017[10]) analyse a sample of Dutch firms from 2000-2008. They observe a significant correlation between environmental regulation and environmental innovations (supporting the 'weak' PH). Similar to Rexhäuser and Rammer (2014[17]), they find that resource-saving innovations increase firms' productivity. Yet, pollution-reducing end-of-pipe innovations tend to reduce productivity. Their findings provide a nuanced view on the strong PH, suggesting that the effect on firms' economic performance depends on the type of innovation. Using cross-country panel data, Rubashkina, Galeotti and Verdolini (2015[18]) test both the 'weak' and the 'strong' version of the PH for manufacturing sectors in 17 countries over the years 1997-2009. They use pollution abatement and control expenditure (PACE) as a proxy for regulatory stringency. They find support for the 'weak' version of the PH, but find no statistically significant relationship between PACE and total factor productivity.

Parts of the literature have also studied the relationship using sector-level data (Franco and Marin, 2017[19]; Ley, Stucki and Woerter, 2016[20]). One advantage of using sector-level variables is that they are based on national statistics and do not suffer from selection issues. However, sector-level analyses suffer from limited variation in the variables of interest and smaller sample sizes. More importantly, the classification of patents at the sector level typically corresponds to the sector-of-use of the technologies. Hence, patents are assigned to the sectors in which they are used, rather than to sectors in which the technology is invented. This can introduce measurement error and a mismatch between sector-level regulatory stringency and innovation.

2.2. The effect of environmental regulation along the supply chain

Most existing studies have focused on the effect of environmental policies on directly regulated firms e.g. Aghion et al. (2016[21]) and Calel and Dechezleprêtre (2016[22])). It is however plausible that firms along the supply chain of regulated entities (both upstream and downstream) are also indirectly exposed to the regulation and respond by innovating (Bellas and Lange, 2010[23]; Bellas, Finney and Lange, 2013[24]). These mechanisms are theoretically put forward by Greaker (2006[25]) and Heyes and Kapur (2011[26]). These papers illustrate the mechanisms in a two-sector model, in which the downstream polluting firm is regulated and the specialised supplier of the technology (upstream) innovates to obtain a temporary monopoly (through a patent) for the supply of pollution abatement technology. Their model suggests that these indirect effects on innovation can be large, and that the innovation response by firms is vastly underestimated when ignoring these effects. So far, few empirical studies have incorporated such supply chain effects.

One of the few exceptions is Franco and Marin (2017[19]) who investigate the effect of environmental policy stringency on innovation and productivity for the manufacturing sectors of eight European countries over the 2001-2007 period. They use sector-level environmental tax intensity to proxy environmental policy stringency at the sector level. The authors find that environmental stringency in downstream sectors is the most relevant driver for innovation and productivity. Within-sector regulations are positively associated with productivity, but not with innovation output (measured by patent filings). Another exception is Miller (2014[27]) who analyses the effects of the European Union Emissions Trading System (EU ETS) on innovation in firms that are indirectly regulated through increased electricity prices. He finds that such indirect effects of induced innovation are at least as large as the direct effects. Hence, ignoring such indirect effects underestimates the true innovation response of firms to the introduction of the EU ETS.

One part of the Porter Hypothesis literature has expanded beyond the standard setting and studies the effects of environmental regulation on cross-border innovation effects. Dechezleprêtre and Glachant (2014[28]) study for instance the effect of domestic and foreign demand-pull policies in wind power across OECD countries on the rate of innovation in this technology. They find that wind technology improvements respond positively to both domestic and foreign policies, but that the effect of domestic policies dominates because of barriers to cross-border technology diffusion. Recent work by Brunel (2019[29]) shows that domestic environmental regulation induces innovation abroad. Technologies that are adopted as a response to a policy are often licensed foreign technologies rather than domestically developed. This is relevant to understanding the channels of the Porter Hypothesis, because it suggests that environmental regulation largely stimulates the economy through manufacturing (using licensed technologies) and not through domestic innovation. Similarly, Fabrizio, Poczter and Zelner (2017[30]) analyse the cross-border transfer of energy storage technologies using the IEA's Renewable Energy Policies and Measures database. They distinguish between demand-pull and supply-push policies. Their results show that the adoption of a demand-pull policy is followed by a significant increase in imports of foreign technology into the policy-passing country. Yet, they find no such pattern for supply-push policies. Similar findings are observed by Peters et al., (2012[31]) in a panel of 15 OECD countries between 1978 and 2005. This suggests that supply chains likely play an important role when determining the overall effect of environmental policy on innovation.

2.3. Limitations of previous literature and contribution

This paper contributes to the existing literature by adopting a more comprehensive approach to study the effect of environmental regulation on firms' innovation output and economic performance, using both firm- and sector-level data. Specifically, it uses sector-level variation in environmental policy stringency and estimates the effect of environmental regulation on firm-level outcome variables. It analyses both the 'weak' and the 'strong' version of the Porter Hypothesis. This is important for policy making because concerns about potential impacts of environmental regulation on firms' competitiveness are often a major barrier for the implementation of policies. It is therefore important to analyse both effects – on innovation as well as on economic performance. Moreover, the paper investigates the effect of environmental regulation along the supply chain. Current analysis may underestimate the effects of policy on induced innovation by looking only at regulated entities. Using input-output data in combination with novel sector-level CO_2 emissions data, the paper is the first to investigate the effects of environmental regulation along the supply chain using firm-level data.

Some analyses in the previous literature that looked at the relationship between environmental policy and innovation used proxies for environmental policy stringency such as pollution abatement costs (Shadbegian and Gray, 2005[32]; Carrion-Flores and Innes, 2010[33]) or emissions (Rubashkina, Galeotti and Verdolini, 2015[18]). Such variables can be endogenous because confounding factors could affect both innovation and the measure of regulatory stringency, leading to an omitted variable bias. Similarly, reverse causality may arise if innovation reduces pollution abatement control expenditure or emissions. More exogenous measures of environmental regulation – such as energy prices or the OECD's Environmental Policy Stringency indicator (EPS) – would be preferable to estimate the effects. These direct measures of environmental policy are more exogenous than indirect measures that may include behavioural responses. Nevertheless, environmental policies or energy prices may be adjusted for political reasons as a response to competitiveness concerns. The lag structure in our environmental policy indicators can help to mitigate this concern.

For example, Franco and Marin (2017[12]) use sector-level environmental taxes (as a share of value added) to measure environmental policy stringency. However, environmental taxes – which largely consist of energy taxes – are only one source of environmental regulation that excludes non-market policy instruments such as fuel-efficiency standards for example. Furthermore, their analysis covers a relatively small group of eight European countries. The OECD's Environmental Policy Stringency (EPS) indicator combines taxes as well as standards into a quantitative measure for over 30 countries. Using this indicator allows us to go beyond market-based instruments and expand the analysis to further countries. Combining the country-level EPS with a novel dataset on sector-level CO_2 emissions (developed by Yamano and Guilhoto (forthcoming[34])) enables us to construct a sector level indicator of policy stringency. Since the EPS consists predominantly of energy-, and climate mitigation policies, the interaction with CO_2 emissions (-intensity) creates a sector level indicator with a focus on climate mitigation policies. We interact the EPS and CO_2 intensity because we expect the impact of EPS should be greater for sectors with a high CO_2 intensity. Similarly, the energy price index developed by Sato et al., (2019[35]) covers more than 40 economies and provides detailed sector-level information. We are thereby able to use sector-level variation in environmental policy stringency on firm-specific outcomes.

Chapter 3. Empirical Model

This paper estimates two separate types of models, where the type of outcome variable, being either a measure of innovation outcome or economic performance, drives the choice of the model. In the first model, we investigate the direct effect of environmental policy stringency on innovation. In the second model, we estimate the effect of environmental innovation on economic performance using an Instrumental Variable strategy. Taken together, the two models enable us to analyse the entire causality chain of the Porter Hypothesis, from environmental policy to economic performance through environmental innovation.

3.1. Model 1: The effect of environmental policy on innovation

The paper measures firms' innovation outcome by the number of patent applications in climate change mitigation technologies, which are based on the new "Y02" tagging system developed by the European Patent Office and available on all patent applications recorded in the global PATSTAT database. It includes inventions in climate change mitigation technologies related to buildings (e.g. efficient home appliances), clean energy generation, smart grid technologies, transportation, as well as mitigation technologies in the production or processing of goods (e.g. metals, chemicals, minerals) among others (see European Patent Office (2016[36]) for further details). Low-carbon patents are one possible measure of clean innovation that cover patentable technologies. Alternatives can for instance be R&D investments in clean technologies. To the best of our knowledge cross-country panel data at the firm level is however not available for clean R&D investments. One advantage of patent data is that globally comprehensive data – including all patents filed in any of the major patent offices – is maintained and regularly updated by the European Patent Office through the PatStat database. To estimate the effect of environmental policy on innovation, we use the Pseudo Poisson Maximum Likelihood (PPML) estimator developed by Silva and Tenreyro (2006[37]).[6] The authors demonstrate that their PPML approach performs better than log-linearized models, in particular in cases with many zeros in the dependent variable, as well as compared to models where a small constant is added to the dependent variable (Silva and Tenreyro, 2011[38]). Moreover, the PPML estimator can handle overdispersed dependent variables.[7]

We follow the convention in the literature to lag all explanatory variables by one year across our models, and by two years in robustness checks. Many existing papers show that the reactions of firms to environmental policies can be relatively fast and occur already after one or two years (Franco and Marin, 2017[19]; van Leeuwen and Mohnen, 2017[39]; Ley, Stucki and Woerter, 2016[20]). The variables are lagged because firms' require time to respond to changes in environmental policy. Moreover, lagging our main explanatory variables reduces concerns of reverse causality, even though this does not fully resolve the concern due to path dependency for

[6] Using Ordinary Least Squares (OLS) estimation is inappropriate when the dependent variable is a count variable. Only few firms apply for patents, skewing the distribution of patent counts towards zero. Some papers address this problem by transforming patent counts into logarithmic counts, which however excludes observations with zero patents. Adding small constants to the patent counts to avoid losing observations can be similarly problematic because it adds proportionally more weight to the firms with few patents, potentially biasing the results.

