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The Drivers and Macroeconomic Impacts of Low-Carbon Innovation: A Cross-Country Exploration

Zeina Hasna, Henry Hatton, Florence Jaumotte, Jaden Kim, Kamiar Mohaddes, and Samuel Pienknagura

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ABSTRACT: This paper investigates how climate policies affect low-carbon innovation (as measured by patents) and assesses the link between such innovation and economic activity. Climate policies, including international cooperation, spur both specific and overall innovation, with regulations, emissions-trading systems, and expenditure measures such as R&D subsidies and feed-in tariffs being particularly impactful. In turn, low-carbon innovation raises economic activity as much as other types of innovation and past technological revolutions. However, the mechanisms are different: low-carbon innovation increases capital accumulation, while other types of innovation increase total factor productivity (TFP).

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WORKING PAPERS

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1 Introduction

The growing evidence that climate change is detrimental to economic activity (Kahn et al., 2021) highlights the importance of reducing emissions. According to recent research by the International Energy Agency, while most of the global reductions in CO_2 emissions needed in the short-term (through) 2030 can be achieved through existing from technologies, medium-term reductions will require the development of new technologies (IEA, 2021). The importance of new technologies to meet medium-term objectives is even higher in sectors such as heavy industry and long-distance transport. Thus, achieving net zero by 2050 requires the rapid deployment of existing technologies, alongside the development and widespread adoption of emerging technologies. Importantly, major innovation efforts must occur over this decade in order to bring these new technologies to market in time.

A key question facing policymakers is whether policies designed to nudge firms into investing in low-carbon (green) technologies will boost economic performance or hamper it. The long-term benefits of green innovation for economic activity, as a result of a reduction in damages from climate change, are well understood (Acemoglu et al., 2012). However, what is also critical for the public debate is whether the green transition entails short-to-medium term economic benefits (Pisani-Ferry, 2021). On the one hand, incorporating new technologies may initially disrupt existing production processes, thus reducing potential TFP benefits from these new technologies in the short to medium term, what is deemed in the literature as path-dependency (Acemoglu et al., 2016; Aghion et al., 2016). On the other hand, green innovation could initially lead to higher investment and progressively raise productivity by increasing energy efficiency and reducing the cost of inputs (especially energy, given recent advancements in renewables), see for example Ambec and Lanoie (2008). In addition, there is evidence that green innovation generates larger knowledge spillovers than its carbon-intensive counterparts and could therefore lead to higher innovation overall, as well as facilitating the manufacturing of new products and accessing to new markets (Dechezleprêtre et al., 2017).

The previous arguments suggest that, from a conceptual standpoint, innovation associated with the transition to a low carbon economy—which we label green innovation—could have higher or lower pro-growth effects compared to other forms of innovation depending on whether energy efficiency, cheaper energy sources, and knowledge spillover forces dominate path dependency. The seeming tension between the disruptive nature of green technologies compared to nongreen ones and their relative growth potential is also present in the public debate. In his recent address in the context of the United Nations' Climate Conference (COP29), UK Prime Minister Keir Starmer emphasized the potential for higher growth and investment that the green transition and green innovation bring.[1] At the same time, public perception about the economic impacts of climate policies, which could spark green innovation, are typically negative (Dabla-Norris et al., 2023). The relative pro-growth potential of green innovation is, thus, an open question that requires exploration.

Against this backdrop, this paper tackles two fundamental questions about green innovation: Firstly, what

[1] https://www.gov.uk/government/speeches/pm-remarks-at-cop29-12-november-2024

are the macroeconomic implications of green innovation, and how do they compare to those of nongreen innovation? And secondly, can the implementation of environmental policies effectively foster green innovation? These questions are closely related to the hypotheses posed in the seminal work by Porter and Linde (1995), which argued that well designed environmental policies can stimulate green innovation (the "weak" version of the Porter hypothesis), and climate policies, in turn, can spur competitiveness (the "strong" version). Thus, contrary to most of the existing literature, which has focused exclusively on the weak version of the Porter hypothesis, this paper provides a more comprehensive assessment, albeit at times indirect, of both strands of the hypothesis in two distinct steps. First, it estimates the impact of green innovation on economic activity—i.e. addressing the second part of the hypothesis in isolation. This is only a partial assessment of the strong version of the Porter hypothesis, as it does not study directly the impact of climate policies on economic activity[2] and it only focuses on one channel through which policies could potentially affect economic performance, namely innovation. Second, the paper estimates the impact of climate policies on green innovation.

We begin by delving into the link between green innovation and economic activity, a matter that has been less studied and contributes to the ongoing debate about the economic benefits of stimulating green innovation.Convincing policymakers to encourage green innovation could be rather hard if its economic aftermath is not well understood. Thus, highlighting the positive effects of green innovation on economic activity and how they help offset some of the potentially negative effects of climate policies on productivity is critical to encouraging the adoption of such policies. Therefore, by delving into these inquiries, the aim is to not only to ascertain the effectiveness of policy interventions in incentivizing and accelerating the pace of innovation in sustainable technologies but also to establish how these efforts could impact economic activity in the short- to medium-term. This approach could be particularly relevant as there is evidence suggesting that climate strategies perceived to entail economic costs receive less support than those with positive or no apparent economic impact (Dabla-Norris et al., 2023). Thus, our findings could help policymakers understand better the political economy trade-offs of climate policies.

This paper makes two contributions to the growing literature on the impacts of green innovation and climate policies. First, the paper provides a comprehensive assessment of the economic impact of green innovation, by: (i) comparing it to nongreen innovation, (ii) exploring the channels through which green and nongreen innovations affect economic activity, and (iii) comparing how the economic impact of green innovation compares to that seen in the technological breakthrough associated with Information Communication Technologies (ICTs). The paper's second contribution relates to the link between climate policies and green innovation. In particular, the paper estimates the impact of climate policies on green innovation using a broader set of patents and policies than in previous studies (Bettarelli et al., 2023), and addressing endogeneity concerns. In addition, the paper investigates the role of international agreements and global policies in boosting green innovation - a topic that is essential to address when international efforts are critically needed to achieve global net zero targets, yet protectionism is on the rise.

[2] Strictly speaking the Porter hypothesis refers to competitiveness as the economic outcome of interest. Some studies proxy competitiveness with productivity. This paper focuses more broadly on GDP, disentangling the different channels through which green innovation affects GDP.

Using local projection methods and leveraging patent filings data over the years 1990–2019 for a sample of OECD and BRICS countries, we find that green patent filings have a positive impact on economic activity, especially over the medium term, that is not statistically distinguishable from that of non-green patent filings. In particular, we find that an increase in the flow of patent filings—that is, an acceleration in patenting—of 7 percent (the annual growth rate observed in the data) leads to a 0.14 percent increase in GDP after five years relative to the baseline scenario. These estimates represent a lower bound, as they are up to twice or four times as large when controlling for climate policies and when instrumenting domestic patent filings to account for the potential reverse impact of economic growth on patent filings, respectively. The positive impact of green patents on GDP appears to be driven primarily by a boost in investment, with no visible impacts on aggregate productivity. The negligible initial response of productivity to green innovation, a relatively new technological development, is consistent with the experience seen for past technological breakthroughs, notably the advent of ICTs.

Our results are indirectly related to the strong version of the Porter hypothesis, as they suggest that, to the extent that they spur green innovation, climate policies could entail relatively smaller economic costs than previously anticipated. Put differently, our results indicate that green innovation could be one factor mitigating the potential adverse short-term economic impacts of compliance with climate policies.

Turning to the impact of climate policies on patents, our findings confirm the role of climate policies in boosting green innovation and highlight the importance of synchronized climate policy action and global policies. Consistent with previous literature, we find that a major jump in climate policies (equivalent to one standard deviation of the distribution of changes in the number of climate policies) boosts green patent filings by 10 percent in five years, with regulations, emissions-trading systems that put quantity limits on emissions, and expenditure measures such as R&D subsidies and feed-in tariffs, being particularly impactful. Importantly, we present novel evidence that global climate policies affect domestic green patent filings even more than domestic policies do, and international climate agreements (such as the Kyoto Protocol and Paris Agreement) amplify the impact of domestic policies. These results point to the role of policy certainty, global market size, and technology spillovers as important determinants of innovation.

The rest of this paper is structured as follows: Section 2 provides a brief literature review on the two questions addressed; Section 3 describes the data utilized in the paper; Section 4 discusses the empirical methodology and results on the macro effects of green innovation; Section 5 discusses the empirical methodology and results on the effect of climate policies in bolstering green innovation; and finally Section 6 provides concluding remarks.

2 Literature Review

The two questions at the heart of the paper relate to two strands of the literature. The first question on the macroeconomic effects of green innovation belongs to the economics of innovation literature, which has mostly focused on the effect of total innovation on economic performance with a few papers emerging more recently focusing on green innovation. The second question addressed belongs to the burgeoning literature on the role of climate policies in stimulating green innovation. The following two subsections provide a brief literature review on each strand, and highlights how our paper contributes to each of them.

2.1 (Green) Innovation and Growth

The empirical innovation literature has been primarily concerned with relating *total* innovation to economic growth (Coe and Helpman, 1995; Crosby, 2000; Wang, 2013). Nevertheless, in recent years a few papers emerged quantifying the impact of *green* innovation on economic performance and its role in facilitating the green transition (Dechezleprêtre and Kruse, 2022; Acemoglu et al., 2020; Fernandes et al., 2021; Töbelmann and Wendler, 2020).

The relationship between innovation and economic growth has been a central focus of economic research for decades. Early work, like the endogenous growth theory by Romer (1990), highlights how technological innovation drives long-term growth by boosting productivity and creating new industries. Empirical evidence, such as the meta-analysis by Bloom et al. (2020), supports the idea that innovation, especially through research and development, leads to productivity gains and economic expansion. Different types of innovation, including technological and organizational, are noted for their positive impacts on growth (Griffith et al. (2006) and Aghion et al. (2005)). However, this relationship can be complex, influenced by factors like institutional frameworks, market conditions, and human capital. Overall, innovation is critical for enhancing productivity and advancing economic growth (see for example Acemoglu et al. (2012)).

From a narrower perspective, the relationship between green innovation and economic growth has been a topic of increasing interest among researchers and policymakers alike. A few studies have explored this dynamic interaction, seeking to understand the extent to which investments in green technologies and sustainability initiatives at the macro- and micro-levels contribute to economic prosperity. For example, from a macro perspective, Acemoglu et al. (2012) introduce endogenous and directed technical change in a growth model with environmental constraints and find that technological innovation is important to address environmental challenges while simultaneously promoting economic development. Fernandes et al. (2021) use aggregate-level data to investigate the impact of sustainable innovation (inventions) and technology diffusion (patent filings) on economic growth via a GMM approach. They conclude that an increase in both green patent filings and inventions results in an increase in environmentally adjusted productivity, and, in turn, this bolsters economic growth. Unlike evidence from theoretical and empirical macro studies, evidence is more mixed at the micro-level. On one hand, Hart and Dowell (2011) argue that adopting green innovations boosts firms' operational efficiencies and provides competitive advantages by offering differentiated products. Similarly, Zhu et al. (2013) show that green innovation practices positively impact financial performance, driving cost savings and market share growth. On the other hand, some studies show mixed or negative results. For example, del Río González (2005) points out that the high costs of green technologies may outweigh benefits, especially for small and medium enterprises (SMEs) with limited resources. Jaffe et al. (2005) note that firms often face barriers such as limited capital or insufficient knowledge about sustainable practices, which hamper the impact of innovation on firm performance. Meanwhile, Lanoie et al. (2011) draw a unique dataset covering around 4,200 facilities in seven OECD countries and find strong support for the effect of climate stringency on green innovation, but no support for the effect of green innovation on business performance.

2.2 Climate Policies and Green Innovation

There is a large and growing literature investigating the effects of climate policies on green innovation, as climate policy gathers significant attention amongst policymakers. For example, Johnstone et al. (2010) examined a panel of OECD countries and found that public policies aimed at developing renewable energy sources[3] play a significant role in stimulating innovation in renewable energy sectors. The effectiveness of these policies varies depending on the specific technologies and their associated power generation costs. Additionally, Nesta et al. (2014) observed in a sample of 27 OECD countries that the interplay between green policies and market competition influences green innovation, with energy policies exerting a stronger effect in more competitive energy markets. Zhang et al. (2022) evaluated the impact of environmental regulatory frameworks in 33 OECD and non-OECD countries using the OECD environmental policy stringency index. They found that an increase in policy stringency positively affects green innovation, especially in geothermal, hydro, and marine energy sectors. Moreover, they highlighted that the effects of policy are amplified in countries with high innovation capacity, economic development, and emission levels. Popp (2019) examines recent empirical findings on climate policies and green innovation, and highlights successful advancements in various technological areas and across diverse countries. The author distinguishes between local and foreign policies as well as different policy instruments. One of his many findings is how supply-side environmental policies, such as R&D support, tend to favor local inventors while demand-side policies might promote foreign innovation. Turning to differences across countries, the author discusses how enhanced technologies for pollution control, like catalytic converters in automobiles, have significantly decreased air pollution in developed nations. Moreover, the affordability of clean energy alternatives such as wind and solar power has reached levels where they can effectively compete with fossil fuels, consequently lowering emissions from the electricity generation sector. Other papers also reach similar findings, see for example Popp et al. (2010), Ambec and Lanoie (2008), Dechezleprêtre and Kruse (2022).

Our climate policy analysis is most similar to the following two cross-country studies by Bettarelli et al. (2023) and Eugster (2021), mostly focusing on OECD countries. Bettarelli et al. (2023) investigate the dynamic response of green innovation to climate change policies across a diverse selection of 40 countries

[3] The authors distinguish between six different types of policies: R&D support; investment incentives (e.g. risk guarantees, grants, low-interest loans); tax incentives (e.g. accelerated depreciation); tariff incentives (e.g. feed-in tariffs); voluntary programs; obligations (e.g. guaranteed markets, production quotas); and, tradable certificates.

and 5 sectors, from 2000 to 2021. They rely on the Environmental Policy Stringency Index (EPS) provided by the OECD as a measure to assess the rigor of nations' climate mitigation policies. They find that a change in the EPS has a positive, albeit delayed, effect on renewable energy patents. The effect is stronger during periods of stronger economic activity, and in sectors with limited financial constraints. Eugster (2021) focuses on estimating the effect of climate mitigation policies as measured by the EPS on patent inventions in clean energy technologies. These effects typically manifested rapidly, within 2 to 3 years following the implementation of the policy changes, and were propelled by notable individual impacts of both market-oriented policies – such as feed-in tariffs and trading schemes – and non-market policies, such as subsidies for research and development or emission limits. Specifically focusing on innovation in the electricity sector, the study reveals a positive overall effect on total innovation, suggesting that the increase in innovation in clean technologies is not counteracted by a reduction in innovation in more polluting technologies. From a policy perspective, these findings underscore the necessity for robust policy initiatives aimed at decisively steering innovation towards clean technologies. However, these papers focus exclusively on the role of domestic policies. Thus, our study expands and complements them by highlighting the role of international climate policies in boosting domestic green innovation, particularly via instilling policy certainty.