[7] PPML is consistent under over-dispersion and even optimal when the conditional variance is proportional to the conditional mean.

example. To identify the effect of environmental policy on clean innovation, we estimate equation 1:

$$n_{icst} = \exp(\, \gamma EnvPol_{cst-1} + \sum_k \partial_k x^k_{icst-1} + \mu_i + \tau_t + \varepsilon_{icst} \,) \qquad (1)$$

Where:

- n_{icst} is the number of patents in mitigation technologies applied for by firm *i*, sector *s*, country *c*, year *t*.
- $EnvPol^{\,j}_{cst-1}$ measures the sector-level environmental policy stringency. We use two separate variables to measure environmental policy. First, we use the sector-level energy price index (FEPI) developed by Sato et al., (2019[35]), which varies at the country-sector-year level. As an alternative measure, we use the OECD Environmental Policy Stringency (EPS) indicator, interacted with sector-level emissions-intensity data to create variation at the country-sector-year level;
- x^k_{icst-1} is set of firm-level control variables, discussed in more detail below;
- μ_i are firm fixed effects;
- τ_t is a set of year fixed effects, country-year fixed effects, or sector-year fixed effects;
- ε_{icst} is the error term.

Expanding upon this model, we then add supply chain relationships. To identify the effect of environmental policy on clean innovation on directly regulated firms as well as through the supply chain we estimate equation 2:

$$n_{icst} = \exp(\gamma_1 EnvPol_{cst-1} + \gamma_2 EnvPol^{upstr} + \gamma_3 EnvPol^{downstr} + \sum_k \partial_k x^k_{icst-1} + \mu_i + \tau_t + \varepsilon_{icst} \qquad (2)$$

Where:

$EnvPol^{upstr}$ and $EnvPol^{downstr}$ are respectively our upstream and downstream indicators of environmental policy stringency, which are constructed as:

$$EnvPol^{downstr}_{cst} = \sum_c \sum_s w^{downstr}_{cs} * EnvPol_{cst} \qquad \text{where } cs \neq \chi\psi \qquad (3)$$

$$EnvPol^{upstr}_{cst} = \sum_c \sum_s w^{upstr}_{cs} * EnvPol_{cst} \qquad \text{where } cs \neq \chi\psi \qquad (4)$$

Where the downstream weight ($w^{downstr}$) captures exposure to changes in the downstream policy stringency in all other country-sector pairs[8] and is constructed from the ICIO input-output matrix by dividing intermediate output values by the summation of the row vector. The upstream weight (w^{upstr}) is constructed by dividing intermediate input values in all other country-sector pairs by the summation of the column vector. More specifically, for the downstream weights we multiply the ICIO share (intermediate output / summation of the row vector) by the sector-level environmental policy indicator of the country-sector *using* the intermediate output as input. For the upstream weight we multiply the ICIO share (intermediate input / summation of the column vector) by the sector-level environmental policy indicator of the country-sector *supplying* the intermediate outputs.[9] Values in the ICIO that have the same country-sector pair (i.e. intermediate output that is used as input in the same country-sector) are replaced by zero to avoid that the supply chain weights are driven by within-sector effects. The data used to construct the weights is discussed in detail in Section Chapter 4.

The weights are then multiplied either by the energy price index (FEPI) or the sector-level EPS.

3.2. Model 2: The Effect of low-carbon innovation on Economic Performance

To estimate the effects of low-carbon innovation induced by environmental policy on economic performance, we would like to estimate an equation of the form:

$$Y_{icst} = \sigma + \beta MPS_{ics,t-1} + \sum_k \partial_k x^k_{ics,t-1} + \mu_i + \tau_t + \varepsilon_{icst} \qquad (5)$$

Where:

- MPS_{icst} is the natural logarithm of the mitigation patent stock for firm *i*, country *c*, sector *s*, and year t;
- Y_{icst} is the respective economic performance variable (log of multifactor productivity (MFP), or log of value added (VA))[10];
- σ is a constant;
- $x^k_{ics,t-1}$ is the set of control variables;
- μ_i are firm fixed effects;
- τ_t is a set of year fixed effects, country-year fixed effects, or sector-year fixed effects;
- v_{icst} and ε_{icst} are error terms.

---

[8] Where the country-sector pair *cs* is unequal to the specific country-sector pair $\chi\psi$. In other words, for values that are not on the diagonal of the input-output matrix.

[9] The sector-level environmental policy indicator is either the FEPI or the sector-level EPS (log(EPS) * log(CO_2-intensity)).

[10] The construction of MFP is based on Wooldridge (2009[45]). Further information on the variable is also available in Gal (2013[43]) and Andrews, Criscuolo and Gal (2013[44]). MFP is defined as: $MFP = va - \hat{\beta}^W{}_K * k - \hat{\beta}^W{}_L * l$; where *va* is the log deflated value added, and $\hat{\beta}^W{}_K$ and $\hat{\beta}^W{}_L$ are production function parameters for capital and labour, based on the estimation in Wooldridge, (2009[45]). Value added is defined as: $= wL + EBITDA$; where *w* is the average labour cost and *L* the number of employees. *EBITDA* are the Earnings Before Interest Taxes Depreciation and Amortisation.

We measure economic performance through two alternative measures, (log) multifactor productivity (MFP)[11] or (log) value added (VA). Note that in this equation, we use the accumulated stock of low-carbon patents as the explanatory variable instead of the flow of patents because it takes time for firms to benefit from innovation, which first need to be turned into marketable products. Similarly, the uptake of new technologies by the market may not be immediate. Using the firm's patent stock in low-carbon technologies is therefore more suitable to assess the effect of low-carbon innovation on economic performance.[12]

However, to estimate effects of innovation induced by environmental policy on economic performance, we require an instrumental variable approach because of the simultaneity between economic performance and innovation outcomes (Lanoie et al., 2011[10]). In other words, firms that become more productive may also be more likely to innovate in low-carbon technologies. For instance, the decision to invest in clean innovation may be impacted by factors that also effect firms' economic performance, such as an unobserved change in the management of the firm (any factors affecting both innovation activity and firm performance that are constant over time are already controlled for by the inclusion of firm fixed effects). Without an instrument, the estimated effect of firms' low-carbon patent stock on economic performance could therefore be biased. Our instrument Z consists of the product of two parts. The first part is constructed as the share of firm-specific pre-sample mitigation patent stock divided by the firm-specific pre-sample patent stock in any technology. The second part is constructed as the share of firms in a country-sector-year that apply for a strictly positive amount of mitigation patents. We add 1 to the mitigation patent stock before transforming it into the natural logarithm of mitigation patent stock. Equation (6) represents the construction of the instrument

$$Z_{icst} = \frac{Mitig\_PS_{ics}}{Alltech\_PS_{ics}} * \left(\frac{F_{cst}^{lcp}}{F_{cst}}\right) \qquad , \forall\, t > t+4 \qquad (6)$$

Where:

- Z_{icst}: is the instrumental variable for firm *i,* in country *c,* sector *s*, and time *t;*
- $Mitig\_PS_{ics}$: is the pre-sample mitigation patent stock at time t+4;
- $Alltech\_PS_{ics}$: is the pre-sample patent stock in any technology at time t+4;
- F_{cst}^{lcp} : is the number of firms with a strictly positive number of low-carbon patents (lcp) in a country-sector-year;
- F_{cst} is the total number of firms in a country-sector-year.

For the instrumental variable approach to yield unbiased estimates, the identifying assumptions of First Stage, Monotonicity and Independence need to be met (Imbens and Angrist, 1994). The First Stage requires that the instrument (the interaction between the share of past innovation activities directed at low-carbon technologies and the share of firms in the same country-sector-year that apply for climate mitigation patents) is significantly correlated with firms' stock of low-carbon innovation, meaning that the instrument is relevant. This assumption can be tested empirically. Monotonicity rules out the existence of firms for which the instrument has systematically the opposite effect on economic performance than in general. Independence requires that the instrument only affects firms' economic performance through its effect on firms' own innovation

[11] Our MFP measure is built following Wooldridge (2009[45]).

[12] To compute the knowledge stock we follow the literature and apply an annual 15% depreciation factor to patent filings using the perpetual inventory method (Dechezleprêtre and Glachant, 2014[28]; Franco and Marin, 2017[19]).

– also known as the exclusion restriction. If these assumptions hold and the treatment effects are constant conditional on covariates, the model will give unbiased estimates of the local average treatment effect (LATE). For our specific case, it is necessary to identify an instrument that is correlated with the decision to patent clean technologies, but that is not directly affecting firms' economic performance.

Our instrument choice builds upon previous papers in the literature. Lanoie et al., (2011[10]) use the average share of facilities in the same sector and country with a positive environmental R&D budget to instrument for firms' environmental R&D investments. The authors argue that this share is likely correlated with the decision to undertake environmental R&D in a specific firm, but to have insignificant effects on the firm's economic performance. The share of firms that file low-carbon patents is likely correlated with many unobserved determinants of low-carbon patent filing, including environmental policies and consumers' preferences. Thus, the number of 'similar' firms that file low-carbon patents is likely to be correlated with a firm's decision to also innovate and file patents in low-carbon technologies. The first-stage results presented below confirm that the instrument is relevant.

The independence assumption (exogeneity) requires that the instrument only affects firms' economic performance through its effect on innovation. There are two ways in which the instrument could affect firms' economic performance. First, through knowledge spillovers (i.e., a firm's innovation is affected by other firms' innovation because knowledge is a public good and can be used freely by other firms to come up with new innovations). This effect definitely happens through a firm's innovation activity. Secondly, through competition (business stealing). On this, the fact that a large number of 'similar' firms has low-carbon patents is unlikely to impact the specific firm's economic performance, in particular for the study period until 2015 for which annual clean patent filings never exceeded 7% of all patents (Dechezleprêtre, 2016[5]). More generally, we argue that the instrument is exogenous to the firm because it is constructed out of the innovation activity of other firms and our groups are large enough so that no single firm has influence on the decision on others. This type of instrument has also been used in the industrial organisation literature (Nevo, 2000[40]; Nevo, 2000[41]). Similar instruments are also used for a sector-level analysis by Franco and Marin (2017[19]). The downside of using sector-level averages to instrument for firm-specific innovation, is the limited variation, potentially making the instrument 'weak', which can bias estimates. To address this limitation, we make the instrument firm-specific by interacting the share of firms in the same country-sector-year that have a strictly positive number of mitigation patents with the pre-sample share of firms' climate mitigation patent stock relative to their total patent stock in any technology. Past innovation in clean technologies is likely positively correlated with current innovation because firms have accumulated human- or physical capital in such technologies making further innovations in similar technologies likely.

A potential drawback in this approach is that many firms start applying for climate mitigation patents during the sample period (1990-2015). To address this problem, the firm-specific share is computed at time $t+4$, where t is the first year in which the firm applies for a mitigation patent, which can lie within our period of analysis or prior to 1990. We restrict the analysis to years greater than $t+4$, meaning that the years of analysis vary by firm depending on the year of their first climate mitigation patent application. While this approach increases the instrument relevance, it does so at the cost of reducing the sample size, potentially making inference in the second stage more difficult.

The following two equations represent the empirical specification that is implemented for the two-stage least square (2SLS) estimation:

$$MPS_{icst} = \gamma + \rho Z_{icst} + \sum_k \partial_k x_{icst}^k + \theta_i + \eta_t + v_{icst} \tag{7}$$

$$Y_{icst} = \sigma + \beta \widehat{MPS_{icst-1}} + \sum_k \partial_k x_{ics,t-1}^k + \mu_i + \tau_t + \varepsilon_{icst} \tag{8}$$

Where:

- MPS_{icst} is the natural logarithm of the mitigation patent stock for firm *i*, country *c*, sector *s*, and year t;
- Y_{icst} is the respective economic performance variable (log of multifactor productivity (MFP), or log of value added (VA))[13];
- Z_{icst} is the instrumental variable defined as above;
- γ and σ are constants;
- $x_{ics,t-1}^k$ is the set of control variables;
- θ_i and μ_i are firm fixed effects;
- η_t and τ_t is a set of year fixed effects, country-year fixed effects, or sector-year fixed effects;
- v_{icst} and ε_{icst} are error terms.

[13] The construction of MFP is based on Wooldridge (2009[45]). Further information on the variable is also available in Gal (2013[43]) and Andrews, Criscuolo and Gal (2013[44]).

Chapter 4. Data

This section describes the different datasets used in the analysis. It begins with the main dependent variables followed by the independent variables of interest for the analysis and the control variables. It also explains how we construct the supply chain weights. Table 4.1 provides an overview of the respective variables and their source. Table 4.2 reports descriptive statistics.

Table 4.1. Overview of variables and sources

	Type	Variable	Source
Dependent variables	Innovation	Patent applications in climate mitigation technologies (Y02)	PATSTAT
	Economic performance	Multifactor productivity (MFP)	ORBIS[14]
		Value added (VA)	ORBIS
Covariates	Energy Price data	Fixed weights Energy Price Index (FEPI) (fixed weights averaged over 1995-2014)	Sato et al., (2019[29])
	Environmental Policy Stringency (EPS)	Environmental Policy Stringency Indicator (EPS)	OECD
	CO_2 intensity	CO_2 intensity per gross output (measured in tonnes of CO_2 per million USD of output)	Yamano and Guilhoto (forthcoming[30])
	Input-Output data	OECD Inter-Country Input-Output (ICIO) table, 2018 edition	OECD
	Economic control variables	(employees, average wage, capital intensity)	ORBIS

Source: Authors.

4.1. Dependent variables

Throughout the paper, we use two separate types of dependent variables, one measuring clean innovation output, and one measuring economic outcomes (productivity and value added). Patent data comes from PATSTAT, which covers patent filings from all major patent offices in the world. The analysis is based on patents in climate change mitigation technologies (Y02) which reflect most closely innovations that we would expect to occur as a response to changes in energy prices or the EPS. Technologies to reduce energy consumption are typically recorded within the Y02 class. Similarly, the EPS indicator consists largely of policies that impact greenhouse gas emissions. Moreover, our measure of exposure to changes in EPS, is sector-level CO_2-intensity.

[14] MFP is computed following Wooldridge (2009[45]).

Inventions that reduce CO_2 and other greenhouse gas (GHG) emissions are also within the Y02 class. The analysis uses patent applications to measure innovation outcomes. Descriptive statistics of the variables are reported in Table 4.2. Annex A shows the time trends of total mitigation patents in our sample.

4.2. Main independent variables

As one of our main explanatory variable, we use sector-level energy price data developed by Sato et al., (2019[35]). The authors provide yearly energy price data for 12 sectors in up to 48 countries, covering the period between 1995 and 2015. The energy price data, which is inclusive of energy taxes, covers four major types of fuel carriers (electricity, gas, coal and oil).[15] One benefit of the energy price data is that it provides a measure of energy prices which varies across sectors, countries, and time and that is directly comparable across units. Specifically, we use their Fixed weights Energy Price Index (FEPI), with fixed weights averaged over the entire sample period, as recommended by Sato et al., (2019[35]) for panel analysis. The FEPI index is the natural logarithm of the weighted geometric mean of the underlying prices (net of inflation) of the various fuels used by a particular sector (for example, if a sector used 50% electricity and 50% gas, the price in this sector would be ½ the unit price of electricity + ½ the price of gas in the operating country). The advantage of using FEPI over their variable weights energy price index is that the weights of fuel shares are fixed. The index is not driven by fuel switching as a response to price shocks, for example. The ability to switch fuel type is closely related to the production processes or rate of technological change of sectors or countries. The FEPI variable captures the variation in fuel prices alone – including from policies and taxation – and excludes price variation that is endogenously related to technology choices of firms.[16] Sato et al., (2019[35]) show that policies (such as taxes) play a major role in explaining the variation in energy prices across countries, relative to market forces. They show for a subset of OECD countries that the tax component of their index explains large shares of the price variations. Specifically, between 80% to 90% for coal, between 40% to 80% for oil, and between 30% to 70% for electricity. The component of the energy price index that is driven by market forces (such as global oil prices for example) are picked up by the year fixed effects in our specification. Figure 4.1 shows the average trend of the FEPI variable over time. Across countries (and sectors), average industry energy prices have risen since 1995, but they started declining since 2012.

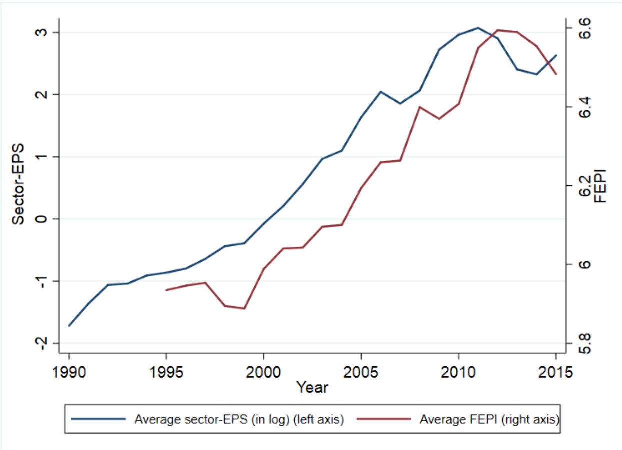
Since many environmental policies are not directly linked to energy prices (such as fuel efficiency standards for example), energy prices can only provide a partial picture of the overall environmental policy stringency. Furthermore, the FEPI index is limited to 12 manufacturing sectors, and is focused on a specific section of the economy. We therefore use the OECD Environmental Policy Stringency (EPS) indicator as an alternative measure of regulatory stringency. The EPS quantifies the policy stringency of both market- and non-market based environmental policies into a single index. The index exists for the period between 1990 and 2015. The advantage of using this index is that it captures price mechanisms (e.g. carbon pricing) as well as standards and other non-market based measures, thereby providing a comprehensive indicator of policy stringency (Botta and Koźluk, 2014[42]). A limitation of the EPS indicator is that only varies at the country-year level, and is not sector-specific.

[15] The energy price component for electricity aggregates electricity prices from renewable and non-renewable sources.

[16] As Sato et al., (2019[35]) state, it is important to keep in mind that only the change in this variable is meaningful, not its level. It therefore needs to be combined with country- or sector-level fixed effects in empirical estimations.

To develop a sector-specific indicator, we interact the (log) EPS with novel sector-level (log) CO_2-intensity data developed by Yamano and Guilhoto (forthcoming[34]) because we expect the impact of EPS should be greater for sectors with a high CO_2 intensity. Since the EPS predominantly consists of energy- and climate mitigation policies – which regulate greenhouse gases such as CO_2 – the interaction with CO_2 emissions intensity creates a sector-specific indicator of policy stringency with focus on climate mitigation policies. The CO_2-intensity data covers 65 economies, 36 industries over the years 2005-2015, providing to our knowledge the most detailed (sector-level) and comprehensive (cross-country) dataset on CO_2-emissions intensity. CO_2-intensity is measured in tonnes of CO_2 per million USD of value added. The dataset uses the OECD ANBERD (Analytical Business Enterprise Research and Development) sector classification, which is roughly at the 2-digit ISIC level, but for some sectors groups several 2-digit industries together (e.g. ISIC 05 and ISIC 06 are grouped into a single industry group). Based on this data we compute the country-sector average CO_2-intensity over the available time period (2005-2015). Figure 4.1 shows the average trend of the sector-level EPS over time. Annex A shows the time series of the raw average country-level EPS. The average EPS has increased since 1990. Between 2011 and 2014, the average has seen a decline, but it increased again in 2015.[17]

Figure 4.1. Average Energy Price (FEPI) and EPS trends



Note: The red line shows the trend in the average FEPI index (right axis). The blue line shows the trend in the average sector-level EPS.
Source: Authors' calculation based on OECD EPS and Sato et al., (2019[35]).