2.3 Bridging the two strands of literature and our contributions

In general, the literature on green innovation has been mostly focused on exploring its determinants, mostly climate policies, but little attention has been given to its effects. Only a few papers have addressed both our questions of interest and, drawing on firm-level data from multiple countries, results point to a nuanced picture. In support of the Porter Hypothesis, Ambec and Lanoie (2008) provide empirical evidence demonstrating that climate regulations can incentivize firms to invest in innovation, ultimately resulting in positive economic outcomes. Dechezleprêtre and Kruse (2022) evaluate the impact of the stringency of climate policies on firm-level innovation for a sample of OECD countries, both directly within regulated sectors and indirectly through their supply chain connections, and the impact of innovation on firm-level performance. They do not find that environmental policies reduce or enhance the economic performance of firms through innovation in clean technologies. This supports the notion that past climate policies have not heavily burdened firms' competitiveness and implies that clean innovation efforts may help firms offset potential costs associated with new climate policies. On the other hand, Albrizio et al. (2017) find no significant evidence supporting the Porter Hypothesis for the average firm. Their results indicate that a tightening of climate policies is linked to a short-term increase in productivity growth, particularly in the most technologically-advanced countries. However, these effects diminish as countries approach the global productivity frontier, eventually becoming negligible. Turning to firm-level heterogeneity, the authors find that the most productive firms experience a temporary surge in productivity growth from more stringent climate policies, while less productive ones encounter a slowdown resulting in no significant effects for the average firm. The authors discuss the role of entry and exit of firms and relocation of economic activities in driving this result, and conclude that stringent environmental policies should be implemented with minimum barriers to entry and competition in order to support both economic and environmental outcomes. Finally, Benatti et al. (2023) draw on firm-level data for six Euro-Area countries and find that tightening policies negatively affects the productivity of high-polluting firms more than their less-polluting counterparts. However, among high-polluting firms, larger ones experience positive total factor productivity growth due to better access to financing and higher levels of innovation. Overall, their findings do not strongly support the Porter hypothesis; however, for firms with ample resources and under certain technology support policies, policy tightening can indeed enhance productivity. In sum, the evidence from aggregated firm-level data presents a mixed picture with the Porter Hypothesis holding in larger firms with better access to financing and in more technologically advanced countries, thus suggesting the sensitivity of the results to firm-heterogeneity.

In the spirit of the above mentioned papers, this paper aims to investigate both channels of the Porter Hypothesis (Porter and Linde, 1995), but using *national*-level patenting data as opposed to focusing on firm-level innovation and then aggregating up to the country level, as other studies have done. Note that, while allowing for a more focused understanding of the complex links between climate policies, innovation and economic performance, micro studies are not well suited to quantify the aggregate macroeconomic implications of the green transition. For example, they focus on specific sectors of the economy (e.g. the corporate sector), potentially missing responses by other sectors (e.g. public investment) to green innovation. In this sense, our macroeconomic approach allows us to assess the expected overall impact of an innovation-based climate strategy. From a more technical perspective, our approach focuses on national data and conducts independent analyses for each leg of the Hypothesis for better identification purposes.[4] Moreover, in addition to providing a comprehensive assessment of the Porter hypothesis, our work makes contributions to each of the strands. Our work adds to the economics-strand of the green innovation literature by focusing on the short-to-medium term effects of green innovation on economic activity, comparing its effects to those of other innovations including nongreen and ICT technologies, and distilling the channels through which green innovation effects on economic activity materialize. With respect to the policy strand, we contribute to the literature by: (i) focusing on patent filings in all green technologies, not just renewables; (ii) utilizing a novel dataset on the count of climate policies to leverage its detailed classification of policy instruments, in addition to referring to climate stringency measures (indices for climate policy enforcement) as well; and (iii) exploring the role of international coordination and cooperation in driving green innovation quantitatively.

3 Data

In order to analyze the effects economic impacts and determinants of green innovation, we combine different datasets spanning country-level innovation, economic aggregates, and climate policies.

Patents Data. Patent data is collected from the European Patent Office's (EPO) Worldwide Patent

[4] For example, Dechezleprêtre and Kruse (2022) investigate both strands of the hypothesis simultaneously, by regressing firm-level performance on firm-level innovation that's instrumented by national policy.

Statistical Database (PATSTAT) 2023 Fall Edition. PATSTAT covers patent filings to 92 application authorities worldwide, spanning from 1960–2019, thus reflecting official data.[5] For this paper, we employ patent filings as the proxy for innovation for two key reasons. Firstly, almost half of all patent applications fail to record the country of residence of the inventor(s). This implies inventions will only cover half of all patent applications, whereas patent filings accurately cover all patent applications (Pasimeni, 2019). Secondly, a patent filing is more likely to be associated with economic activity as it indicates the applicant's intention to pursue a profitable activity in the market where they plan to operate (Acemoglu et al., 2020), whereas inventions are a measure of the inventive activity, which is not necessarily related to the economic impact of the invention.[6] As such, the main measure of interest in this paper is technological innovation and deployment proxied by patent filings.[7]

- **Patent Count.** To avoid double counting within a country, we aggregate patent filings at the level of DOCDB families. Such families represent groups of patents covering the same invention within the same country, although they might cover slightly different claims. To situate the patent family in time for the cross-country analysis, we use the earliest filing year across patents in the same family in a given country. Patents for the same invention can also be filed in different countries. A patent's family size indicates the number of application authorities in which a patent has been sought for the same invention (Harhoff et al., 2003). A patent with a lower family size can be indicative of a lower patent value, whereas patents with a greater family size are indicative of higher value patents that likely have a greater economic impact (Haščič et al., 2015).

- **Patent Quality.** To control for patent quality, we proceed in two ways. First, we restrict our analysis to *granted* patent filings which already filters out low(er)-quality patents. Second, we restrict our dataset to patents with a family size of 2 (i.e. filed in at least two application authorities).[8]

- **Green Patents.** Patents are identified as green by referring to their technical classification(s) from the Cooperative Patent Classification (CPC) scheme. Green patents are identified with a Y02 tag, which is a broad classification scheme that identifies patents that are related to climate change mitigation technologies (Angelucci et al., 2018). This class covers selected technologies that (1) control, reduce or prevent anthropogenic emissions of greenhouse gases, or (2) allow adapting to

[5] Given there is an 18-month lag between the earliest application filing date and a filing's publication, and given the Covid shock, we end our analysis in 2019 (inclusive) for data completion purposes.

[6] Within the endogenous growth framework (Romer, 1990), we can conceptualize inventions as the monopoly rent commanded by the research sector, whereas patent filings relate to the degree of product variety in the production function, which drives economic growth.

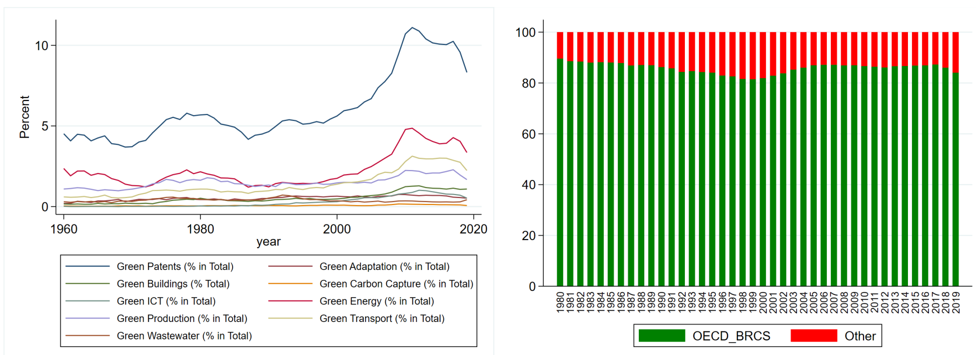
[7] Note that there are two limitations of patents as a gauge of innovation. First, they capture only technological—product and process—innovations, and thus miss organizational and managerial innovations that could result in reduced emissions. Second, they fail to capture innovations that are not patented for strategic reasons.

[8] Some authors in the literature employ the number of forward citations to control for a patent's quality. Whilst the number of forward citations is indicative of a patent's market impact (Harhoff et al., 2003), the count of forward citations must be normalized up to a period (usually 5-7 years), to stop a positive trend for older patents. As it is not possible to use the most recent patent filings, the time dimension of the dataset will be restricted. Harhoff et al. (2003) indicate that forward citations and patent family sizes are positively correlated with patent value, hence we opt to use patent family size to control for quality, and to maximize the time dimension of the panel.

the adverse effects of climate change. Non-green patents are simply total patents at the country-year level less green patents identified by the Y02 tag. Figure 1a plots the evolution of green patents and its eight subcategories as a share of total patents. While there has been an increase in green patent filings since the 1980s, they have hit a plateau/decline in the last few years, which is noticeable across most of its subcategories as well. This recent slowdown in green innovation re-emphasizes the importance of addressing the topics raised in this paper. Finally, part of the analysis compares green patents to patents in the ICT sector. In order to identify ICT patents, we refer to the new taxonomy provided by Inaba and Squicciarini (2017).

Figure 1: Evolution of Green Patents

(a) Green Patents and Subcategories as a share of Total Patents **(b)** Breakdown of Green Patents by Countries



- **Sample.** We focus on patent filings to OECD & BRCS (Brazil, Russia, China and South Africa) economies from 1990–2019, as these 42 countries over the last three decades cover almost 90% of green patent filings as shown in Figure 1b.[9] Furthermore, we set a common minimum year of 1990 to control for application authority inconsistencies prior to 1990 (Haščič et al., 2015).

Economic Data. We obtain real GDP, sectoral value added, and population data from OECD Statistics. We collect data on national total factor productivity and on real investment and its subcomponents (investment in machinery, structures, transport and other) from the Penn World Tables. Macroeconomic variables are deflated to be in 2015 constant USD prices and divided by population to get per capita values for better comparison across countries. Finally, we obtain data on growth expectations from the World Economic Outlook.

Climate policies. In order to estimate the effect of climate policies on green innovation, we rely on two measures of climate policy: the first is the national count of cimate policies provided by the Climate Policy Database; and the second is the stringency of climate policies provided by the Environmental Policy Stringency Index by OECD.

- **Climate Policy Database:** It provides a national count of climate change mitigation policies,

[9] We exclude India from the BRICS economies given incomplete coverage of its patenting records in PATSTAT.

such as greenhouse-gas-emissions-reduction strategies; energy policies that help to decarbonize the energy supply and/or reduce energy demand; and policies that aim to introduce low-emissions practices and technologies to non-energy sectors, such as agriculture and land use. A policy can be a law, a strategic document, a target, or any other policy document that results in a lasting reduction of the country's emissions intensity (see Nascimento et al. (2022)). The main advantage of this measure, which has been used widely in scientific publications, is its comprehensive coverage of countries and policy actions, both from an instrument and sectoral perspective. This is particularly important in a context where countries have often resorted to regulations and subsidies instead of economy-wide carbon pricing.

  - **Policy Instruments.** We split policies into three main categories: (i) "neutral measures", policies which have no impact on the government's budget; (ii) "revenue-based measures", policies which generate revenue for the government's budget; (iii) "expense-measures", policies which incur an expense on the government's budget. We further split neutral policies into regulations and non-regulatory measures; revenue measures into price-based and quantity-based measures; expense measures into feed-in-tariffs & subsidies, and other expense measures.

  One drawback of the policy count dataset is that it does not capture the intensity of each policy. For robustness we also use the OECD's Environmental Policy Stringency Index.

- **Environmental Policy Stringency:** It quantifies the stringency of a country's climate policies. The index has three subcomponents: market-based measures, non-market-based measures, and technological support.

  Figure 2a presents the evolution of the total count of active climate policies and average EPS stringency index for all countries in our sample. We also mark the date of key international climate events, which we will use later in the analysis. These include the IPCC report issuance dates (IPCC1 in 1990, IPCC2 in 1995, Kyoto Protocol in 1997, IPCC3 in 2001, IPCC4 in 2007, IPCC5 in 2013, Paris Agreement in 2015). In Figure 2b, we present the evolution of the three main categories of national climate policies. Figures A1a, A1b and A1c present the evolution of the sub-subcategories of climate policies.

Table 1 presents summary statistics for the policy variables in the analysis. Panel A presents statistics for the aggregate policy variables (CPD and EPS) and Panel B presents statistics for the different policy subcomponents.

4 The Macroeconomic Effects of Green Innovation

This section studies the macroeconomic impact of green innovation. It begins by presenting the econometric strategy used to estimate these effects. Then it presents results for the baseline specification, explores the channels through which green innovation affects economic activity, studies sectoral heterogeneity,

Figure 2: Evolution of Climate Policies

(a) Climate Policies in Count and Stringency

(b) Breakdown of Climate Policies

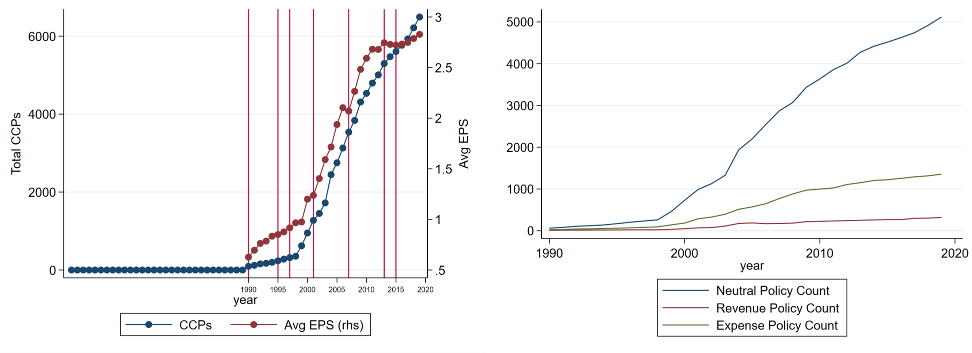


Table 1: Summary Statistics of Policy Variables

Variable	Obs	Mean	Std. dev.	Min	Max
Panel A: Total National Policy in Count and Stringency Measures					
Policy Count Shock	1,049	5.76	6.69	-16	67
Policy Stringency Shock	1,102	0.076	0.23	-0.83	1.5
Panel B: Breakdown of National Policy Count by Instrument					
Neutral Policies Count Shock	1,049	4.53	5.28	-6	58
Regulations Count Shock	1,049	1.93	2.44	-3	24
Other Neutral Policies Count Shock	1,049	2.60	3.47	-8	34
Revenue Policies Count Shock	1,049	0.27	0.74	-4	5
Price-based Revenue Policies Count Shock	1,049	0.17	0.50	-3	4
Quantity-based Revenue Policies Count Shock	1,049	0.10	0.47	-1	3
Expense Policies Count Shock	1,049	1.22	2.40	-13	31
Subsidies & FITs Policies Count Shock	1,049	0.62	1.41	-12	11
Other Expense Policies Count Shock	1,049	0.81	1.82	-7	29
Panel C: Distance-weighted Global Policies					
Distance Weighted Global Policies	1,218	1.37	0.99	0.08	5.04

Source: Climate Policy Database, OECD, Authors' calculations.

compares the impact of green innovation to those observed during previous technological breakthroughs, and addresses endogeneity concerns.