4.3. Control variables

Our choice of control variables is based on the previous literature (in particular: (van Leeuwen and Mohnen (2017[39]) and Franco and Marin (2017[19]). Firm size is an important control variable because larger firms are more likely to have the resources to start an innovation project and to file patents. Similar to Franco and Marin (2017[19]) we use the logarithm of the number of employees as a measure of firm size. In addition, better skilled employees are more likely to deliver innovation outcomes, we therefore control for (log) average wages. Similar to Franco and Marin (2017[19]), we also use gross output divided by total tangible fixed assets as a measure of capital intensity. Capital intensity can be used as a proxy for barriers to market entry in a particular industry, which may in turn affect firms' economic performance.

[17] The CO_2-intensity data developed by Yamano and Guilhoto (forthcoming[34]) has not been cleared for publication yet. We are therefore not able to publish any further descriptive statistics beyond the information included in Table 4.2.

Table 4.3 shows the correlation matrix between the covariates. None of the pairwise correlations between the economic covariates are larger than 0.2, reducing concerns of introducing into the model.

All economic control variables are taken from a cleaned version of Bureau van Dijk's Orbis database, which is maintained as the OECD productivity dataset (OECD-Orbis). The steps in preparing the dataset are detailed in in Gal (2013[43]) and Andrews, Criscuolo and Gal (2013[44]). The advantage of that data is that it has been carefully cleaned for erratic and implausible values in the Orbis dataset, which may otherwise drive results in the estimation. Our measure of multifactor productivity is also taken from the OECD-Orbis database and is based on the methodology proposed by Wooldridge (2009[45]) (It is based on residuals from an industry-level production function estimation with non-constrained coefficients). The sample is restricted to unconsolidated accounts as recorded by Orbis, to ensure that a firm is exposed to the regulation in its recorded location.

Beyond the economic controls, we compute the knowledge stock of firms in climate mitigation technologies using the perpetual inventory method. We aggregate patents by firm from 1950 onwards and apply a yearly depreciation factor of 15%, which is commonly used in the literature (Franco and Marin, 2017[19]; Dechezleprêtre and Glachant, 2014[46]). The distribution of this variable is skewed because most firms do not have any patents in climate mitigation technologies, while a small number of firms has many (See Table 4.2for descriptive statistics). Since many firms have a zero knowledge stock in climate mitigation technologies, we add a small constant of 1 to the patent stock patents before applying the logarithmic transformation.[18]

Table 4.2. Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
FEPI	91,526	6.419	.385	5.228	7.613
Log (EPS)	97,184	.938	.33	-.652	1.419
Log(Avg. CO2 intensity)	104,224	3.406	1.401	.609	9.397
Number of mitigation patents	104,224	1.031	12.211	0	734.083
Log (Know. Stock mitigation patents)	104,224	.595	.831	0	8.095
Log (employees)	95,037	4.606	1.897	0	12.744
Log (average wage)	94,186	10.147	.964	1.47	15.709
Log (capital intensity)	94,783	-1.955	1.527	-12.944	7.562
Log (MFP)	79,616	2.388	.107	.854	2.863
Log (VA)	80,306	15.438	2.281	3.761	23.644

Note: The descriptive statistics are based on the observations in the analysis.

[18] We apply this transformation only to the patent stock variable, and not to the patent flow variable that is used as a dependent variable.

Table 4.3. Correlation Matrix of main independent variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FEPI	1.000						
(2) Log (EPS)	0.372	1.000					
(3) Log (Avg CO_2 intensity)	-0.198	-0.005	1.000				
(4) Log (Knowledge Stock mitig.)	0.122	0.149	-0.008	1.000			
(5) Log (employees)	0.065	-0.038	0.063	0.314	1.000		
(6) Log (average wage)	0.302	-0.014	0.004	0.086	0.193	1.000	
(7) Log (capital intensity)	-0.027	-0.002	0.103	0.070	0.118	-0.167	1.000

Note: The correlation matrix is produced based on observations included in the analysis.

4.4. Supply-chain variables

To construct the supply chain weights, we use data from the OECD Inter-Country Input-Output (ICIO) tables (OECD, 2018[47]). Weights are constructed based on the square intermediate-use input-output matrix[19].[20] We use ICIO values from 2005, which are the earliest available data. The weights from the ICIO are fixed over time to ensure that any variation comes from changes in environmental policy, rather than changes in the supply chain relationships. [21] The ICIO values provide the trade relationships between sectors and countries. These are used to construct weights that measure the exposure of a specific industry to changes in policy in another industry. Weights capturing exposure to changes in downstream policy changes are constructed by dividing intermediate output values by the summation of the row vector. Upstream weights are constructed by dividing intermediate input values by the summation of the column vector. These weights are respectively multiplied either by the energy price index (FEPI) or the sector-level EPS indicator as described in Section Chapter 3. (see Franco and Marin (2017[19])) for a similar approach). Table 4.4 reports the correlation matrix between the within-sector, upstream, and downstream variables of environmental policy stringency. Annex A shows the average trends in these variables over time. We overall see high correlations between the within-sector, upstream- and downstream weights. This makes it difficult to clearly identify effects of the supply chain variables because these may be partially driven by the within-sector variation. A challenge is that data on supply-chain relationships does not exist at the firm-level. Using sectoral input-output data is the most granular data that allows estimation based on exposure to both up- and down-stream environmental policy. Further work could use the sector-of-use that is provided with patent filings to construct firm-specific downstream supply chain weights. [22]

[19] The square matrix is constructed separately for analysis on FEPI and EPS data. It is restricted to countries that either have FEPI or EPS data. Therefore the square matrix includes a different group of countries before constructing the weights for FEPI and EPS respectively.

[20] Values in the diagonal of the matrix (intermediate outputs used in the same country-sector as inputs) are replaced by 0 to limit issues of multicollinearity and to avoid that the weights are partly driven by within-sector environmental regulation.

[21] The advantage of keeping the supply chain variables fixed at one point in time is that it ensures that any variation comes from the changes in the environmental policy. This choice however involves a trade-off. If trade patterns change dramatically, the fixed supply chain weights may not accurately reflect trade relationships, specifically in later years.

[22] Additionally interacting the FEPI variables with CO_2 intensity does affect the correlations substantially because CO_2-intensity is time invariant. Hence, the additional interaction cannot help reduce concerns of multicollinearity. Constructing firm-specific weights may help reduce the correlations between the supply chain variables.

Exposure to upstream policy stringency measures how much on average firms are exposed to upstream changes in regulation. Exposure to downstream environmental stringency measures how much on average suppliers are exposed to changes in regulation by downstream sectors. In the context of innovation outcomes, firms may for example decide to invest in innovation and patent as a response to changes in environmental policy of their primary downstream sector because the downstream firms demand more energy-efficient technologies as inputs. Similarly, firms may respond to changes in upstream environmental policy because upstream firms change their products as a response to regulation.

The weighting approach captures for example the response of a steel producer in country A to strengthened environmental regulation in the automobile sector either in country A or in country B through international trade. The weights do however not include potential responses by automobile firms to the embodied emissions in the steel that is supplied to them. We therefore do not capture for example differences in the emissions generated during the mining of iron ore or the transportation of iron ore to the steel manufacturer. Such end-to-end supply chain tracing has not been at the core of environmental regulations over the sample period. Hence, this paper argues that firms' responses to such embodied emissions have likely been negligible over the sample period.

One limitation of the weighting approach is that we apply the supply-chain weights to firms, based on their country-sector classification. It therefore assumes that firms in our sample have on average the same supply chain links as the sector in which they are classified. Firms in our dataset may however not be entirely representative of their respective country-sector and may have different supply chain linkages. Future work could therefore construct firm-specific supply chain weights. One possible approach would be to use patent data, and in particular the sector-of-use, stated in each patent application, to assign such weights. The share of patent filings to individual sectors-of-use could give firm-specific supply chain weights based on the sectors to which the patent technologies belong. This would allow for more accurately measured supply chain weights that could be used in the regressions.

Table 4.4. Correlation Matrix for Supply Chain Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) FEPI	1.000							
(2) Downstream FEPI	0.802	1.000						
(3) Upstream FEPI	0.810	0.984	1.000					
(4) Log (EPS)	0.487	0.576	0.575	1.000				
(5) Log (Avg. CO_2 Int.)	-0.229	-0.105	-0.102	-0.045	1.000			
(6) Log (EPS)*Log(Avg. CO_2 int.)	0.328	0.449	0.450	0.850	0.375	1.000		
(7) Downstream EPS	0.436	0.524	0.524	0.967	0.039	0.873	1.000	
(8) Upstream EPS	0.469	0.544	0.542	0.972	0.024	0.871	0.972	1.000

Note: The correlation matrix is produced based on observations included in the analysis.

Chapter 5. Results – The effect of environmental policy on firms' low-carbon innovation

We present the results first for the effect of the energy price index (FEPI), followed by results using the Environmental Policy Stringency (EPS) indicators. For each variable, we begin by showing the results for the within-sector effects only. In our baseline specification, we control for firm fixed effects, as well as year fixed effects. We then add country-specific year fixed effects in order to control for country-specific shocks that may be correlated with both environmental policy and clean innovation. Governments may for instance subsidise clean innovation while increasing energy prices. Without country-specific time fixed effects this could result in biased estimates in particular for the effect of energy prices. More generally, country-specific time fixed effects allow us to control for macro-economic shocks at the country-level. Finally, we also estimate the models with additional sector-specific time fixed effects that control for sector-specific shocks. Sato et al., (2019[35]) show that most of the variation in their index is across countries, rather than across sectors within countries. We may therefore expect that coefficients change relatively little when controlling for additional sector-year fixed effects, on top of the country-specific time fixed effects. In models with patents as the dependent variable, we use the Pseudo Poisson Maximum Likelihood (PPML) estimator, as discussed above, unless otherwise specified. We cluster standard errors conservatively at the country-sector level throughout.

5.1. Energy Prices

Table 5.1 shows the effects of energy prices on firms' patents in climate mitigation technologies. All columns include firm fixed effects, and in addition column 1 includes year fixed effects, column 2 includes country-specific year fixed effects and column 3 includes both country-specific and sector-specific year fixed effects. The results clearly show the importance of controlling for country-specific shocks though country-year fixed effects as results in column 1 seem to suffer from a large negative bias. Across columns 2 and 3 though, the effect of energy prices (inclusive of taxes) on mitigation patents is positive and highly statistically significant. In Poisson models, coefficients on logged independent variables can be interpreted as elasticities. Hence, a 1% increase in the energy price index increases mitigation patents by about 1.4%. The effects are similar in magnitude and significance when additionally including sector-year fixed effects, which strengthens the robustness of the results.

Regarding control variables, we see that the knowledge stock in climate mitigation technologies is consistently positively associated with firms' clean innovation output and significant at the 1% level. Similarly, the number of employees is positive and statistically significantly associated with clean innovation output. The coefficient on average wage is positive, but not statistically significant.

We estimate several alternative specifications to test the robustness of our results. To address concerns that average wage of firms might be a bad control because it may be endogeneously determined by firms' economic performance, which may in turn be driven by regulation, we also estimate the model without our wage control. The results remain stable in magnitude and statistical significance (Table D.1. in Annex D). We also observe similar effects when including both policy indicators – FEPI and the EPS – within the same specification (Table E.1. in Annex E), as discussed in more detail below. In Table C.1. in Annex C we report the results with two-year lags for all independent variables. Coefficients tend to increase with the 2-year lag, which is expected because the process of patenting a technology takes time, and firms require time to respond to changes in energy prices. A 1% increase in the energy price index is associated with a 2.3% increase in mitigation patents when allowing for a two-year time lag.

Table 5.1. The Effect of Energy Prices on Clean Innovation

	(1) Mitigation patents	(2) Mitigation patents	(3) Mitigation patents
FEPI$_{(t-1)}$	0.07	1.45***	1.47**
	(0.35)	(0.56)	(0.62)
Log (Mitig. Know. Stock) $_{(t-1)}$	0.23***	0.23***	0.21***
	(0.08)	(0.07)	(0.07)
Log (employees) $_{(t-1)}$	0.33***	0.32***	0.34***
	(0.08)	(0.08)	(0.08)
Log(Avg. wage) $_{(t-1)}$	0.03	0.02	0.01
	(0.07)	(0.07)	(0.07)
Log(Cap Int) $_{(t-1)}$	-0.01	-0.01	-0.01
	(0.03)	(0.02)	(0.02)
Constant	-1.33	-10.17**	-10.20**
	(3.22)	(4.40)	(4.17)
N	100554	100380	100197
Firms	9844	9842	9842
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-year FE	No	Yes	Yes
Sector-year FE	No	No	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The PPML algorithm drops observations that are either singletons or separated by a fixed effects, hence the number of observations drops slightly when including more detailed fixed effects.

Table 5.2 shows the effects of energy prices on clean innovation, including the supply chain linkages. The coefficients on within sector energy prices remain positive and significant and very similar in magnitude between 1.4 and 1.5 in the most robust specifications that include country-year and sector-year fixed effects. We again observe positive and significant coefficients for the number of employees and knowledge stock. The coefficients on upstream and downstream energy prices are not significant. They are also not significant in specifications with additional sector-specific time fixed effects, or in the specification with two-year lags.[23] The results suggest that energy prices affect clean innovation activity only among directly regulated firms. We also do not find evidence that changes in energy prices in up- and downstream industries significantly induce clean innovation. We explored heterogeneity, but did not find evidence that supply chain relationships matter for particular sectors. However, the high correlations between the within-sector, upstream, and downstream variables raises concerns that we may not be able to robustly separate such effects from one another.

The weights used to construct the supply chain variables are based on input-output data at the sector level. A potential limitation of this approach is that the weights are assigned to firms based on their country-sector classification. Firms may however have different supply chain relationships compared to the average relationships observed at the sector-level in the ICIO database. This may introduce measurement error. Further work could refine the supply chain weights using firms-

[23] This analysis assumes that the time lag is the same for directly regulated sectors and for up- and downstream sectors. Future work could explore heterogeneous time lags in these relationships.

specific information to identify the effect of environmental regulation along the supply chain more granularly.

Table 5.2. The effect of energy prices on clean innovation (including supply chain)

	Mitigation patents	Mitigation patents	Mitigation patents
$FEPI_{(t-1)}$	1.10***	1.50***	1.37**
	(0.42)	(0.55)	(0.58)
Downstream FEPI $weight_{(t-1)}$	-0.07	0.08	0.97
	(0.64)	(0.56)	(1.32)
Upstream FEPI $weight_{(t-1)}$	-1.63	-0.52	-0.21
	(1.11)	(1.19)	(1.35)
Log (Mitig. Know. Stock) $_{(t-1)}$	0.23***	0.23***	0.19***
	(0.07)	(0.07)	(0.05)
Log (employees) $_{(t-1)}$	0.31***	0.33***	0.34***
	(0.08)	(0.08)	(0.08)
Log (Avg. wage) $_{(t-1)}$	0.02	0.02	0.01
	(0.07)	(0.07)	(0.07)
Log(Cap Int) $_{(t-1)}$	-0.01	-0.01	-0.00
	(0.02)	(0.02)	(0.02)
Constant	3.13	-7.67	-14.48
	(4.63)	(9.06)	(10.24)
N	100550	100380	100197
Firms	9843	9842	9842
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-year FE	No	Yes	Yes
Sector-year FE	No	No	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * p < 0.10, ** p < 0.05, *** p < 0.01. The PPML algorithm drops observations that are either singletons or separated by a fixed effects, hence the number of observations drops slightly when including more detailed fixed effects.

5.2. Environmental Policy Stringency

Table 5.3 reports the effects of sector-level environmental policy stringency on firms' clean innovation output. We observe positive coefficients for the relationship between EPS and clean patents. The size of the effect is notably smaller than for the energy price index. On average, a 1% increase in the sector-level EPS leads to a 0.14% increase in mitigation patents. Since the EPS combines different types of policies (both market based and non-market based), this difference may reflect that some policies, such as emission concentration limits, may be less suitable at inducing environmental innovation than energy prices. Furthermore, the EPS consists of policies not only including climate regulation, but also for example end-of-pipe technology standards to reduce local pollutants. Such policies may not directly induce innovation in climate mitigation technologies. The construction of the EPS, which aggregates several policy instruments into a single index, may also explain why the effects are smaller for EPS compared to the effects for energy prices. Overall, energy prices are likely to be a more accurate driver of innovation in mitigation technologies compared to the EPS. The magnitude of the within-sector effects increases slightly to 0.2 when adding the supply chain weights.[24]

Again, we estimate several alternative specifications to test the robustness of our results. Effects for EPS also remain similar in magnitude and significance when including both policy indicators – FEPI and the EPS – within the same specification (Table E.1. in Annex E). To address concerns that the average wage of firms may be a bad control, because it may be endogenously determined by firms' economic performance, which may be driven by regulation, we also estimate the model without our wage control. The results remain stable in magnitude and statistical significance (Table D.1. in Annex D). Again, as in the case of the energy prices, we observe that the coefficient increases in a specification with two-year lags. A 1% increase in EPS is associated with a 0.27% increase in mitigation patents when allowing for a two year time lag (Table C.1. in Annex C). The coefficients on knowledge stock and employees are positive and significant. Overall, the control variables are similar in sign, magnitude and significance to the coefficients in the energy price models.

Table 5.4 reports the effects of the EPS including the supply chain relationships. The within-sector coefficients increase slightly to 0.20. The coefficients on the control variables are similar to the previous model with employment and the clean knowledge stock, being positive and significantly associated with clean innovation. Similarly to the results for energy prices, we do not observe strong effects on the supply chain variables. The coefficient for upstream EPS is negative and significant in columns (2), however these effects disappear when adding sector-year fixed effects in column (3). We also do not observe significant relationships between downstream EPS and clean innovation. Overall, these results show that environmental policy stringency induces innovation in directly regulated sectors. A 1% increase in EPS is associated with a 0.13-0.20% increase in mitigation patents. Again, the construction of the supply chain weights based on sector-level input-output tables may introduce measurement error in the supply chain variables, potentially making their estimation less precise.

[24] The specification on the EPS with additional sector-year fixed effects and without supply chain weights did not converge because of the large number of fixed effects. Table 5.3 therefore only shows the results with firm- and year fixed effects (column 1) and the main specification with country-year fixed effects (column 2).

Table 5.3. The effect of sector-EPS on clean innovation

	Mitigation Patents	Mitigation patents
Log(EPS) $_{(t-1)}$*Log(AvgCO2-int) $_{(t-1)}$	0.13**	0.14**
	(0.06)	(0.07)
Log(EPS) $_{(t-1)}$	-0.41	(omitted)
	(0.26)	
Log(Avg. CO2-intensity) $_{(t-1)}$	(omitted)	(omitted)
Log(Know. Stock mitig.) $_{(t-1)}$	0.23***	0.23***
	(0.08)	(0.08)
Log(employees) $_{(t-1)}$	0.33***	0.33***
	(0.08)	(0.08)
Log(average wage) $_{(t-1)}$	0.03	0.02
	(0.06)	(0.07)
Log (cap. Int.) $_{(t-1)}$	-0.01	-0.01
	(0.03)	(0.02)
Constant	-0.90	-1.32
	(1.06)	(1.41)
N	104224	104124
Firms	10212	10209
Firm FE	Yes	Yes
Year FE	Yes	Yes
Country-year FE	No	Yes
Sector-year FE	No	No

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The specification with additional sector-year dummies did not converge because of the large number of fixed effects. The PPML algorithm drops observations that are either singletons or separated by a fixed effects, hence the number of observations drops slightly when including more detailed fixed effects.