4.1 Empirical Model

We employ an ARDL specification to estimate dynamic effects, leveraging its flexibility to include multiple lags of both dependent and independent variables. This approach helps capture short- and long-run dynamics, control for autocorrelation, and mitigate bias from slow-moving or unobserved confounders. By ensuring temporal ordering and absorbing persistence, ARDL provides a credible strategy for causal inference in non-experimental settings. The baseline regression analysis captures the dynamic impact of new patent filings at time t on real economic activity over multiple horizons, in the spirit of the local projection method proposed by Jordà (2005). The baseline specification is most related to work by Hasna et al. (2021) but with a shifted focus to capturing short- to medium-term effects. The baseline parsimonious specification is as follows:

$$\log(Y_{i,t+h}) - \log(Y_{i,t-1}) = \alpha + \beta_h \log(P_{i,t})^j + \sum_{k=1}^{3} \lambda_{t-k} \log(P_{i,t-k})^j + \sum_{k=2}^{3} \mu_{t-k} \log(Y_{i,t-k}) + \eta_i + \nu_t + \epsilon_{it}; \text{where h} \in [0{:}5], \tag{1}$$

The dependent variable captures the percentage change in annual real GDP per capita in country i between year $t-1$ and year $t+h$. The main independent variable is the logarithm of annual patents per capita of type j where $j \in \{\text{green patents, non-green patents}\}$ in country i in year t. The coefficient β_h represents the effect of a 1 percent change in the flow of patents per capita of type j in country i at time t on real economic activity in country i at time $t+h$ (relative to the pre-shock period). η_i is a country fixed effect which removes baseline differences across countries and accounts for, among other factors, variations in initial levels of technological developments (proxied by patent stocks), economic development, and institutional quality (the latter affects the granting procedure of patents and the implementation of climate policies in each country). Thus accounting for country fixed effects controls for such time-invariant (or slow-moving) country-level characteristics and allows us to better isolate the effects of additional patent flows on economic activity. ν_t is a time fixed effect which controls for global factors such as global climate events, global economic shocks, etc. ϵ_{it} is the idiosyncratic error term. We use robust standard errors to address potential heteroskedasticity concerns.

To ensure consistency, the panel ARDL model requires a sufficient number of lags such that the regressors become weakly exogenous (Chudik et al., 2016). We employ a common lag order of $k = \lfloor T_{Avg}^{\frac{1}{3}} \rfloor$ which results in $k = 3$ for equation 1 (Chudik et al., 2016). Since the impact of green innovation on output growth could be long lasting, the lag order should be long enough, and as such we set p = 3 for all the variables/countries. Given the moderate persistence of growth rates, these lag orders should be sufficient to account for the short-run dynamics. We follow a similar approach to Pesaran and Smith (2014) and Mohaddes and Raissi (2014) and omit control variables in the baseline specification in favor of a parsimonious model; this allows the model to capture both the direct and indirect effects of innovation on economic growth, as opposed to the *ceteris paribus* relationship.

For robustness purposes, we subsequently address potential omitted variable concerns by adding controls covering potential correlation between green and non-green innovation, growth expectations, and changes in the nation-wide count of climate policies. While this structure already offers strong identification, we complement it with an instrumental variable (IV) analysis to address any endogeneity concerns and further strengthen the robustness of our findings. All robustness exercises are discussed in detail in section 4.4.

Finally, we use local projection methods instead of vector autoregressive (VAR) models to estimate equation 1 for two reasons. First, local projection methods are more flexible than VARs as they estimate the equation for each horizon separately, as opposed to VARs that estimate the entire system at once. Second, local projections are more robust to potential misspecification arising from omitted variable bias (for more on this, see also Plagborg-Møller and Wolf (2021); Leduc and Wilson (2013)).

4.2 Results

Figure 3 shows the estimated effects of green innovation on real economic activity. Results, represented by the green impulse response function, show that an increase in the flow of green innovation – i.e. an acceleration in green patent filings – boosts real economic activity in a hump-shaped pattern, with effects peaking after three years. In particular, a 1 percent increase in green innovation increases GDP by 0.021 percent within three years, and 0.017 percent within five. To fix ideas, this implies that a one-off doubling of green patent filings (i.e. a 100 percent increase) boots real GDP by 2.1 percent in three years, and 1.7 percent in five years according to the parsimonious specification.

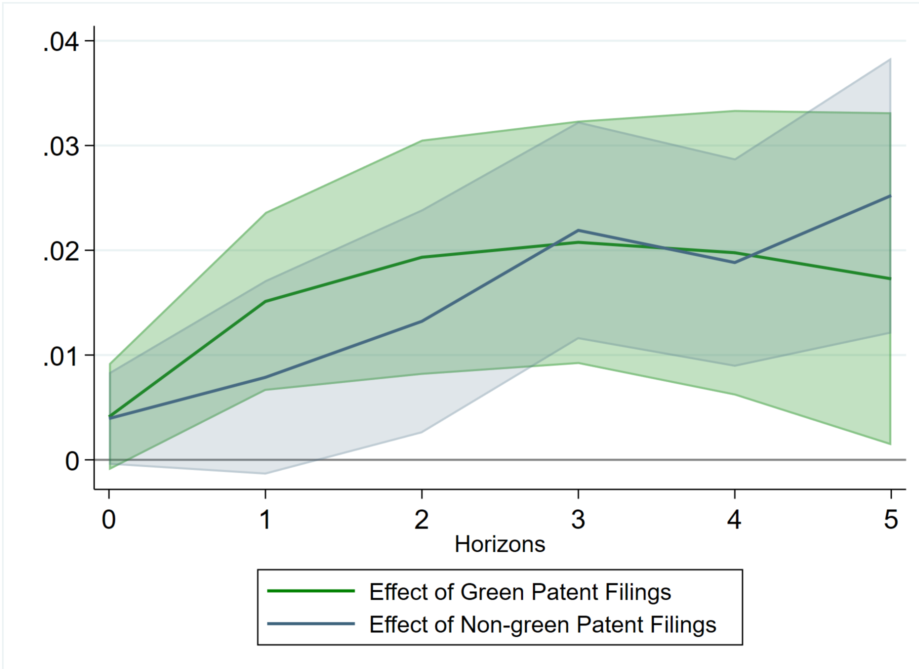
To better understand the effect green innovation has on economic activity, we compare its impacts to those of non-green innovation. The blue impulse response function of Figure 3 shows the results of regressing changes in real economic activity on contemporaneous changes in non-green patent filings. Economic effects of non-green innovation are quantitatively similar to those of green innovation but reveal a slightly different timing. Non-green innovation has positive and significant effects materializing within two years, and they exhibit an almost monotonously increasing effect, with a peak within five years. More importantly, the confidence bounds of the two impulse response functions are similar, suggesting that the effects of green and non-green innovation on economic activity are not significantly different from each other. This dual result of: (1) pro-growth effects of green innovation, and (2) green innovation's effects not necessarily less than those of non-green innovation, is quite helpful in mitigating some of the concerns regarding the economic activity costs associated with the green transition.

4.3 Additional Results

4.3.1 Sectoral Heterogeneity

To explore potential differences in the economic impact of green innovation across sectors, we estimate separately the econometric model in specification 1 for the value added per capita of energy intensive and trade exposed (EITE) sectors. These sectors are, presumably, more directly affected by changes in the cost of energy and climate mitigation policies more broadly. Thus, green innovations, through their impact on energy costs and by easing compliance with climate mitigation policies, can have a disproportionate impact on EITE sectors. We build on work by Chateau et al. (2022) and define EITE sectors to be Manufacturing of paper and paper products, Manufacturing of chemicals and chemical

Figure 3: Effects of Green and Non-green Innovation on Real GDP



products, Manufacturing of other non-metallic mineral products, and Manufacturing of basic metals.

Results, presented in Figure 4a, show that, compared to their impact on GDP, green patent filings have a faster and larger positive economic effect on EITE value added (three- to five-fold larger). In line with aggregate results, green patents have a larger impact on EITE value added compared to non-green patent filings, albeit results are not statistically different. This is potentially linked to the role that green technologies can play in increasing efficiency and reducing cost, especially in the energy intensive sectors, which contributes to overall positive effects on real economic activity. This does not preclude the possibility that other channels, such as higher investment, could explain positive impact that green innovation has on EITE sectors' value added (more on this below).

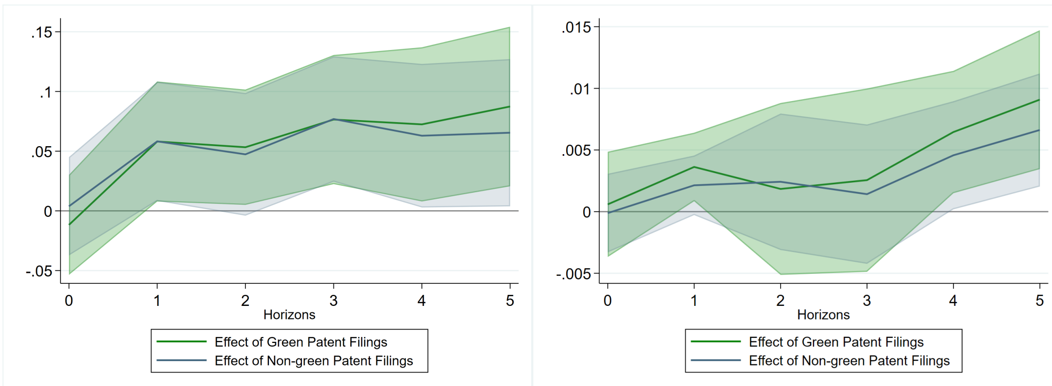
When compared to non-EITE sectors, the patterns remain broadly similar: green patents tend to have slightly larger and more significant effects than non-green patents. However, the magnitude of these effects is notably smaller than in EITE sectors (Figure 4b). This suggests that while green innovation also contributes to cost reduction and efficiency gains in non-EITE sectors, its impact is more limited—consistent with the fact that these sectors are, by definition, less energy intensive and therefore face weaker incentives to adopt energy-saving innovations.

4.3.2 Channels

So far, we have established a positive link between innovation, particularly green, and economic activity. Next, we turn to exploring the channels through which green innovation affects activity. To this end,

Figure 4: Effects of Green and Non-green Innovation on (non)EITE Value Added

(a) Effect on EITE Value Added **(b)** Effect on non-EITE Value Added



we estimate specification (1) for the following dependent variables: investment, investment in machinery, investment in structures (all of which in real per capita terms), and the national total factor productivity index.

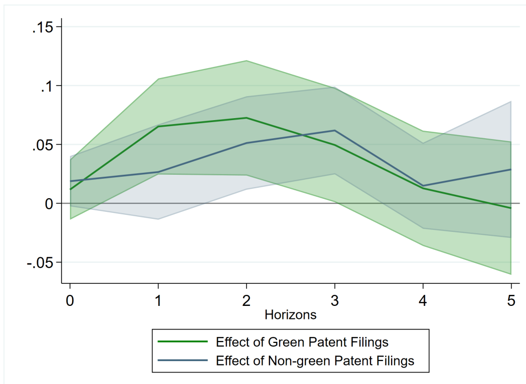
We find that green patents yield a short-term increase in real investment, which is slightly larger than the increase caused by non-green patent filings, albeit non-statistically different (Figure 5a). Moreover, compared to non-green patent filings, green patents have a larger and more significant effect on aggregate and machinery investment in the short run, and investment in structures in the short and medium runs (Figures 5b and 5c, respectively). This confirms that one important channel for green innovation to impact aggregate economic performance is via boosting investment, in addition to potentially increasing efficiency and reducing costs.

However, when turning to aggregate total factor productivity (TFP), our findings suggest that green patent filings do not have a significant effect on TFP over the horizon we study, while non-green patent filings do (Figure 5d). This could reflect two factors. First, in contrast to other types of innovation (including non-green innovation), some green technologies are not directly aiming at increasing productivity; rather they are geared at decarbonization. In this regard, it is not surprising that the effects of green patents on TFP are smaller than those found for non-green patents. Moreover, green innovation could increase productivity over the longer term, as such innovations could improve energy efficiency or reduce the cost of inputs like renewable energy in the medium- to long-term.

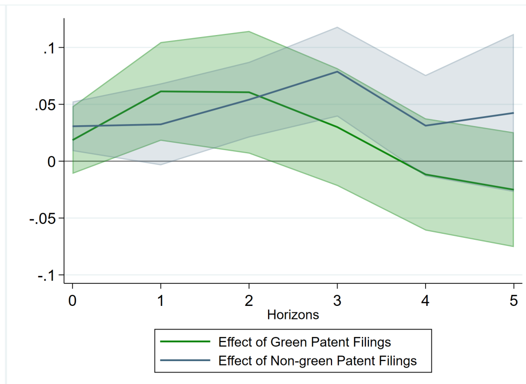
A second potential factor behind the negligible impact of green innovation on TFP is path dependency (see Acemoglu et al. (2016) and Aghion et al. (2016)). Behind path dependency arguments lies the argument that incorporating new technologies may initially disrupt existing production processes, thus reducing potential TFP benefits from these new technologies in the short to medium term. As argued, this does not preclude long-term productivity benefits, once green technologies become more widely adopted. In fact, the experience of past technological breakthroughs suggests that productivity improvements from new technologies materialize over longer horizons, an issue we turn to next.

Figure 5: Channels of Transmission

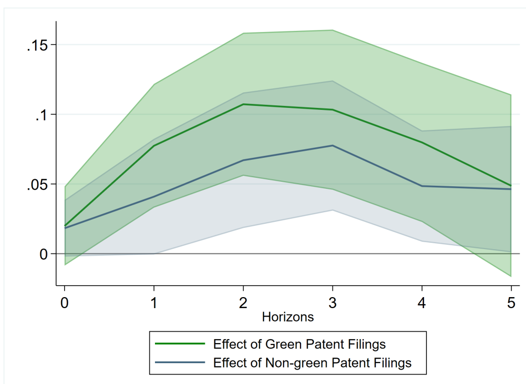
(a) Effect on Investment



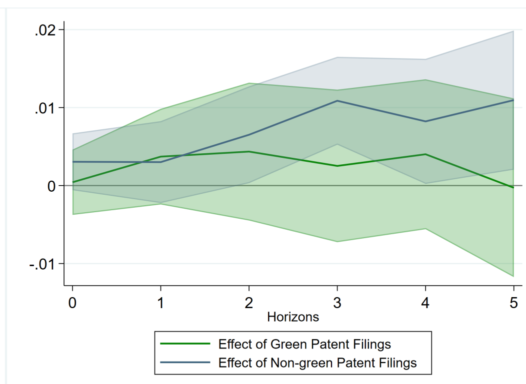
(b) Effect on Investment in Machinery



(c) Effect on Investment in Structures



(d) Effect on Total Factor Productivity



4.3.3 Comparison with the ICT Revolution

Note that green technologies are relatively new and the "green transition" is still ongoing, suggesting that the way that these technologies affect the economy may change as they mature. To gain insights about how the relationship between new technologies and the economy evolves, this section focuses on ICT patents, distinguishing between the period when they were first introduced and more recent years, when the technology was more mature.