Table 5.4. The effect of EPS on clean innovation (including supply chain)

	Mitigation patents	Mitigation patents	Mitigation patents
Log(EPS)*Log(Avg. CO2 int) (t-1)	0.18**	0.22**	0.20***
	(0.09)	(0.09)	(0.08)
Log(EPS) (t-1)	0.13		
	(0.44)		
Log(Avg. CO2int) (t-1)	(omitted)	(omitted)	(omitted)
Downstream EPS weight (t-1)	0.08	0.00	-0.01
(Downstr. weight * (EPS*CO2int))	(0.13)	(0.11)	(0.16)
Upstream EPS weight(t-1)	-0.28	-0.28**	-0.18
(Upstr weight * (EPS*CO2 int.))	(0.19)	(0.14)	(0.17)
Log (Mitig. Know. Stock) (t-1)	0.24***	0.23***	0.20***
	(0.08)	(0.08)	(0.07)
Log (employees) (t-1)	0.36***	0.34***	0.37***
	(0.08)	(0.09)	(0.08)
Log(Avg wage) (t-1)	0.04	0.02	0.01
	(0.07)	(0.07)	(0.07)
Log (Cap. Int.) (t-1)	-0.01	-0.02	-0.01
	(0.03)	(0.03)	(0.02)
Constant	-1.17	-0.58	-0.85
	(1.18)	(1.67)	(1.71)
N	91608	91569	91321
Firms	8984	8983	8978
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-year FE	No	Yes	Yes
Sector-year FE	No	No	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The PPML algorithm drops observations that are either singletons or separated by a fixed effects, hence the number of observations drops slightly when including more detailed fixed effects.

Chapter 6. Results – The Effect of environmental innovation on firms' economic performance

Table 6.1 reports the results from the first stage regression (Equation 7), analysing the strength of the instrument on firms' patent stock in clean technologies. We observe that the instrument is positively and significantly associated with the mitigation patent stock. One concern for the presented analysis is that the instrument may be correlated with firm-specific characteristics that effect both their economic performance and the stringency of regulation. We therefore include firm fixed effects and covariates to control for firm-specific characteristics. The coefficients of the instrument on the clean knowledge stock is significant at the 1% level, and the Kleinberger-Paap (K-P)-statistic is larger than 10 in our preferred specification with country-year fixed effects, and which provides evidence that the first stage assumptions hold and that our instrument is relevant for firms' clean patent stocks.[25]

Table 6.2 reports the results of the second stage of the two-stage least square (2SLS) estimation, estimating the effect of energy prices on (log) multifactor productivity (MFP) (columns 1-3) and (log) value added (VA) (columns 4-6). The coefficient of the instrumented mitigation patent stock is insignificant across models. Hence, we do not observe a significant effect of clean innovation on firms' economic performance (either positive or negative). In our main 2SLS models we do not control for environmental policy stringency because of concerns that environmental policy stringency may potentially be a bad control when estimating the effect of clean innovation on economic performance. Environmental policy stringency could absorb any effect that low-carbon innovation might have. However, we also estimate separately the 2SLS including FEPI and EPS respectively, and the effect of low-carbon innovation on economic performance remains insignificant (Table G.1. in Annex G). Coefficients also remain insignificant in specifications with two-year lags (see Table F.1. in Annex F).

In addition, we may be concerned that the economic control variables may be endogenous in specifications with economic performance variables as the dependent variable. We therefore follow McGowan, Andrews and Millot, (2017[48]) and Andrews, Criscuola and Gal (2016[49]) who estimate effects of public policy on productivity, and only control for firm size and a binary age variable taking the value of 1 for young firms (age<6 years), instead of the control variables used previously. Similarly, we do not observe significant effect of clean innovation on firms' economic performance (Table I.1. in Annex I). Lastly, we estimate the 2SLS using a control function approach. In the conventional 2SLS the first stage regression is estimated through OLS. Since the dependent variable in the first stage regression (Mitigation Knowledge Stock) has a skewed distribution, using PPML to estimate the first stage regression may be preferred. We therefore use the residuals from the first stage regression, which we estimated with PPML, as a control function in the second stage regression (Wooldridge, 2015[50]). Again, we do not observe significant effects of low-carbon innovation on firms' economic performance (Table J.1. in Annex J).

Under the assumptions outlined in Section Chapter 3. these regression results provide unbiased estimates of the causal effect of clean innovation on firms' economic performance. The paper argues that the first stage assumption of instrument relevance likely holds, as supported by the results of the first-stage above. The assumption of independence is crucial for the causal interpretation of the coefficients. It requires that the instrument does not affect the economic performance of firms, except through their effect on clean patenting. Specifically, this requires that

[25] The K-P statistic is similar to a F-statistic that controls for heteroscedasticity.

the instrument is not correlated with the error term ε_{icst} in equation (8). For the instrument to be valid (independent), we require that the correlation between pre-trends in the economic performance variables and the instrumental variable to be not significantly different from zero. We compute two proxies for pre-trend economic performance. First, the pre-sample average of the change in the economic outcome variable, and second, the pre-sample average of the economic outcome variable. We then regress the instrumental variable on the pre-trend proxies interacted with a time trend. Table H.1 in Annex H reports the results, showing that the pre-trend proxies are not statistically significant, which supports the independence of our instrument.

Table 6.1. First stage – The effect of the instrumental variable on mitigation knowledge stock

	(1) OLS Mitig. Know. Stock	(2) OLS Mitig. Know. Stock	(3) OLS Mitig. Know. Stock	(4) OLS Mitig. Know. Stock	(5) OLS Mitig. Know. Stock	(6) OLS Mitig. Know. Stock
Instrumental	0.043***	0.029***	0.018***	0.043***	0.028***	0.018***
Variable	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log(employees)	0.081***	0.073***	0.069***	0.080***	0.072***	0.069***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Log (Avg. wage)	0.051***	0.031***	0.029***	0.051***	0.031***	0.029***
	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)
Log (Cap. Int.)	0.003	-0.002	-0.003	0.003	-0.002	-0.003
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
N	47781	47735	47709	48147	48102	48078
Firms	7145	7137	7134	7199	7192	7189
F-stat (K-P)	48.91	26.40	9.53	48.07	25.39	9.67
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-year FE	No	Yes	Yes	No	Yes	Yes
Sector-year FE	No	No	Yes	No	No	Yes
Sample	MFP	MFP	MFP	VA	VA	VA

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * p < 0.10, ** p < 0.05, *** p < 0.01. Models 1-3 are estimated on the sample of firms for which multifactor productivity (MFP) is available. Models 4-6 are estimated on the sample of firms for which value added (VA) is available. The instrumental variable is constructed as the share of firms in the same country-sector-year that have a strictly positive number of mitigation patents multiplied by the pre-sample share of firms' climate mitigation patent stock relative to their total patent stock in any technology.

Table 6.2. The effect of low-carbon innovation on economic outcomes (2SLS)

	2SLS Log(MFP)	2SLS Log(MFP)	2SLS Log(MFP)	2SLS Log(VA)	2SLS Log(VA)	2SLS Log(VA)
Log(Mitig. Know. Stock)$_{(t-1)}$	-0.007 (0.017)	0.006 (0.028)	-0.002 (0.047)	0.257 (0.166)	0.023 (0.260)	-0.095 (0.458)
Log (employees) $_{(t-1)}$	0.008*** (0.002)	0.008*** (0.003)	0.009** (0.004)	0.634*** (0.024)	0.646*** (0.027)	0.653*** (0.037)
Log(Avg. wage) $_{(t-1)}$	0.015*** (0.002)	0.016*** (0.002)	0.017*** (0.002)	0.325*** (0.024)	0.336*** (0.026)	0.339*** (0.028)
Log (Cap. Int.) $_{(t-1)}$	-0.009*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)	-0.041*** (0.009)	-0.038*** (0.008)	-0.038*** (0.008)
R^2	0.018	0.017	0.019	0.167	0.171	0.169
N	47781	47735	47709	48147	48102	48078
Firms	7145	7137	7134	7199	7192	7189
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-year FE	No	Yes	Yes	No	Yes	Yes
Sector-year FE	No	No	Yes	No	No	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * p < 0.10, ** p < 0.05, *** p < 0.01. Models 1-3 are estimated on the sample of firms for which multifactor productivity (MFP) is available. Models 4-6 are estimated on the sample of firms for which value added (VA) is available. The instrumental variable is constructed as the share of firms in the same country-sector-year that have a strictly positive number of mitigation patents multiplied by the pre-sample share of firms' climate mitigation patent stock relative to their total patent stock in any technology.

Chapter 7. Discussion and Conclusion

This paper analyses the effect of environmental policy on innovation and economic performance, both directly on regulated sectors and indirectly through supply chain relationships. Using two separate measures of environmental policy – energy prices and the Environmental Policy Stringency (EPS) indicator – the paper finds that environmental regulation induces clean innovation in directly regulated sectors. The paper does not find evidence that environmental policy induces significant innovation in up- or downstream sectors. This would imply that the most carbon-intensive sectors need to be regulated directly to induce clean innovation within these sectors. Based on our results – and to the extent that effects of past policies can predict effects of future policies – relying only on indirect regulation through supply chain relationships appears unlikely to induce sufficient clean innovation to decarbonize the economy rapidly.

The most carbon-intensive sectors are however also industries that may suffer the most from additional regulation because they may find it more difficult to switch to cleaner technologies. Additional environmental regulation may create social and economic tensions between potential winners and losers if not actively managed (OECD, 2017[51]; OECD, 2019[52]). The impacts of regulation on the economic performance of firms is therefore even more important. In this paper, we do not find support that environmental policies reduce or enhance the economic performance of firms through innovation in clean technologies. Specifically, our findings do not support concerns that environmental regulation channels resources into innovation activity that reduces the productivity or competitiveness of firms. These findings are in line with previous OECD work (see for example: Dechezleprêtre, Nachtigall and Stadler (2020[53]); Albrizio, Kozluk and Zipperer (2017[54]); and Dlugosch and Kozluk (2017[55])) showing that stringent environmental regulation has little effect on economic outcomes such as investment, productivity and employment. However, the findings do also not support over-optimistic claims that policy-induced environmental innovation would enhance firm performance. Instead, clean innovation activities may be able to offset the costs of environmental policy, which is already a reassuring finding.

A clear limitation of the paper is that data on supply-chain relationships does not exist at the firm-level so that the supply chain weights are based on sector-level information. Using sectoral input-output data is the most granular data available that allows estimation based on exposure to both up- and down-stream environmental policy. Firms in our analysis may however not have the same supply chain relationships as implied by sector-level input-output tables. This may introduce measurement error in the estimation of the supply chain relationships. Moreover, high correlations between the within-sector, up- and downstream policy indicators make it difficult to clearly separate supply chain effects. Further work could use information on the sector-of-use that is provided with patent filings to construct firm-specific supply chain weights. Such firm-specific supply chain weights could allow for a more granular estimation of supply chain relationships.

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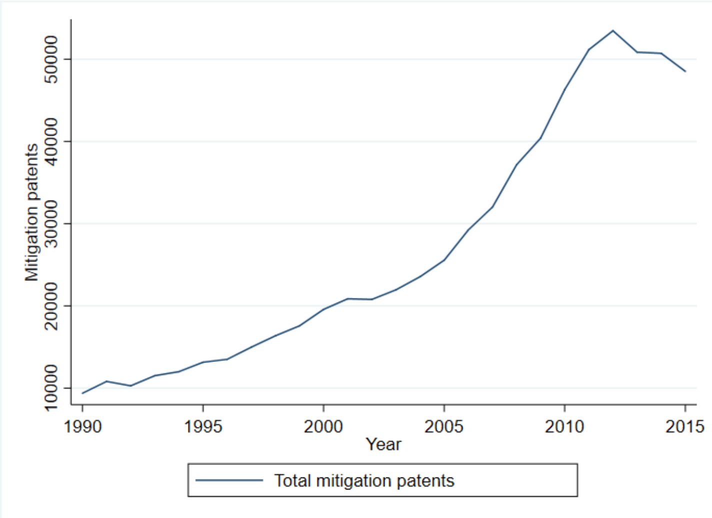
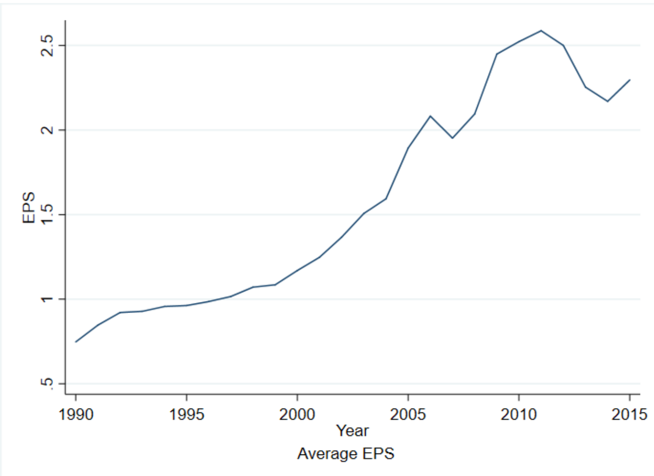
Annex A. Time trends in mitigation patents, EPS, and supply chain weights (FEPI and EPS)

Figure A.1. Total mitigation patents in the sample



Note: Authors' calculations.
Source: PATSTAT

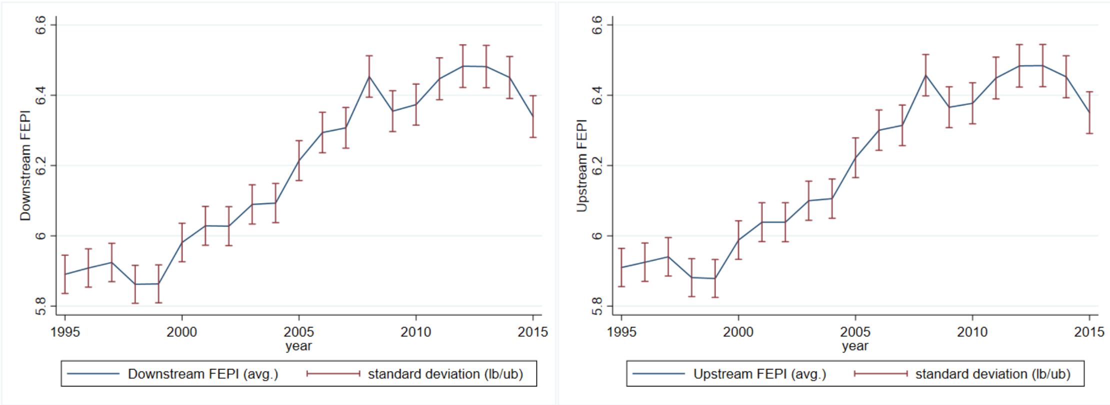
Figure A.2. Time series of average country-level Environmental Policy Stringency (EPS)



Source: Authors calculations based on OECD Environmental Policy Stringency indicator.

Figure A.3. Time series of average Downstream and Upstream FEPI weights.

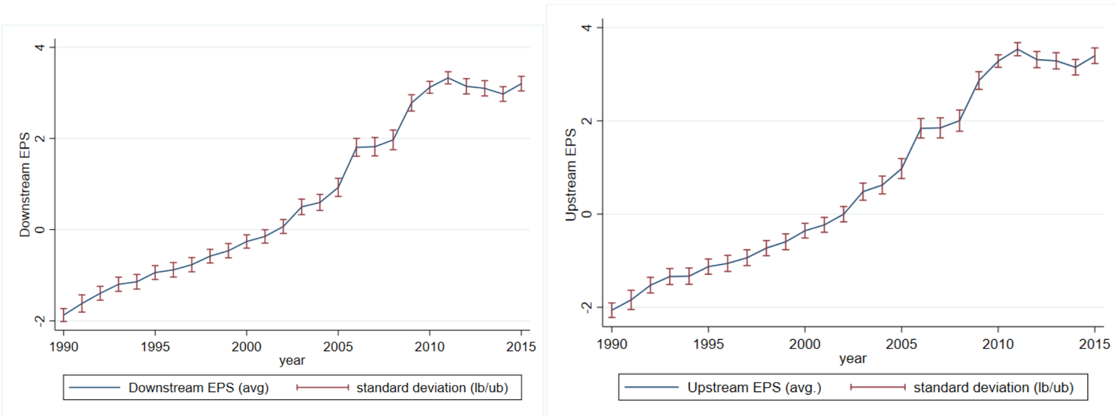
Panel A: Avg. Downstream FEPI   Panel B: Average Upstream FEPI.



Source: Authors calculations based on OECD Environmental Policy Stringency and OECD Inter-Country Input-Output dataset.

Figure A.4. Time series of average Downstream and Upstream EPS weights

Panel A: Avg. Downstream EPS weight   Panel B: Avg. Upstream EPS weight



Source: Authors calculations based on OECD Environmental Policy Stringency and OECD Inter-Country Input-Output dataset.

Annex B. Country Coverage

Table B.1. Country coverage in the analysis

Count	Countries included in EPS analysis	Countries included in energy price (FEPI) analysis
1	AT (Austria)	AT (Austria)
2	BE (Belgium)	BE (Belgium)
3	DE (Germany)	DE (Germany)
4	DK (Denmark)	DK (Denmark)
5	ES (Spain)	FI (Finland)
6	FI (Finland)	FR (France)
7	FR (France)	GB (United Kingdom)
8	GB (United Kingdom)	HU (Hungary)
9	HU (Hungary)	IN (India)
10	IE (Ireland)	IT (Italy)
11	IN (India)	JP (Japan)
12	IT (Italy)	KR (Korea)
13	JP (Japan)	NL (Netherlands)
14	KR (Korea)	PL (Poland)
15	NL (Netherlands)	PT (Portugal)
16	PT (Portugal)	RO (Romania)
17	RU (Russia)	SE (Sweden)
18	SE (Sweden)	
19	SI (Slovenia)	

Note: The country-coverage is constrained by several factors: 1) The availability of FEPI or EPS data, 2) The availability of firms that file a strictly positive number of low-carbon patents between 1990 and 2015, and 3) firms that can be matched to unconsolidated accounts in the OECD-Orbis data.
Source: Authors.

Annex C. Results with 2-year lags

Table C.1. The effect of environmental policy on clean innovation (2-year lag)

	Mitigation patents	Mitigation patents	Mitigation patents	Mitigation patents
$FEPI_{(t-2)}$	2.23**	2.31**		
	(0.94)	(0.94)		
Downstream FEPI $weight_{(t-2)}$		-0.21		
		(0.74)		
Upstream FEPI $weight_{(t-2)}$		-0.77		
		(1.62)		
Log(EPS) $_{(t-2)}$			(omitted)	(omitted)
Log(Avg. CO2-int.) $_{(t-2)}$			(omitted)	(omitted)
$Log(EPS)_{(t-2)}$*Log(Avg. CO2-int.) $_{(t-2)}$			0.18**	0.26***
			(0.09)	(0.10)
Downstream EPS $weight_{(t-2)}$				-0.05
				(0.11)
Upstream EPS $weight_{(t-2)}$				-0.22*
				(0.13)
Log(Mitigation Know. Stock) $_{(t-2)}$	0.01	0.01	0.01	0.01
	(0.09)	(0.08)	(0.09)	(0.09)
Log (employees) $_{(t-2)}$	0.28***	0.27***	0.28***	0.31***
	(0.09)	(0.09)	(0.09)	(0.10)
Log(average wage) $_{(t-2)}$	0.12	0.12	0.12	0.12
	(0.09)	(0.08)	(0.08)	(0.09)
Log (Cap Int) $_{(t-2)}$	-0.04*	-0.04	-0.04	-0.06*
	(0.03)	(0.03)	(0.03)	(0.03)
Constant	-14.80**	-9.00	-1.02	-0.51
	(7.13)	(12.80)	(1.63)	(1.94)
N	97946	97946	102130	89646
Firms	9437	9437	9847	8650
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The PPML algorithm drops observations that are either singletons or separated by a fixed effects, hence the number of observations drops slightly when including more detailed fixed effects.