Studying ICT patents is useful for two reasons. First, they are a relatively recent technological breakthrough with a similar world economic setup to the present, in contrast to comparing green patents to the introduction of electricity or the first auto vehicle. Second, the ICT revolution period is clearly dated to be the decade from 1995 to 2005, whereas other technological breakthroughs might not be as clearly defined.

As such, we update the specification to equation 2 as follows:

$$
\begin{aligned}
\log\left(Y_{i,t+h}\right) - \log\left(Y_{i,t-1}\right) = \alpha + \beta_h \log\left(P_{i,t}\right)^{ICT} + \gamma_h \log\left(P_{i,t}\right)^{ICT} \cdot ICT_{\text{period}} \\
+ \sum_{k=1}^{3} \lambda_{t-k} \log\left(P_{i,t-k}\right)^{ICT} + \sum_{k=2}^{3} \mu_{t-k} \log\left(Y_{i,t-k}\right) + \eta_w e + \nu_t + \epsilon_{it}
\end{aligned}
\tag{2}
$$

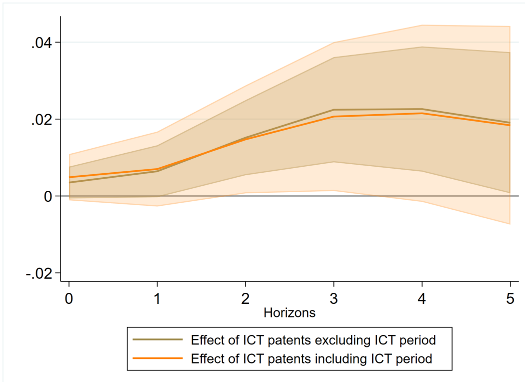
where we identify ICT patents based on the new taxonomy provided by Inaba and Squicciarini (2017) and ICT_{period} is a dummy variable taking value one if the year is between 1995 and 2005. The interaction of the log flow of ICT patents with the ICT period dummy will capture the *marginal effect* of ICT patents on the macroeconomic variables of interest during the ICT period. This will help us better understand the transition costs associated with the adoption of ICT technologies. Nevertheless, there are important differences to keep in mind when comparing ICT and green patents. On the one hand, information and communications technologies were general purpose technologies, with potential applications throughout the economy, and were adopted mostly in response to profit motives and increasing efficiency, i.e. they were "demand driven". On the other hand, green technologies are more sector-specific and are being deployed in response to policies that mandate the reduction of carbon-intensive technologies, i.e. they are rather "policy-driven". Nevertheless, green technologies have the potential to affect vast sectors of the economy, as they typically benefit key upstream sectors such as energy and transportation. Dechezleprêtre et al. (2014) argue that green technologies are similar to ICT in that they have strong knowledge spillover effects as measured by the number of citations they receive.

Looking at the effect of ICT patents on GDP, Investment and TFP in Figure 6, a few key results emerge. First, the effect of ICT patents on real economic activity throughout the entire sample is comparable to that of green patents, whereby a 1 percent increase in the ICT patent flow increases real GDP per capita by 0.02 percent in three years. Second, the effect of ICT patents on GDP is almost similar between including or excluding the ICT revolution years [1995-2005]. Third, looking at the channels through which ICT affects economic activity, we find similar results to what we observed with green innovation in Figures 3 and 5. ICT filings initially boosted economic activity primarily through higher investment in structures during the ICT period, whereas TFP gains accumulated more progressively and were not significant during the years of the breakthrough. In fact, the impact on TFP was almost half during the ICT revolution than its average impact over the rest of the sample period. Overall, the findings suggest that technological breakthroughs initially increase economic activity mostly through investment rather than productivity, arguably as a result of transition costs. They also point to potentially higher productivity benefits once the technologies have been incorporated on a larger scale in the economy. Therefore, the green transition seems to be at least as promising as the ICT revolution with expectations of green technologies boosting TFP after they have been brought up to scale and their efficiency gains start materializing.[10]

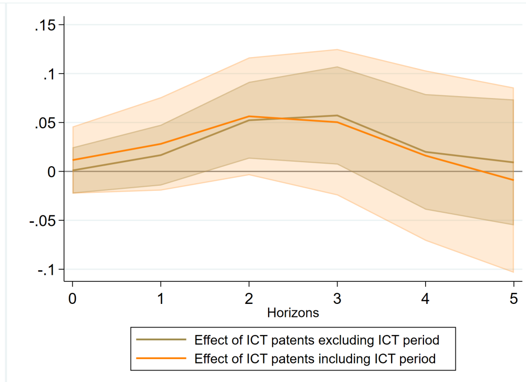
[10] Detailed results on the average and marginal effects are presented in Table B3.

Figure 6: Effects of ICT Patents During ICT Revolution

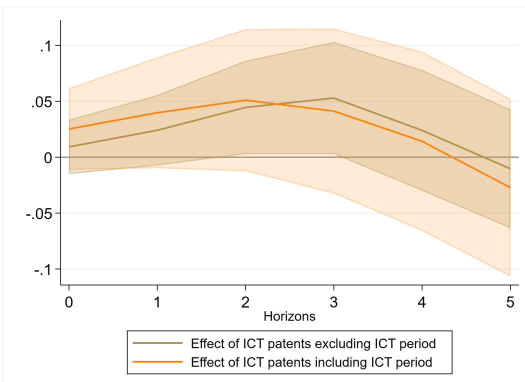
(a) Effect on GDP



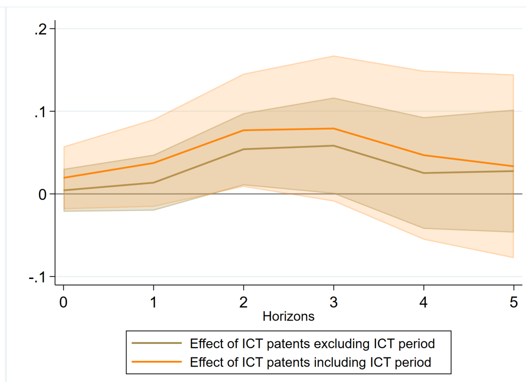
(b) Effect on Investment



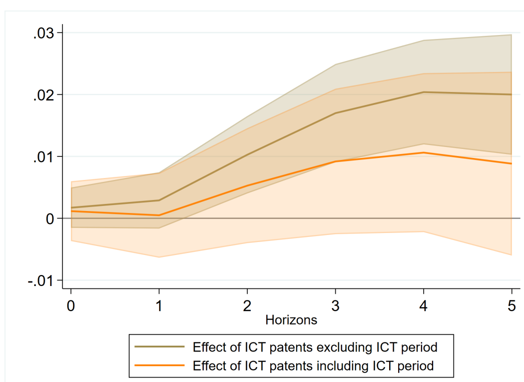
(c) Effect on Investment in Machinery



(d) Effect on Investment in Structures



(e) Effect on Total Factor Productivity



4.4 Robustness of the Main Results to Additional Controls and Instrumental Variables Estimation

To address potential mis-specification in the baseline result, we conduct a battery of robustness checks to the parsimonious specification 1. We find the effects of green innovation being significantly positive and not statistically different from those of non-green innovation to be robust on all accounts.

Correlation between green and non-green innovation. To expand on the role of green patents on economic activity, we modify equation 1 to include the log of total patent filings and control for the share of green patent flow in total patent flow in a given-country year. The idea is that green and non-green patent filings might be correlated as a more prosperous economy might demonstrate higher patent filings in all technologies. In this modified specification, we control for this potential correlation to make sure that the green effects were not just representing omitted effects from non-green innovation. Table B4 shows that a 1 percent increase in total patent filings has a positive, significant and increasing effect on real economic activity reaching up to 0.032. More importantly, the share of green patent flow over total patent flow and its lags are largely insignificant. This implies that, once the total number of patents is accounted for, an increase in the share of green patents over total patents does affect economic performance.[11] This lends support to results from Figure 1 that the effects of green and non-green innovation on economic activity are not statistically different from each other.

Additional controls. We augment the baseline specification to add additional controls whose omission could have led to omitted variable bias. First, we augment the baseline specification by adding a control on growth expectations, proxied by the IMF's World Economic Outlook October forecasts. The idea is that growth and patent activity could be affected by unobservable information about the country's future prospects. For example, economic reforms, the discovery of resources, or other factors could shape a country's growth prospects and make patenting more appealing. Ignoring such factors could lead to biases in our estimated coefficients. As shown in Tables B5 and B6, and expected, the inclusion of growth expectations lowers the point estimate of the coefficient for patents; however, the statistical significance of the estimated coefficient remains. Second, in Tables B7 and B8, we add the change in climate policies as reported by the climate policy database as a control. The introduction of climate policies can affect economic performance and shape innovation decisions. Results are similar to the baseline results whereby both types of innovation have a positive significant effect on growth but now with a larger magnitude. This is consistent with policies having a potentially adverse, possibly small, impact on activity, and boosting innovation (more on this in the next section). This enhancement also manifests with non-green innovation potentially due to knowledge spillovers between green and non-green innovation as discussed by Dechezleprêtre et al. (2014) and Noailly and Shestalova (2017). Third, in tables B9 and B10, we add both controls to the specifications and again results are robust. The addition of control variables (separately or simultaneously) serves as a robustness by helping in isolating and highlighting the positive impact of innovation (green or non-green) on real economic activity. Finally, in all exercises, the effects of green patent filings on economic activity are comparable to those of non-green patent filings.

Endogeneity. As discussed above, there are a number of factors that could potentially affect simultaneously growth and patents. Their omission from our baseline specification could lead to biases in our estimated coefficients. As discussed, there are variables that could result in upward biases (e.g., omitting

[11] Alternatively, from the alternative specification that controls for the share of green patents over total, one can calculate the impact of an additional green patent as $share_{green} * (\beta + (1 - share_{green}) * \omega)$, where β is the coefficient for the log of total patents and ω is the coefficient for the contemporaneous value of the green share. Because $share_{green}$ is bounded between zero and one, and given the estimated coefficients in B4, our results suggest that green patents have a positive impact on economic activity over the horizon we consider.

growth expectations), other could lead to downward biases (e.g., omitting climate policies), and for some variables the sign of the bias is a priori uncertain (e.g., the size of global markets). To complement the analysis above, and recognizing the possibility of other factors biasing our estimates, we conduct an instrumental variables exercise that isolates a plausible exogenous source of variation in domestic patent filings. To that end, we instrument green patents in a given country-year with global green patent filings (that is, the sum of all filings in year t excluding those in country i, denoted as rest of the world "RoW", divided by the population of RoW). The idea is that higher green innovation by other countries can signal a larger future global market for green technologies, thus boosting incentives to innovate by local inventors. Tables B11 and B12 present the 2SLS estimates upon instrumenting each innovation type by its respective filings per capita in the rest of the world, and controlling for sufficient lags of GDP, domestic patent filings, RoW patent filings, and change in domestic climate policies. As noticed, 2SLS estimates are more than double the baseline estimates, further stressing the pro-growth effects of green patent filings. The larger coefficient from the 2SLS approach suggests that the omission of variables leading to downward biases in the OLS coefficient outweigh the omission of variables that affect positively both growth and patents. In addition, even with 2SLS, the effect of green patent filings is still not statistically different from that of non-green patent filings, showcasing robustness of the baseline results and findings. Tables B13 and B14 repeat the same exercise but control for growth expectations as well. Results are consistently robust.

5 The Role of Climate Policies in Fostering Green Innovation

Having established that green innovation can be beneficial for the economy beyond its expected climate benefits, the second part of the paper switches focus to studying the role that climate policies play in bolstering green innovation. It begins by presenting the econometric strategy used to estimate these effects. Then it presents additional results including the effect of climate policies on priority filings, heterogeneity in climate policy effects by instrument, and finally the role of international coordination and cooperation. It concludes by presenting a battery of robustness checks for the main result.

5.1 Empirical Model

The empirical setup is very similar to the one described in Section 4.1. Consistent with other studies on the topic, see for example Eugster (2021) and Bettarelli et al. (2023), we also apply local projection methods to capture the dynamic effects of a change in the policy metric in country i and time t on the flow of patents in country i over multiple horizons. The baseline specification is as follows:

$$\log\left(P^j_{i,t+h}\right)-\log\left(P^j_{i,t-1}\right) = \alpha+\beta_h\Delta\text{Policy}_{i,t}+\sum_{k=2}^{3}\lambda_{t-k}P^j_{i,t-k}+\sum_{k=1}^{2}\mu_{t-k}\Delta\text{Policy}_{i,t-k}+\ln(\text{oil})_t+\text{year}+\eta_i+\epsilon_{it} \tag{3}$$

Our dependent variable of interest is green (or total) patent filings at the domestic patenting authority, which include both new innovations and existing innovations in other countries that are later patented at the domestic patenting authority. It is thus both a measure of innovation and of a country's adoption of technologies developed abroad. The main independent variable is the change in the policy metric considered. We consider two policy metrics: the stock of active policies in a given country-year provided by the Climate Policy Database, and the Environmental Policy Stringency index provided by the OECD for a stringency measure. In subsequent exercises, we modify specification 4 to include different types of policy measures, and a global climate policy control by constructing a distance-weighted climate policy variable.

The specification also includes sufficiently many lags of the dependent variable and independent variable in line with what was discussed for equation 1. The specification abstracts from the typical time fixed effects, and includes instead a linear time trend and global oil prices, for two main reasons. First, most countries implement climate policies at similar times, often following key global events (like the Paris Agreement for example), therefore including time fixed effects will absorb much of the variation. Second, the abstraction of time fixed effects allows us to quantify the roles played by global policies, key international climate events, as well as oil prices, in fostering green patent filings. Oil prices are necessary to proxy for global changes in supply and demand for oil, which is a substitute for green technologies. Lower oil prices—as experienced with the fracking revolution in the 2010s—are found to be associated with less green innovation, which reflects fewer incentives for firms to find cheaper, more efficient energy sources and helps explain the observed slowdown in green innovation, as discussed in Aghion et al. (2019) and Hasna et al. (2023).

Different from Eugster (2021) and Bettarelli et al. (2023), the framework contributes to the literature by focusing on a comprehensive measure of green technologies (instead of focusing on renewable energy technologies only) with a particular focus on the differentiated impact of different types of policy measures within the country, as well as on the impact of global policies and key global events in shaping patent filings.

5.2 Results

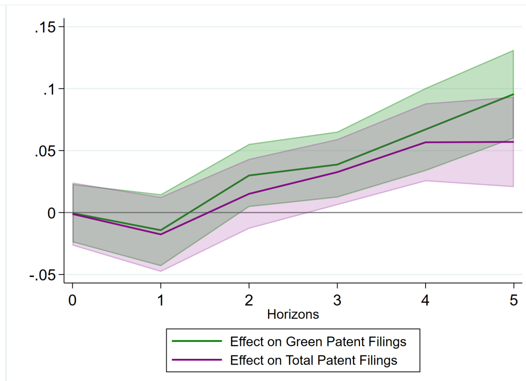
Figure 7 shows that adopting climate-change-mitigating policies is associated with higher green patent filings in the medium term. In particular, Figure 7a demonstrates that a one standard deviation increase in climate policies boosts green patent filings by 2.9 percent in two years and up to 10.3 percent in five years. Note that there are two forces shaping the response plotted in the figure. On the one hand, it will take time for firms to respond to new policies by developing new technologies and filing them. On the other hand,since applications to the domestic patent authority include existing patents in other countries for which patent owners are seeking protection in new markets, there may be a rapid response to new policies. Thus the delayed response depicted in the figure is expected if the former force dominates.

Figure 7a only captures the effect of a change in the climate policy *count*, which might dilute the effect of climate policies if the measure is crowded by numerous, yet less effective, policies. As such, Figure 7b repeats the same analysis for a change in climate policy stringency as measured by the OECD EPS index. It shows that a one standard deviation increase in the index raises green patent filings by 2.5 percent in two years and up to 7.2 percent in five years. The qualitative and quantitative similarity in results affirms that the number of climate policies is an adequate measure of policy effects, even if it does not capture stringency.

Figure 7: Climate Policy and Green Patent Filings

(a) Climate Policy (Count & Stringency) and Green Patent Filings

(b) Climate Policy and Green & Total Patent Filings



One obstacle hindering the adoption of climate policies is its potential adverse effect on the non-green sectors. As such, it is key to understand whether a push for climate policies will advance green technologies at the expense of, or in tandem with, other technologies. The former would signal potential substitutability between high- and low-carbon technologies, while the latter would signal complementarity between green and other technologies. As such, in Figure 7b, we regress changes in total domestic filings on the change in the climate policy count. We show that a one standard deviation increase in the stock of climate policies increases total patent filings by 6.9 percent after five years.

Two points are worth stressing about the link between climate policies and overall patents. First, note that, as expected, the relationship between climate policies and green policies is stronger compared to that of climate policies and overall patents. This provides reassurance that climate policies affect mostly incentives for green/dirty innovation and, indirectly, technologies that complement these technologies. For other technologies, the effects are expected to be negligible. Second, the fact that climate policies lead to greater overall innovation is a point that must be taken into account when quantifying the net economic impact of the green transition.

An increase in overall innovation could result from ongoing parallel research in both high- and low-carbon technologies as carbon-intensive technologies are still widely used in the economy. Or it could reflect the need for complementary non-LCT innovations triggered by the incorporation of new LCTs into upstream sectors of the economy as well as the knowledge spillovers of green innovation to other technology fields, as highlighted by Dechezleprêtre et al. (2017).

5.3 Additional Results

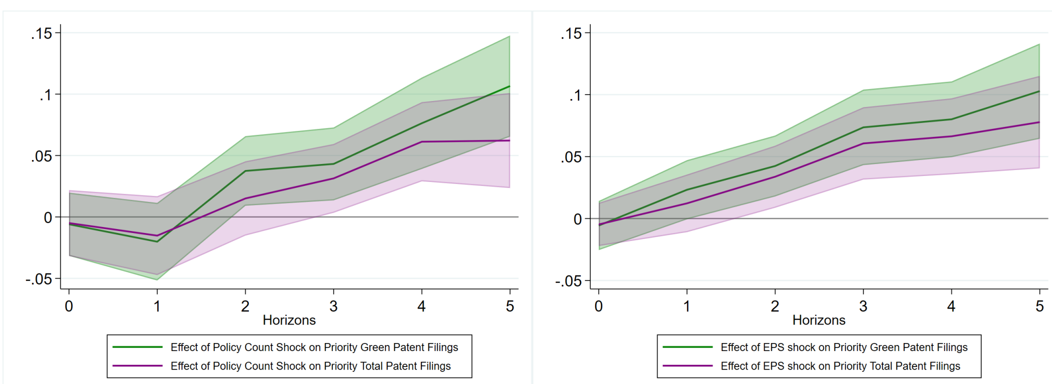
5.3.1 Priority Filings

In this subsection, we explore whether domestic climate policies increase the flow of priority patent filings. Priority filings capture the first filing of an application for a patent. The priority right allows the claimant to file a subsequent application in another country for the same invention as of the date of filing the first application. In this sense, focusing on priority filings allows us to study how newer ideas respond to climate policies.

In Figure 8, we show that the effects of a standard deviation increase in the policy count or stringency on priority filings is very similar to those on overall filings. We repeat the analysis of a policy shock in Figure 9 on the share of priority filings in overall filings for green and total innovation, respectively. In Figure 9a, we show that priority filings increase as a share of overall filings, in both green and total innovation, as a result of a standard deviation increase in domestic policy count. However, looking at policy stringency in Figure 9b, we find that the share of priority filings only increases for green innovation. Meanwhile, the share of priority filings in total innovation does not improve as a result of a rise in environmental policy stringency.

Figure 8: Policy Effects on Levels of Priority Filings in Green and Overall Innovation

(a) Policy Count Shock **(b)** EPS shock

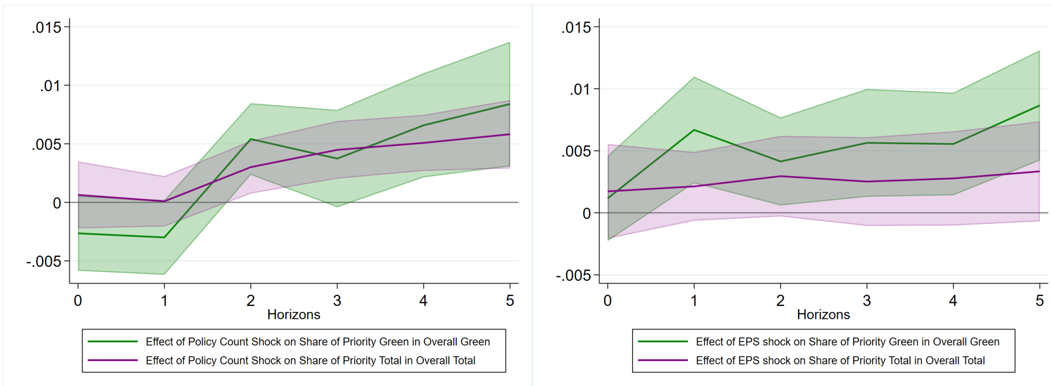


5.3.2 Heterogeneity by Policy Instrument

Countries typically apply a broad range of instruments in their climate policy agenda (see for example, Nascimento et al. (2022) and Linsenmeier et al. (2022)). As such, in order to understand the differential effects of different policy instruments, we leverage the granular information the Climate Policy Database provides about the type of instruments used in each climate policy in a given country-year. By exploiting the database's detailed classification of climatel policies, we classify the policies into three broad categories as a first step: (1) "budget-neutral" policies that do not have a pronounced effect on the government's

Figure 9: Policy Effects on Shares of Priority Filings in Green and Total Innovation

(a) Policy Count Shock **(b)** EPS shock



budget such as regulations; (2) "revenue-generating" policies that generate revenue for the government such as carbon taxes or emission trading schemes; and (3) "expenditure-generating" policies that incur an expense for the government such as subsidies. As a second step, we further divide budget-neutral policies into regulations and other non-regulatory measures (such as targets related to energy efficiency, green house gas emissions, and energy use, among others). We break down revenue-generating policies into quantity measures (such as emissions trading schemes) and price measures (such as carbon taxes). Finally, we break down expenditure-generating measures into two categories: subsidies and feed-in-tariffs, and other expenditure-related measures like direct investments or loans.

Table 2 shows the effect of a policy change in either of the six categories on green patent filings over the medium term. We find that regulations, within the budget-neutral category, are particularly effective at stimulating green patent filings both in the short and medium-run. A one standard deviation increase in the stock of regulations can increase green patent filings by 5 percent four years after the change. Within revenue-generating policies, only quantity-based instruments that limit emissions boost green patent filings by 4.7 percent after four years; meanwhile, evidence on revenue-pricing measures (including carbon taxes and other pricing policies) is still weak. The latter is consistent with findings of other studies ((Eugster, 2021; Bettarelli et al., 2023)), This could be the case for several reasons. First, implementation of carbon taxes has been relatively sporadic until recently, so the relatively short and aggregate nature of the revenue-pricing data employed does not help in generating significant effects of carbon taxes despite theoretical expectations. Second, most of the carbon tax is ultimately borne by consumers and not necessarily firms, which limits the extent to which firms might alter their production processes in the short- to medium-run (Morris and Mathur, 2015). Third, emission trading schemes give clear quantitative guidance which tends to provide more certainty as to where the technology needs to go in terms of reduction in emissions and therefore garner more support from firms as opposed to marginal adjustments to production processes (Parry et al., 2022). Nevertheless, the absence of effect of carbon taxation should not be taken at face value. Emission-trading-schemes are still implicitly imposing a price on carbon, albeit from the quantity channel, which makes the case of the importance of pricing carbon as an environmental policy.

Finally, on the expenditure side, feed-in tariffs and subsidies increase green patents by 5.6 percent in four years, whereas other expenditure measures are not, on average, associated with higher levels of innovation. These results are particularly helpful in understanding which policies are most effective in fostering green patent filings.

Table 2: Breaking Down Effect of Policies on Green Patent Filings by Policy Subcategory

Panel A: Breaking down neutral policies, while controlling for revenue and expense policies						
	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Regulations Count Shock	0.0098*	0.0223***	0.0249***	0.0190***	0.0190**	-0.0155
	[0.0054]	[0.0069]	[0.0068]	[0.0070]	[0.0086]	[0.0123]
Other Neutral Policies Count Shock	-0.0029	-0.0089	0.0086	-0.0011	0.0029	0.0320***
	[0.0040]	[0.0055]	[0.0061]	[0.0059]	[0.0077]	[0.0096]
Panel B: Breaking down revenue policies, while controlling for neutral and expense policies						
	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Price-based Revenue Policies Count Shock	0.0126	-0.0280	-0.1408***	-0.0405	-0.0755*	-0.0941
	[0.0171]	[0.0272]	[0.0423]	[0.0321]	[0.0444]	[0.0665]
Quantity-based Revenue Policies Count Shock	0.0171	0.0455**	0.0636**	0.0809***	0.1000***	0.0942**
	[0.0124]	[0.0201]	[0.0265]	[0.0261]	[0.0321]	[0.0385]
Panel C: Breaking down expense policies, while controlling for neutral and revenue policies						
	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Subsidies & FITs Policies Count Shock	-0.0147**	-0.0081	0.0136	0.0241**	0.0400***	0.0404**
	[0.0066]	[0.0113]	[0.0095]	[0.0098]	[0.0124]	[0.0162]
Other Expense Policies Count Shock	0.0042	-0.0088	-0.0160	-0.0109	-0.0262**	-0.0045
	[0.0058]	[0.0081]	[0.0106]	[0.0095]	[0.0102]	[0.0131]

Notes: This table presents the results of three different specifications investigating the effect of the respective policy subcategory shock on log green patents per capita on the horizon considered. Panel A estimates the effect of regulations and other neutral policies, while controlling for revenue and expenditure measures (see Table C17). Panel B estimates the effect of quantity-based and price-based quantity measures, while controlling for neutral and expenditure measures (see Table C18). Panel C estimates the effect of subsidies & feed-in-tariffs and other expenditure measures, while controlling for neutral and revenue measures (see Table C19). In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

5.3.3 Role of International Coordination and Cooperation

Given the multi-dimensional and multi-country aspect of climate change, this subsection goes beyond domestic policymaking and explores the role of international climate policy in driving domestic green innovation. We do so in two separate exercises. In the first exercise, we identify key dates of global climate events that were critical in the climate policy nexus. These dates include the years of IPCC report issuances since 1990, the Kyoto Protocol, and end with the Paris Agreement (2015). We modify specification 4 by adding a dummy variable for those key events (plus the two-year window succeeding the event) and interacting that dummy with the domestic policy shock in order to capture the marginal effect of these seminal climate events. The specification is as follows:

$$\log\left(P^j_{i,t+h}\right) - \log\left(P^j_{i,t-1}\right) = \alpha + \beta_h \Delta\text{Policy}_{i,t} + \nu_h KD_t * \Delta\text{Policy}_{i,t} + \xi_h KD_t + \sum_{k=2}^{3} \lambda_{t-k} P^j_{i,t-k} + \sum_{k=1}^{2} \mu_{t-k} \Delta\text{Policy}_{i,t-k} + \ln(\text{oil})_t + \text{year} + \eta_i + \epsilon_{it}; \quad (4)$$

where $h \in [0{:}5]$ and KD is a dummy representing key dates.

Table 3 shows that key events almost double the impact of domestic policies on green patent filings over the medium term. This may reflect the fact that climate policy landmarks create more policy certainty about the resolve of governments to embark on the green transition and make climate policies more credible, thus reinforcing their impact on innovation.[12]

Table 3: Effect of Policy Count Shock Around Key Climate Policy Dates

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Policy Count Shock	0.0022	0.0011	0.0046	0.0037	0.0066**	0.0100***
	[0.0029]	[0.0034]	[0.0030]	[0.0027]	[0.0030]	[0.0034]
Interaction of Policy Count Shock with Key Dates	-0.0047	-0.0070*	-0.0003	0.0052	0.0088*	0.0112*
	[0.0030]	[0.0040]	[0.0043]	[0.0044]	[0.0052]	[0.0063]
Key Global Climate Policy Dates	0.1809***	0.2904***	0.0876*	0.0479	-0.0083	-0.0652
	[0.0349]	[0.0501]	[0.0496]	[0.0500]	[0.0596]	[0.0802]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification based on 4 and augmented with an interaction term of the main policy shock with key dates of climate policy. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

In the second exercise, we construct a weighted count of global policies. We follow the method by David et al. (2022) and create a distance-weighted sum of all environmental policies in the rest of the world (excluding the country itself). We add the weighted count of global policies as a control to the regressions that explore the impact of different types of policy instruments presented in Table 2. Table 4 summarizes these exercises (full results are presented in Appendix C). Two key points emerge. First, in the exercises breaking down each policy sub-category at a time,[13] the addition of global policies does not affect the size and significance of most domestic policies, except for weakening the medium-term effect of regulations and non-regulatory revenue-neutral policies (the latter include less binding measures, such as government strategy documents and voluntary emissions- reduction targets).[14] Second, the exercise shows that global

[12] Full results of the specification are presented in Table C22.