Annex D. Additional Results without wage control

Table D.1. Additional Results without wage control

	Mitigation patents	Mitigation patents	Mitigation patents	Mitigation patents
FEPI$_{(t-1)}$	1.50***	1.37**		
	(0.55)	(0.58)		
Downstr. FEPI weight$_{(t-1)}$	0.08	0.97		
	(0.56)	(1.32)		
Upstream FEPI weight$_{(t-1)}$	-0.50	-0.20		
	(1.22)	(1.37)		
Log(EPS) $_{(t-1)}$ * Log (Avg. CO2-int) $_{(t-1)}$			0.22**	0.20***
			(0.09)	(0.08)
Log(EPS) $_{(t-1)}$			(omitted)	(omitted)
Log (Avg. CO2-int)			(omitted)	(omitted)
Downstr. EPS weight$_{(t-1)}$			0.00	-0.01
			(0.11)	(0.16)
Upstr. EPS weight$_{(t-1)}$			-0.28**	-0.18
			(0.14)	(0.17)
Log (Know. Stock mitig.) $_{(t-1)}$	0.23***	0.19***	0.23***	0.21***
	(0.07)	(0.05)	(0.08)	(0.07)
Log (employees) $_{(t-1)}$	0.32***	0.34***	0.34***	0.36***
	(0.07)	(0.06)	(0.07)	(0.06)
Log (Cap int.) $_{(t-1)}$	-0.01	-0.00	-0.02	-0.01
	(0.02)	(0.02)	(0.03)	(0.02)
Constant	-7.52	-14.40	-0.30	-0.67
	(8.74)	(10.14)	(0.95)	(1.00)
N	100380	100197	91569	91321
Firms	9842	9842	8983	8978
Firm FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
Sector-year FE	No	Yes	No	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Annex E. Additional Results: The effect of environmental policy on clean innovation (both FEPI and EPS)

Table E.1. The effect of environmental policy on clean innovation (both FEPI and EPS)

	Mitigation Patents	Mitigation Patents	Mitigation Patents
$FEPI_{(t-1)}$	0.08	1.29**	1.48**
	(0.36)	(0.55)	(0.63)
Log(EPS)*Log(Avg. CO2-int)	0.13**	0.13*	0.15**
	(0.06)	(0.07)	(0.06)
Log(EPS)	-0.41	(omitted)	(omitted)
	(0.25)		
Log (Avg. CO2-int.)	(omitted)	(omitted)	(omitted)
Log (Mitig. Know. Stock)	0.23***	0.23***	0.21***
	(0.08)	(0.07)	(0.07)
Log (employees)	0.32***	0.32***	0.34***
	(0.08)	(0.08)	(0.08)
Log(Avg. wage)	0.03	0.01	0.01
	(0.07)	(0.07)	(0.07)
Log (cap. Int.)	-0.01	-0.01	-0.01
	(0.03)	(0.02)	(0.02)
Constant	-1.32	-9.47**	-10.73**
	(3.23)	(4.23)	(4.23)
N	96975	96927	96754
Firms	9606	9604	9604
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-year FE	No	Yes	Yes
Sector-year FE	No	No	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Annex F. Additional Results – 2SLS with 2-year lag

Table F.1. 2SLS Results with 2-year lags. The effects of environmental policy on economic outcomes through clean innovation

	Log(MFP)	Log(VA)
Log (Mitig. Know. Stock)$_{(t-2)}$	0.007	-0.019
	(0.028)	(0.265)
Log (employees) $_{(t-2)}$	0.006**	0.503***
	(0.003)	(0.033)
Log(avg. wage) $_{(t-2)}$	0.008***	0.247***
	(0.002)	(0.030)
Log(Cap Int) $_{(t-2)}$	-0.006***	-0.023***
	(0.001)	(0.009)
R^2	0.006	0.102
N	41092	41430
Firms	6246	6298
Firm FE	Yes	Yes
Year FE	Yes	Yes
Country-year FE	Yes	Yes
1st stage F-stat	25.91	24.78

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * p < 0.10, ** p < 0.05, *** p < 0.01.

Annex G. Additional Results – 2SLS with environmental policy control

Table G.1. 2SLS with environmental policy control

	(1) 2SLS Log(MFP)	(2) 2SLS Log(VA)	(3) 2SLS Log(MFP)	(4) 2SLS Log(VA)
Log (Mitig. Know. Stock)$_{(t-1)}$	0.013 (0.031)	0.077 (0.288)	0.022 (0.033)	0.119 (0.319)
FEPI$_{(t-1)}$	-0.014 (0.015)	0.021 (0.143)		
Log (EPS)$_{(t-1)}$ * Log (CO2 int.)$_{(t-1)}$			-0.001 (0.002)	-0.004 (0.020)
Log(employees)$_{(t-1)}$	0.006** (0.003)	0.623*** (0.032)	0.005 (0.003)	0.609*** (0.035)
Log (Avg. wage)$_{(t-1)}$	0.014*** (0.002)	0.315*** (0.030)	0.015*** (0.002)	0.325*** (0.029)
Log(Cap. Int)$_{(t-1)}$	-0.007*** (0.001)	-0.022*** (0.008)	-0.007*** (0.001)	-0.022*** (0.008)
R^2	0.006	0.162	-0.004	0.157
N	37158	37484	37667	37995
Firms	5839	5891	5910	5963
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
1st stage F-stat (K-P)	21.53	20.42	18.51	17.63

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * p < 0.10, ** p < 0.05, *** p < 0.01

Annex H. Testing the independence of the instrumental variable

Table H.1. Correlations between pre-trends in economic outcome variables and the instrumental variable

	Instrumental Variable	Instrumental Variable
Average change in Log(MFP) * time trend	0.003 (0.022)	
Average Log(MFP) * time trend	-0.020 (0.019)	
Average change in Log(VA) * time trend		0.001 (0.002)
Average Log(VA) * time trend		-0.001 (0.001)
Log(employees)	-0.007 (0.010)	-0.010 (0.010)
Log(avg. wage)	0.006 (0.009)	0.004 (0.009)
Log (Cap. Int.)	0.004 (0.004)	0.004 (0.004)
Constant	91.248 (93.069)	22.127 (24.420)
R^2	0.970	0.970
N	27643	27766
Firms	4865	4892
Firm FE	Yes	Yes
Year FE	Yes	Yes
Country-year FE	Yes	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Averages are computed as within-firm averages for the pre-sample time period.

Annex I. Additional Results – 2SLS Estimation with employees and age controls

Table I.1. 2SLS Estimation with employees and age controls

	(1) 2SLS Log (MFP)	(2) 2SLS Log(MFP)	(3) 2SLS Log(VA)	(4) 2SLS Log(VA)
Log (Mitig. Know. Stock)$_{(t-1)}$	0.006	-0.003	0.022	-0.111
	(0.028)	(0.045)	(0.267)	(0.453)
Log (employees)$_{(t-1)}$	0.002	0.003	0.540***	0.547***
	(0.003)	(0.003)	(0.027)	(0.034)
Age (dummy: young=1)$_{(t-1)}$	-0.001	-0.002	-0.007	-0.014
	(0.003)	(0.003)	(0.033)	(0.036)
N	49403	49375	49896	49870
Firms	7436	7432	7516	7512
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
Sector-year FE	No	Yes	No	Yes
1st stage F-stat (K-P)	28.00	11.36	26.65	11.28

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The age dummy variable takes the value of 1 for young firms (<6 years) and 0 for all other firms.

Annex J. Instrumental variable estimation with control function

Table J.1. The effect of the instrumental variable on Mitigation Knowledge stock (1st stage to estimate residuals for control function)

	(1) Log (Mitig. Know. Stock)	(2) Log (Mitig. Know. Stock)
Instrumental Variable$_{(t-1)}$	0.063***	0.049***
	(0.010)	(0.008)
Log (employees) $_{(t-1)}$	0.108***	0.102***
	(0.011)	(0.011)
Log (average wage) $_{(t-1)}$	0.033***	0.029***
	(0.010)	(0.010)
Log (cap. Int.) $_{(t-1)}$	-0.001	-0.002
	(0.005)	(0.005)
Constant	-0.303**	-0.323**
	(0.147)	(0.145)
N	74011	73985
Firm	10883	10881
Firm FE	Yes	Yes
Year FE	Yes	Yes
Country-year FE	Yes	Yes
Sector-year FE	No	Yes
PPML	Yes	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The residuals from Model 1 and 2 are used as the control function in the 2nd stage (Table H2 in the Appendix).

Table J.2. Instrumental variable with control function (2nd stage)

	(1) Log(MFP)	(2) Log(MFP)	(3) Log(VA)	(4) Log(VA)
Log(Mitig. Know. Stock)$_{(t-1)}$	-0.003 (0.006)	-0.004 (0.006)	-0.035 (0.054)	-0.035 (0.054)
Log (employees) $_{(t-1)}$	0.010*** (0.002)	0.011*** (0.002)	0.666*** (0.022)	0.666*** (0.022)
Log(avg. wage) $_{(t-1)}$	0.018*** (0.003)	0.018*** (0.003)	0.375*** (0.030)	0.374*** (0.030)
Log(Cap Int) $_{(t-1)}$	-0.008*** (0.001)	-0.009*** (0.001)	-0.040*** (0.010)	-0.040*** (0.010)
Control function (based on spec. with C-Y dummies) $_{(t-1)}$	0.001 (0.006)		0.039 (0.054)	
Control function (based on spec. with C-Y & S-Y dummies) $_{(t-1)}$		0.000 (0.006)		0.033 (0.054)
Constant	2.160*** (0.033)	2.156*** (0.034)	8.780*** (0.383)	8.789*** (0.386)
R^2	0.829	0.831	0.961	0.961
N	38953	38926	39269	39244
Firms	6015	6010	6064	6059
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
Sector-year FE	No	Yes	No	Yes
Control Function	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses are clustered at the country-sector level. Significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The control function included in models 1 and 3 were estimated with country-year fixed effects. The control functions in models 2 and 4 were estimated with additional sector-year fixed effects. Models are estimated using OLS. The control functions were estimated using PPML in a 'first stage'.