[13] As in 2, we estimate three specifications. The first breaks down revenue measures into price measures and quantity measures, while controlling for the overall change in both expenditure and neutral policies, and global policies. The second specification breaks down expenditure measures into subsidies and feed-in-tariffs, and other expenditure-related measures, while controlling for the overall change in both revenue and neutral policies, and global policies. The third specification breaks down neutral policies into regulations and non-regulatory measures, while controlling for the overall change in both revenue and expenditure policies, and global policies

[14] We also construct a trade, import, and export-based weighting counts of climate policies, and results are robust

policies have an even larger effect than domestic policies, whereby a one standard deviation increase in distance-weighted global policies increases domestic patent filings by close to 20 percent after five years.[15]

The significance of global policies for domestic green patenting points to the large potential effect of synchronized global climate action, and this is largely due to two main reasons. First, the "market-size effect" whereby firms respond to policies in the country of their headquarters and in the countries in which they operate given the global nature of value chains and business operations. Beyond contemporaneous considerations, the implementation of climate policies by a greater number of policies increases the revenue potential of green innovations, as these policies could boost future demand for green technologies .Second, "technology spillovers" whereby green patent filings capture and build on inventions from other countries. A larger number of countries implementing climate policies implies a greater stock of green knowledge at the global level through the link between climate policies and green innovation. this, in turn, provides a larger pool of knowledge from which domestic inventors can rely on when developing green technologies.

5.4 Robustness of the Main Result and Instrumental Variation

In the subsection, we test for the robustness of the main result by adding additional controls and implementing an instrumental variables approach.

Additional Controls. We rerun the baseline specification and add growth expectations as a control. Results presented in Table C20 are robust.

Endogeneity. One concern regarding the estimates in Figure 7 is that they might be biased downwards due to possible endogeneity issues. As Bettarelli et al. (2023) discuss, countries with weaker domestic patent filings in green technologies might be more likely to implement climate policies, thus biasing the earlier estimates downwards towards zero. In order to isolate a more plausibly exogenous change in climate policies, we instrument domestic policies with the total number of climate disasters in the world in a given year less the annual number of disasters in the country itself.[16] Table C21 presents the 2SLS results and show that the positive and significant effect of policies on domestic green patent filings is robust, and even stronger, with effects materializing throughout all the horizons considered.

[15] In this specification we include the distance-weighted count of policies abroad and the count of each of the the three domestic policy categories: revenue-generating, expenditure-generating, and budget-neutral policies.

[16] Our instrument is in the spirit of that of Bettarelli et al. (2023) who interact the number of floods worldwide with various country-specific variables capturing exposure to climate disasters (a country's coast line length, the distance between the center of the country and the coast, the number of people affected by natural disasters). We differ on two fronts. First, we count all climate disasters instead of restricting the focus on floods or hurricanes only. Second, we do not interact global disasters with the country characteristics described above, as these characteristics typically penalize small countries (typically vulnerable to climate disasters). Instead we count all disasters, except those of the country in consideration. In our instrument, besides giving more equal weights across countries, we also account for spillover effects across countries, as an increase in the count of disasters elsewhere is still likely to influence global climate policy making which will affect domestic policies in turn.

Table 4: Effect of Different Policy Instruments While Controlling for Global Policies

Panel A: Breaking down neutral policies, while controlling for revenue & expense policies and global policies	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Regulations Count Shock	0.0075	0.0224***	0.0172**	0.0092	0.0093	-0.0343***
	[0.0057]	[0.0075]	[0.0069]	[0.0072]	[0.0089]	[0.0106]
Other Neutral Policies Count Shock	-0.0054	-0.0206***	-0.0063	-0.0139**	-0.0143*	0.0051
	[0.0041]	[0.0058]	[0.0063]	[0.0058]	[0.0079]	[0.0085]
Panel B: Breaking down revenue policies, while controlling for neutral & expense policies and global policies	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Price-based Revenue Policies Count Shock	0.0215	-0.0069	-0.1279***	-0.0305	-0.0693	-0.0465
	[0.0174]	[0.0265]	[0.0416]	[0.0307]	[0.0440]	[0.0635]
Quantity-based Revenue Policies Count Shock	0.0300**	0.0530**	0.0705***	0.0895***	0.1066***	0.1190***
	[0.0128]	[0.0220]	[0.0266]	[0.0258]	[0.0304]	[0.0325]
Panel C: Breaking down expense policies, while controlling for neutral & revenue policies and global policies	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Subsidies & FITs Policies Count Shock	-0.0100	0.0003	0.0193**	0.0295***	0.0436***	0.0502***
	[0.0068]	[0.0109]	[0.0093]	[0.0101]	[0.0115]	[0.0150]
Other Expense Policies Count Shock	0.0015	-0.0127	-0.0177	-0.0122	-0.0262**	-0.0120
	[0.0062]	[0.0088]	[0.0114]	[0.0102]	[0.0102]	[0.0144]
Panel D: Breaking down policies into the three main subcategories and controlling for global policies	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Distance-Weighted Policies	-0.0063	0.0379**	0.1034***	0.1132***	0.1816***	0.2305***
	[0.0133]	[0.0167]	[0.0189]	[0.0200]	[0.0263]	[0.0270]
N	874	834	794	754	716	678

Notes: This table presents the results of four different specifications investigating the effect of the respective policy subcategory shock on log green patents per capita on the horizon considered. Panel A estimates the effect of regulations and other neutral policies while controlling for domestic revenue and expenditure measures as well as distance-weighted global measures (see Table C23). Panel B estimates the effect of quantity-based and price-based quantity measures while controlling for domestic neutral and expenditure measures as well as distance-weighted global measures (see Table C24). Panel C estimates the effect of subsidies & feed-in-tariffs and other domestic expenditure measures while controlling for domestic neutral and revenue measures as well as distance-weighted global measures (see Table C25). Panel D estimates the effect of distance-weighted global measures while controlling for domestic neutral, revenue, and expenditure measures (see Table C26). In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

6 Conclusion

Renewed efforts to stimulate innovation are desperately needed to achieve net zero, especially given the recent green innovation slowdown. This paper contributes to the green innovation literature by providing a comprehensive study of its effects on economic activity and its determinants, particularly by comparing it to other technologies and highlighting the roles of global policies and various domestic policies. Our analysis is connected to two key questions that have been at the center of the policy discussion around climate policies since Porter and Linde (1995)'s seminal work, namely: (i) does green innovation contribute to economic activity? and (ii) do climate policies foster green innovation? This paper provides provides a fresh perspective to these questions by providing a thorough comparison at how the impacts of green innovation differ from those of other innovations, and by exploring how global policies and synchronized policy actions affect green patent filings.

We find that green innovation has a positive and significant effect on economic activity over the medium term that is not statistically distinguishable from the effect of non-green innovation or previous technological breakthroughs like Information Communication Technologies. This finding suggests that green innovation can help alleviate potential short-term economic costs from implementing climate change mitigation policies. We also find that the pro-growth effect of green innovation materializes via higher investment initially, however, it will take time for productivity benefits to accrue.

In terms of stimulating green investment, we find that domestic policies, whether in count or stringency measures, play a significant role in bolstering green innovation over the medium term. Zooming into policy subcategories, we find that regulations, revenue-based measures setting quantity restrictions on emissions, and subsidies & feed-in-tariffs are particularly impactful. The paper also underscores the role of international cooperation and coordination as the effect of domestic policies almost doubles around key climate policy events like the Kyoto Protocol and Paris Agreement, and global policies have an even larger effect in bolstering domestic green patent filings than domestic policies.

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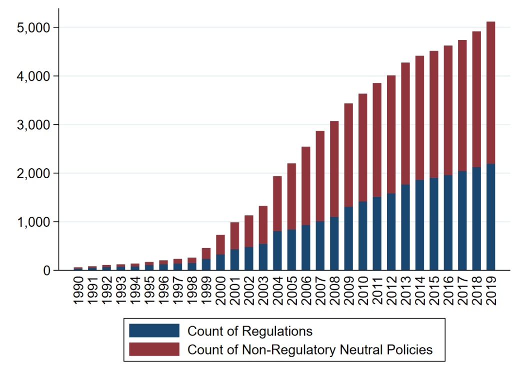
Appendix

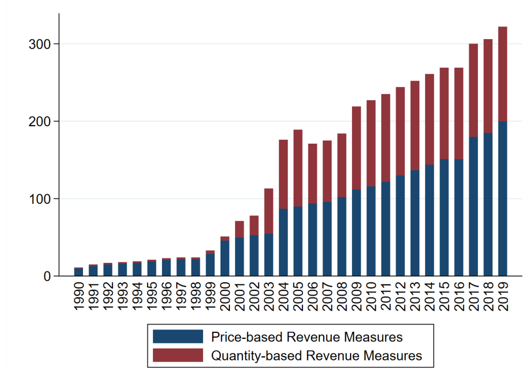
A Additional Data

Figure A1: More Detailed Breakdown of Policy Count

(a) Neutral Policies



(b) Neutral Policies



(c) Neutral Policies

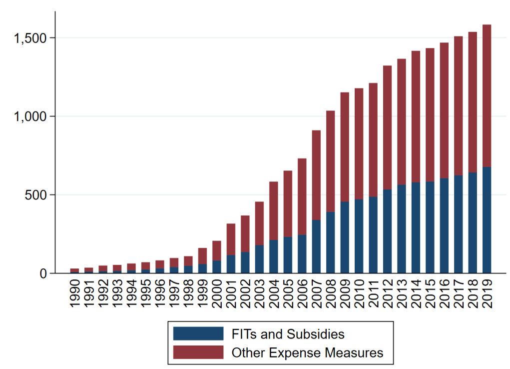
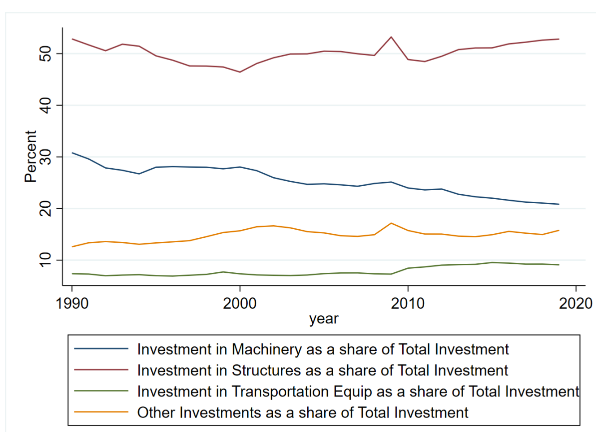


Figure A2: Breakdown of Investment into Subcomponents



B The Macroeconomic Effects of Green Innovation - Additional Results and Robustness

B.1 Parsimonious Results

Table B1: Baseline Effect of Green Patent Filings on Real GDP

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Green Patent Filings pc	0.0041	0.0151***	0.0193***	0.0208***	0.0198**	0.0173*
	[0.0031]	[0.0052]	[0.0068]	[0.0071]	[0.0083]	[0.0097]
Lag 1 - Log Green Patent Filings pc	0.0064	-0.0005	-0.0038	-0.0086	-0.0085	-0.0096
	[0.0058]	[0.0080]	[0.0093]	[0.0102]	[0.0122]	[0.0135]
Lag 2 - Log Green Patent Filings pc	-0.0067	-0.0096	-0.0140	-0.0139	-0.0169	-0.0139
	[0.0046]	[0.0068]	[0.0088]	[0.0115]	[0.0134]	[0.0129]
Lag 3 - Log Green Patent Filings pc	-0.0013	0.0003	0.0043	0.0079	0.0149	0.0195**
	[0.0027]	[0.0047]	[0.0077]	[0.0098]	[0.0092]	[0.0080]
Lag 2 - Log Real GDP pc	0.0320	-0.0094	-0.1069	-0.2473***	-0.4210***	-0.6131***
	[0.0455]	[0.0707]	[0.0863]	[0.0885]	[0.0904]	[0.1007]
Lag 3 - Log Real GDP pc	-0.0706	-0.0701	-0.0167	0.0778	0.2028**	0.3487***
	[0.0443]	[0.0689]	[0.0844]	[0.0876]	[0.0909]	[0.1027]
N	972	935	897	859	821	783

Notes: This table presents the parsimonious specification investigating the effect of log green patent filings per capita on log real GDP per capita on the horizon considered. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B2: Baseline Effect of Non-green Patent Filings on Real GDP

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Non-green Patent Filings pc	0.0039	0.0079	0.0132**	0.0219***	0.0188***	0.0252***
	[0.0027]	[0.0056]	[0.0065]	[0.0063]	[0.0060]	[0.0080]
Lag 1 - Log Non-green Patent Filings pc	-0.0016	-0.0009	0.0021	-0.0103	-0.0014	-0.0112
	[0.0048]	[0.0073]	[0.0085]	[0.0096]	[0.0125]	[0.0130]
Lag 2 - Log Non-green Patent Filings pc	0.0026	0.0043	-0.0056	0.0043	-0.0054	-0.0004
	[0.0052]	[0.0065]	[0.0089]	[0.0117]	[0.0136]	[0.0116]
Lag 3 - Log Non-green Patent Filings pc	-0.0005	-0.0025	0.0041	0.0008	0.0073	0.0092
	[0.0025]	[0.0035]	[0.0062]	[0.0083]	[0.0086]	[0.0072]
Lag 2 - Log Real GDP pc	0.0523	0.0067	-0.1014	-0.2471***	-0.4291***	-0.6083***
	[0.0458]	[0.0695]	[0.0868]	[0.0900]	[0.0920]	[0.1002]
Lag 3 - Log Real GDP pc	-0.0969**	-0.0978	-0.0439	0.0512	0.1847**	0.3208***
	[0.0448]	[0.0676]	[0.0841]	[0.0874]	[0.0907]	[0.1008]
N	992	953	914	875	836	797

Notes: This table presents the parsimonious specification investigating the effect of log nongreen patent filings per capita on log real GDP per capita on the horizon considered. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

B.2 ICT Revolution Period

Table B3: Total Effect of ICT Patent Filings Between 1995-2019 and Marginal Effect Between 1995-2005

Panel A: Aggregate and Marginal Effects of ICT Patent Filings on Real GDP						
	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log ICT Patent Filings pc	0.0035	0.0064	0.0152**	0.0224***	0.0226**	0.0191*
	[0.0025]	[0.0041]	[0.0059]	[0.0083]	[0.0099]	[0.0112]
Interaction of ICT patent flow with ICT period	0.0014	0.0006	-0.0004	-0.0018	-0.0011	-0.0007
	[0.0011]	[0.0018]	[0.0026]	[0.0035]	[0.0041]	[0.0045]
Panel B: Aggregate and Marginal Effects of ICT Patent Filings on Real Total Investment						
	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log ICT Patent Filings pc	0.0010	0.0166	0.0523**	0.0572*	0.0199	0.0092
	[0.0144]	[0.0189]	[0.0239]	[0.0305]	[0.0359]	[0.0391]
Interaction of ICT patent flow with ICT period	0.0106	0.0115	0.0040	-0.0069	-0.0038	-0.0182
	[0.0065]	[0.0101]	[0.0127]	[0.0150]	[0.0170]	[0.0185]
Panel C: Aggregate and Marginal Effects of ICT Patent Filings on Real Investment in Machinery						
	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log ICT Patent Filings pc	0.0092	0.0241	0.0445*	0.0529*	0.0240	-0.0104
	[0.0148]	[0.0192]	[0.0254]	[0.0305]	[0.0329]	[0.0323]
Interaction of ICT patent flow with ICT period	0.0160**	0.0157	0.0065	-0.0117	-0.0097	-0.0168
	[0.0074]	[0.0110]	[0.0132]	[0.0144]	[0.0159]	[0.0160]
Panel D: Aggregate and Marginal Effects of ICT Patent Filings on Real Investment in Structures						
	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log ICT Patent Filings pc	0.0043	0.0136	0.0541**	0.0584*	0.0253	0.0276
	[0.0158]	[0.0206]	[0.0266]	[0.0354]	[0.0411]	[0.0452]
Interaction of ICT patent flow with ICT period	0.0151**	0.0238**	0.0229	0.0208	0.0216	0.0058
	[0.0073]	[0.0117]	[0.0151]	[0.0183]	[0.0211]	[0.0224]
Panel E: Aggregate and Marginal Effects of ICT Patent Filings on TFP						
	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log ICT Patent Filings pc	0.0017	0.0029	0.0103***	0.0170***	0.0204***	0.0200***
	[0.0020]	[0.0028]	[0.0038]	[0.0048]	[0.0051]	[0.0059]
Interaction of ICT patent flow with ICT period	-0.0006	-0.0024*	-0.0050***	-0.0078***	-0.0098***	-0.0112***
	[0.0010]	[0.0014]	[0.0018]	[0.0023]	[0.0027]	[0.0031]
N	909	872	834	796	758	720

Notes: This table presents the results of Equation 2 for different dependent variables: Log of real GDP per capita, log of real investment per capita, log of real investment in structures per capita, log of real investment in machinery per capita, log of total factor productivity. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Estimates of lags are not presented in this table for clarity purposes. Each regression includes state and time fixed effects. Standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1995-2019. N counts the number of country-year observations in each horizon.

B.3 Robustness

B.3.1 Controlling for Correlation between Green and Non-green Patents

Table B4: Robustness to Baseline Effect of Green Patent Filings by Looking at Total Patents and Controling for Share of Green in Total

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Total Patent Filings pc	0.0041	0.0081	0.0132**	0.0217***	0.0182***	0.0248***
	[0.0027]	[0.0054]	[0.0060]	[0.0058]	[0.0057]	[0.0073]
Share of Green Patent Filings in Total Filings	-0.0003	-0.0003	-0.0006	0.0006	0.0034	0.0039
	[0.0006]	[0.0013]	[0.0022]	[0.0023]	[0.0025]	[0.0026]
Lag 1 - Log Total Patent Filings pc	-0.0017	-0.0013	0.0019	-0.0103	-0.0011	-0.0111
	[0.0048]	[0.0069]	[0.0078]	[0.0087]	[0.0114]	[0.0120]
Lag 2 - Log Total Patent Filings pc	0.0026	0.0045	-0.0057	0.0040	-0.0058	-0.0006
	[0.0052]	[0.0061]	[0.0083]	[0.0108]	[0.0126]	[0.0111]
Lag 3 - Log Total Patent Filings pc	-0.0004	-0.0024	0.0042	0.0010	0.0076	0.0095
	[0.0025]	[0.0033]	[0.0060]	[0.0079]	[0.0081]	[0.0070]
Lag 1 - Share of Green Patent Filings in Total Filings	0.0002	-0.0002	0.0007	0.0030	0.0023	0.0016
	[0.0008]	[0.0020]	[0.0024]	[0.0027]	[0.0027]	[0.0031]
Lag 2 - Share of Green Patent Filings in Total Filings	-0.0004	-0.0003	0.0014	-0.0001	-0.0011	-0.0024
	[0.0011]	[0.0016]	[0.0019]	[0.0021]	[0.0025]	[0.0028]
Lag 3 - Share of Green Patent Filings in Total Filings	0.0011	0.0024**	0.0015	0.0010	-0.0000	0.0004
	[0.0008]	[0.0010]	[0.0013]	[0.0016]	[0.0019]	[0.0019]
Lag 2 - Log Real GDP pc	0.0500	0.0030	-0.1005	-0.2424***	-0.4188***	-0.6006***
	[0.0461]	[0.0697]	[0.0872]	[0.0902]	[0.0927]	[0.1017]
Lag 3 - Log Real GDP pc	-0.0942**	-0.0926	-0.0413	0.0518	0.1794**	0.3167***
	[0.0450]	[0.0678]	[0.0845]	[0.0878]	[0.0914]	[0.1015]
N	992	953	914	875	836	797

Notes: This table presents the results of a specification investigating the effect of log total patent filings per capita on log real GDP per capita on the horizon considered while controlling for the share of green patent filings in total patent filings to address potential correlation between green and nongreen patent filings. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the two main independent variables (log total patent filings and share of green in total filings) and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

B.3.2 Controlling for Growth Expectations and/or Change in Policies

Table B5: Robustness to Baseline Effect of Green Patent Filings by Controlling for Growth Expectations

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Green Patent Filings pc	0.0003	0.0094**	0.0130**	0.0147**	0.0149*	0.0134
	[0.0018]	[0.0042]	[0.0060]	[0.0067]	[0.0084]	[0.0099]
Growth Expectations	0.0098***	0.0126***	0.0119***	0.0103***	0.0086***	0.0068***
	[0.0003]	[0.0008]	[0.0012]	[0.0014]	[0.0015]	[0.0015]
Lag 1 - Log Green Patent Filings pc	0.0022	-0.0056	-0.0092	-0.0127	-0.0122	-0.0123
	[0.0027]	[0.0060]	[0.0084]	[0.0102]	[0.0127]	[0.0140]
Lag 2 - Log Green Patent Filings pc	-0.0023	-0.0042	-0.0078	-0.0087	-0.0124	-0.0107
	[0.0026]	[0.0052]	[0.0083]	[0.0120]	[0.0141]	[0.0135]
Lag 3 - Log Green Patent Filings pc	0.0023	0.0054	0.0091	0.0123	0.0185*	0.0226***
	[0.0017]	[0.0044]	[0.0082]	[0.0105]	[0.0099]	[0.0084]
Lag 2 - Log Real GDP pc	-0.0398	-0.0949*	-0.1820**	-0.3122***	-0.4701***	-0.6516***
	[0.0254]	[0.0536]	[0.0744]	[0.0765]	[0.0864]	[0.1021]
Lag 3 - Log Real GDP pc	0.0263	0.0492	0.0923	0.1728**	0.2775***	0.4070***
	[0.0249]	[0.0529]	[0.0731]	[0.0763]	[0.0882]	[0.1058]
N	972	935	897	859	821	783

Notes: This table builds on the baseline specification investigating the effect of log green patent filings per capita on log real GDP per capita by controlling for growth expectations. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B6: Robustness to Baseline Effect of Non-green Patent Filings by Controlling for Growth Expectations

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Non-green Patent Filings pc	0.0013	0.0043	0.0093*	0.0186***	0.0162**	0.0232***
	[0.0012]	[0.0041]	[0.0051]	[0.0061]	[0.0064]	[0.0089]
Growth Expectations	0.0099***	0.0127***	0.0121***	0.0102***	0.0084***	0.0063***
	[0.0003]	[0.0008]	[0.0011]	[0.0014]	[0.0015]	[0.0015]
Lag 1 - Log Non-green Patent Filings pc	-0.0006	0.0002	0.0032	-0.0092	-0.0006	-0.0104
	[0.0018]	[0.0054]	[0.0077]	[0.0102]	[0.0135]	[0.0140]
Lag 2 - Log Non-green Patent Filings pc	0.0013	0.0028	-0.0068	0.0031	-0.0061	-0.0011
	[0.0020]	[0.0052]	[0.0084]	[0.0125]	[0.0146]	[0.0125]
Lag 3 - Log Non-green Patent Filings pc	0.0013	-0.0003	0.0061	0.0027	0.0086	0.0101
	[0.0017]	[0.0035]	[0.0067]	[0.0090]	[0.0092]	[0.0077]
Lag 2 - Log Real GDP pc	-0.0379	-0.1028*	-0.2016***	-0.3323***	-0.4935***	-0.6558***
	[0.0250]	[0.0526]	[0.0749]	[0.0795]	[0.0888]	[0.1022]
Lag 3 - Log Real GDP pc	0.0226	0.0511	0.0958	0.1707**	0.2782***	0.3901***
	[0.0242]	[0.0517]	[0.0725]	[0.0774]	[0.0886]	[0.1047]
N	992	953	914	875	836	797

Notes: This table builds on the baseline specification investigating the effect of log non-green patent filings per capita on log real GDP per capita by controlling for growth expectations. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B7: Robustness to Baseline Effect of Green Patent Filings by Controlling for Change in Environmental Policies

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Green Patent Filings pc	0.0017	0.0173**	0.0306**	0.0407***	0.0472***	0.0500***
	[0.0046]	[0.0082]	[0.0120]	[0.0136]	[0.0107]	[0.0121]
Policy Count Shock	-0.0001	0.0000	-0.0000	0.0001	-0.0001	-0.0004
	[0.0001]	[0.0002]	[0.0002]	[0.0003]	[0.0003]	[0.0003]
Lag 1 - Log Green Patent Filings pc	0.0116	0.0063	-0.0006	-0.0076	-0.0033	0.0049
	[0.0090]	[0.0132]	[0.0174]	[0.0171]	[0.0139]	[0.0134]
Lag 2 - Log Green Patent Filings pc	-0.0044	-0.0074	-0.0086	-0.0027	-0.0034	-0.0057
	[0.0066]	[0.0104]	[0.0125]	[0.0135]	[0.0143]	[0.0140]
Lag 3 - Log Green Patent Filings pc	-0.0029	-0.0009	0.0040	0.0077	0.0131	0.0133
	[0.0036]	[0.0058]	[0.0091]	[0.0109]	[0.0095]	[0.0086]
Lag 2 - Log Real GDP pc	0.0252	-0.0303	-0.1399	-0.3224***	-0.5167***	-0.6840***
	[0.0483]	[0.0809]	[0.1016]	[0.1016]	[0.0947]	[0.1027]
Lag 3 - Log Real GDP pc	-0.0686	-0.0589	0.0036	0.1379	0.2865***	0.4170***
	[0.0470]	[0.0789]	[0.0993]	[0.1001]	[0.0956]	[0.1053]
N	901	864	826	788	750	712

Notes: This table builds on the baseline specification investigating the effect of log green patent filings per capita on log real GDP per capita by controlling for change in environmental policies. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B8: Robustness to Baseline Effect of Non-green Patent Filings by Controlling for Change in Environmental Policies

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Non-green Patent Filings pc	0.0034	0.0093	0.0189**	0.0331***	0.0338***	0.0438***
	[0.0030]	[0.0062]	[0.0082]	[0.0070]	[0.0060]	[0.0047]
Policy Count Shock	-0.0001	0.0000	-0.0000	0.0000	-0.0002	-0.0005
	[0.0001]	[0.0002]	[0.0002]	[0.0003]	[0.0004]	[0.0004]
Lag 1 - Log Non-green Patent Filings pc	0.0001	0.0010	0.0036	-0.0104	-0.0008	-0.0112
	[0.0054]	[0.0081]	[0.0090]	[0.0082]	[0.0085]	[0.0076]
Lag 2 - Log Non-green Patent Filings pc	0.0024	0.0058	-0.0034	0.0086	-0.0007	0.0026
	[0.0055]	[0.0065]	[0.0076]	[0.0078]	[0.0083]	[0.0086]
Lag 3 - Log Non-green Patent Filings pc	0.0007	-0.0019	0.0050	0.0010	0.0069	0.0084
	[0.0027]	[0.0031]	[0.0053]	[0.0065]	[0.0067]	[0.0073]
Lag 2 - Log Real GDP pc	0.0430	-0.0195	-0.1444	-0.3285***	-0.5194***	-0.6593***
	[0.0476]	[0.0777]	[0.0976]	[0.0976]	[0.0944]	[0.1015]
Lag 3 - Log Real GDP pc	-0.0911*	-0.0759	-0.0001	0.1432	0.2999***	0.4101***
	[0.0466]	[0.0761]	[0.0962]	[0.0972]	[0.0953]	[0.1029]
N	921	882	843	804	765	726

Notes: This table builds on the baseline specification investigating the effect of log non-green patent filings per capita on log real GDP per capita by controlling for change in environmental policies. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B9: Robustness to Baseline Effect of Green Patent Filings by Controlling for Change in Policies and Growth Expectations

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Green Patent Filings pc	-0.0008	0.0126*	0.0243**	0.0340***	0.0421***	0.0462***
	[0.0025]	[0.0065]	[0.0104]	[0.0124]	[0.0102]	[0.0119]
Policy Count Shock	-0.0001	0.0000	0.0000	0.0001	-0.0001	-0.0004
	[0.0001]	[0.0002]	[0.0002]	[0.0003]	[0.0004]	[0.0003]
Growth Expectations	0.0098***	0.0126***	0.0116***	0.0094***	0.0072***	0.0052***
	[0.0004]	[0.0008]	[0.0012]	[0.0014]	[0.0015]	[0.0015]
Lag 1 - Log Green Patent Filings pc	0.0030	-0.0050	-0.0127	-0.0164	-0.0103	0.0002
	[0.0036]	[0.0095]	[0.0147]	[0.0158]	[0.0139]	[0.0142]
Lag 2 - Log Green Patent Filings pc	-0.0002	-0.0025	-0.0021	0.0022	0.0005	-0.0034
	[0.0029]	[0.0069]	[0.0111]	[0.0138]	[0.0152]	[0.0147]
Lag 3 - Log Green Patent Filings pc	0.0019	0.0064	0.0106	0.0131	0.0170*	0.0162*
	[0.0018]	[0.0047]	[0.0095]	[0.0116]	[0.0102]	[0.0089]
Lag 2 - Log Real GDP pc	-0.0370	-0.1018*	-0.1975**	-0.3653***	-0.5415***	-0.6992***
	[0.0280]	[0.0603]	[0.0855]	[0.0857]	[0.0874]	[0.1008]
Lag 3 - Log Real GDP pc	0.0220	0.0512	0.0989	0.2125**	0.3365***	0.4503***
	[0.0273]	[0.0596]	[0.0839]	[0.0848]	[0.0888]	[0.1039]
N	901	864	826	788	750	712

Notes: This table builds on the baseline specification investigating the effect of log green patent filings per capita on log real GDP per capita by controlling for change in environmental policies and growth expectations. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B10: Robustness to Baseline Effect of Non-green Patent Filings by Controlling for Change in Policies and Growth Expectations

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Non-green Patent Filings pc	0.0013	0.0062	0.0153**	0.0302***	0.0315***	0.0420***
	[0.0014]	[0.0044]	[0.0062]	[0.0057]	[0.0050]	[0.0048]
Policy Count Shock	-0.0001	-0.0000	-0.0000	0.0000	-0.0002	-0.0005
	[0.0001]	[0.0002]	[0.0002]	[0.0003]	[0.0004]	[0.0004]
Growth Expectations	0.0099***	0.0127***	0.0118***	0.0094***	0.0073***	0.0054***
	[0.0004]	[0.0008]	[0.0012]	[0.0014]	[0.0015]	[0.0015]
Lag 1 - Log Non-green Patent Filings pc	-0.0004	0.0002	0.0031	-0.0107	-0.0012	-0.0111
	[0.0020]	[0.0057]	[0.0076]	[0.0080]	[0.0092]	[0.0083]
Lag 2 - Log Non-green Patent Filings pc	0.0013	0.0046	-0.0043	0.0076	-0.0012	0.0020
	[0.0019]	[0.0048]	[0.0066]	[0.0085]	[0.0092]	[0.0086]
Lag 3 - Log Non-green Patent Filings pc	0.0019	-0.0004	0.0062	0.0021	0.0073	0.0085
	[0.0018]	[0.0031]	[0.0059]	[0.0072]	[0.0072]	[0.0074]
Lag 2 - Log Real GDP pc	-0.0358	-0.1127*	-0.2243***	-0.3888***	-0.5576***	-0.6837***
	[0.0270]	[0.0584]	[0.0828]	[0.0838]	[0.0885]	[0.1001]
Lag 3 - Log Real GDP pc	0.0201	0.0609	0.1222	0.2386***	0.3661***	0.4554***
	[0.0262]	[0.0579]	[0.0820]	[0.0841]	[0.0897]	[0.1021]
N	921	882	843	804	765	726

Notes: This table builds on the baseline specification investigating the effect of log non-green patent filings per capita on log real GDP per capita by controlling for change in environmental policies and growth expectations. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable and second and third lag of the dependent variable. Each regression includes state and time fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

B.3.3 Instrumental Variables Results

Table B11: Robustness to Baseline Effect of Green Patent Filings on Real GDP via 2SLS

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Green Patent Filings pc	0.0110	0.0369*	0.0816**	0.0974**	0.1289**	0.1575**
	[0.0083]	[0.0206]	[0.0400]	[0.0472]	[0.0561]	[0.0678]
Lag 1 - Log Green Patent Filings pc	-0.0008	-0.0188	-0.0562	-0.0687	-0.0878	-0.1027
	[0.0104]	[0.0221]	[0.0395]	[0.0459]	[0.0527]	[0.0610]
Lag 2 - Log Green Patent Filings pc	-0.0015	-0.0024	0.0000	0.0060	0.0095	0.0108
	[0.0074]	[0.0108]	[0.0144]	[0.0136]	[0.0169]	[0.0186]
Lag 3 - Log Green Patent Filings pc	-0.0035	-0.0020	0.0031	0.0072	0.0123	0.0122
	[0.0032]	[0.0060]	[0.0108]	[0.0138]	[0.0125]	[0.0113]
Lag 1 - Log Green Patent Filings pc in RoW	-0.0299*	-0.0510	-0.0663	-0.0998	-0.1395	-0.1523
	[0.0159]	[0.0382]	[0.0672]	[0.0801]	[0.0909]	[0.1032]
Lag 2 - Log Green Patent Filings pc in RoW	0.0137	0.0165	-0.0049	-0.0197	-0.0014	0.0039
	[0.0107]	[0.0209]	[0.0184]	[0.0183]	[0.0246]	[0.0246]
Lag 3 - Log Green Patent Filings pc in RoW	-0.0243*	-0.0492*	-0.0434	-0.0287	-0.0178	-0.0202
	[0.0126]	[0.0288]	[0.0418]	[0.0470]	[0.0582]	[0.0606]
Lag 2 - Log Real GDP pc	0.0179	-0.0485	-0.1714	-0.3623**	-0.5603***	-0.7289***
	[0.0529]	[0.1076]	[0.1398]	[0.1359]	[0.1437]	[0.1740]
Lag 3 - Log Real GDP pc	-0.0750	-0.0684	-0.0044	0.1268	0.2756*	0.4053**
	[0.0508]	[0.1062]	[0.1444]	[0.1395]	[0.1453]	[0.1653]
Policy Count Shock	-0.0001	0.0000	-0.0000	0.0001	-0.0002	-0.0005
	[0.0001]	[0.0002]	[0.0003]	[0.0004]	[0.0005]	[0.0005]
Observations	900	864	826	788	750	712
F-stat CDF	28.90	24.73	36.94	45.74	47.03	47.82
Kleibergen Paap rk Wald F	3.19	3.49	4.67	4.65	4.50	4.66

Notes: This table presents 2SLS results of the baseline specification by instrumenting the log of domestic geen patent filings per capita by the log green patent filings per capita in the rest of the world. It also controls for the change in domestic environmental policy. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable, three lags of the log of patent filings in the rest of the world, and the second and third lags of the dependent variable. Each regression includes state and time fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B12: Robustness to Baseline Effect of Non-green Patent Filings on Real GDP via 2SLS

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Non-green Patent Filings pc	0.0183**	0.0414**	0.0848*	0.1060*	0.1428**	0.1730**
	[0.0088]	[0.0177]	[0.0451]	[0.0533]	[0.0669]	[0.0796]
Lag 1 - Log Non-green Patent Filings pc	-0.0167	-0.0330*	-0.0618	-0.0823	-0.1069*	-0.1378*
	[0.0101]	[0.0181]	[0.0427]	[0.0504]	[0.0629]	[0.0759]
Lag 2 - Log Non-green Patent Filings pc	0.0072	0.0148*	0.0126	0.0257*	0.0253	0.0348
	[0.0047]	[0.0087]	[0.0126]	[0.0141]	[0.0182]	[0.0246]
Lag 3 - Log Non-green Patent Filings pc	0.0001	-0.0031	0.0033	-0.0005	0.0041	0.0061
	[0.0033]	[0.0037]	[0.0061]	[0.0070]	[0.0073]	[0.0083]
Lag 1 - Log Non-green Patent Filings pc in RoW	-0.0425*	-0.0703	-0.0780	-0.1377	-0.1874	-0.2151
	[0.0228]	[0.0483]	[0.0797]	[0.1018]	[0.1187]	[0.1510]
Lag 2 - Log Non-green Patent Filings pc in RoW	0.0288**	0.0501**	0.0130	0.0117	0.0450	0.0688*
	[0.0138]	[0.0205]	[0.0268]	[0.0298]	[0.0399]	[0.0388]
Lag 3 - Log Non-green Patent Filings pc in RoW	-0.0209	-0.0549	-0.0344	-0.0086	-0.0000	-0.0039
	[0.0164]	[0.0348]	[0.0484]	[0.0573]	[0.0773]	[0.0918]
Lag 2 - Log Real GDP pc	0.0110	-0.0927	-0.2985*	-0.5142***	-0.7831***	-0.9703***
	[0.0544]	[0.1076]	[0.1598]	[0.1642]	[0.1976]	[0.2201]
Lag 3 - Log Real GDP pc	-0.0724	-0.0315	0.1122	0.2770	0.5076**	0.6629***
	[0.0508]	[0.1046]	[0.1661]	[0.1764]	[0.2180]	[0.2443]
Policy Count Shock	-0.0000	0.0001	0.0001	0.0001	-0.0001	-0.0004
	[0.0001]	[0.0002]	[0.0004]	[0.0004]	[0.0005]	[0.0005]
Observations	920	882	843	804	765	726
F-stat CDF	12.83	12.86	18.83	20.74	19.85	19.36
Kleibergen Paap rk Wald F	3.45	3.61	3.95	4.05	3.92	4.00

Notes: This table presents 2SLS results of the baseline specification by instrumenting the log of domestic non-green patent filings per capita by the log non-green patent filings per capita in the rest of the world. It also controls for the change in domestic environmental policy. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable, three lags of the log of patent filings in the rest of the world, and the second and third lags of the dependent variable. Each regression includes state and time fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B13: Robustness to Baseline Effect of Green Patent Filings on Real GDP via 2SLS and Both Controls

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Green Patent Filings pc	0.0055	0.0278	0.0635*	0.0853*	0.1201**	0.1519**
	[0.0049]	[0.0188]	[0.0351]	[0.0457]	[0.0547]	[0.0665]
Policy Count Shock	-0.0001	0.0000	0.0000	0.0001	-0.0001	-0.0005
	[0.0001]	[0.0002]	[0.0003]	[0.0004]	[0.0005]	[0.0005]
Growth Expectations	0.0097***	0.0124***	0.0110***	0.0085***	0.0059***	0.0035*
	[0.0003]	[0.0008]	[0.0010]	[0.0014]	[0.0017]	[0.0017]
Lag 1 - Log Green Patent Filings pc	-0.0044	-0.0229	-0.0541	-0.0696	-0.0883*	-0.1026*
	[0.0056]	[0.0209]	[0.0354]	[0.0447]	[0.0510]	[0.0592]
Lag 2 - Log Green Patent Filings pc	0.0015	0.0009	0.0035	0.0091	0.0118	0.0117
	[0.0029]	[0.0065]	[0.0108]	[0.0116]	[0.0154]	[0.0175]
Lag 3 - Log Green Patent Filings pc	0.0017	0.0056	0.0098	0.0126	0.0159	0.0144
	[0.0017]	[0.0059]	[0.0119]	[0.0148]	[0.0132]	[0.0121]
Lag 1 - Log Green Patent Filings pc in RoW	-0.0067	-0.0193	-0.0426	-0.0829	-0.1247	-0.1437
	[0.0072]	[0.0259]	[0.0580]	[0.0730]	[0.0852]	[0.1011]
Lag 2 - Log Green Patent Filings pc in RoW	0.0033	0.0017	-0.0196	-0.0261	-0.0068	0.0007
	[0.0067]	[0.0111]	[0.0173]	[0.0235]	[0.0247]	[0.0256]
Lag 3 - Log Green Patent Filings pc in RoW	-0.0091	-0.0295	-0.0236	-0.0128	-0.0061	-0.0133
	[0.0061]	[0.0232]	[0.0404]	[0.0455]	[0.0576]	[0.0610]
Lag 2 - Log Real GDP pc	-0.0384*	-0.1108*	-0.2185**	-0.3947***	-0.5760***	-0.7365***
	[0.0212]	[0.0578]	[0.0888]	[0.1004]	[0.1271]	[0.1698]
Lag 3 - Log Real GDP pc	0.0189	0.0436	0.0885	0.1970*	0.3193**	0.4293***
	[0.0188]	[0.0573]	[0.0927]	[0.0990]	[0.1224]	[0.1551]
Observations	900	864	826	788	750	712
F-stat CDF	28.78	24.56	36.21	44.86	46.11	46.76
Kleibergen Paap rk Wald F	3.17	3.47	4.56	4.54	4.39	4.52

Notes: This table presents 2SLS results of the baseline specification by instrumenting the log of domestic green patent filings per capita by the log non-green patent filings per capita in the rest of the world. It also controls for the change in domestic environmental policy and growth expectations. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable, three lags of the log of patent filings in the rest of the world, and the second and third lags of the dependent variable. Each regression includes state and time fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table B14: Robustness to Baseline Effect of Non-green Patent Filings on Real GDP via 2SLS and Both Controls

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Log Non-green Patent Filings pc	0.0050	0.0235*	0.0608*	0.0881*	0.1288**	0.1646**
	[0.0055]	[0.0137]	[0.0359]	[0.0471]	[0.0619]	[0.0773]
Policy Count Shock	-0.0001	0.0000	0.0000	0.0001	-0.0001	-0.0004
	[0.0001]	[0.0002]	[0.0003]	[0.0004]	[0.0005]	[0.0005]
Growth Expectations	0.0098***	0.0124***	0.0111***	0.0085***	0.0059***	0.0035*
	[0.0003]	[0.0007]	[0.0010]	[0.0015]	[0.0019]	[0.0019]
Lag 1 - Log Non-green Patent Filings pc	-0.0045	-0.0179	-0.0417	-0.0674	-0.0953	-0.1306*
	[0.0059]	[0.0136]	[0.0344]	[0.0447]	[0.0584]	[0.0738]
Lag 2 - Log Non-green Patent Filings pc	0.0024	0.0092*	0.0064	0.0209*	0.0219	0.0326
	[0.0022]	[0.0052]	[0.0098]	[0.0119]	[0.0170]	[0.0244]
Lag 3 - Log Non-green Patent Filings pc	0.0018	-0.0011	0.0051	0.0009	0.0048	0.0064
	[0.0012]	[0.0030]	[0.0057]	[0.0074]	[0.0071]	[0.0079]
Lag 1 - Log Non-green Patent Filings pc in RoW	-0.0023	-0.0161	-0.0300	-0.0988	-0.1585	-0.1979
	[0.0077]	[0.0281]	[0.0585]	[0.0853]	[0.1072]	[0.1450]
Lag 2 - Log Non-green Patent Filings pc in RoW	-0.0114*	-0.0013	-0.0366	-0.0246	0.0186	0.0528
	[0.0064]	[0.0144]	[0.0232]	[0.0260]	[0.0374]	[0.0383]
Lag 3 - Log Non-green Patent Filings pc in RoW	0.0013	-0.0278	-0.0078	0.0112	0.0138	0.0047
	[0.0072]	[0.0237]	[0.0385]	[0.0503]	[0.0728]	[0.0897]
Lag 2 - Log Real GDP pc	-0.0441**	-0.1510**	-0.3273***	-0.5316***	-0.7847***	-0.9686***
	[0.0207]	[0.0580]	[0.1113]	[0.1345]	[0.1817]	[0.2176]
Lag 3 - Log Real GDP pc	0.0238	0.0809	0.1920	0.3351**	0.5383***	0.6783***
	[0.0191]	[0.0587]	[0.1190]	[0.1449]	[0.1987]	[0.2364]
Observations	920	882	843	804	765	726
F-stat CDF	12.61	12.60	18.20	20.10	19.17	18.61
Kleibergen Paap rk Wald F	3.43	3.59	3.84	3.95	3.80	3.86

Notes: This table presents 2SLS results of the baseline specification by instrumenting the log of domestic non-green patent filings per capita by the log non-green patent filings per capita in the rest of the world. It also controls for the change in domestic environmental policy and growth expectations. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes three lags of the independent variable, three lags of the log of patent filings in the rest of the world, and the second and third lags of the dependent variable. Each regression includes state and time fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

C The Role of Climate Policies in Fostering Green Innovation - Additional Results and Robustness

C.1 Parsimonious Results

Table C15: Baseline Effect of a Climate Policy Count Shock on Green Patent Filings

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Policy Count Shock	-0.0001	-0.0021	0.0045*	0.0058**	0.0100***	0.0143***
	[0.0021]	[0.0026]	[0.0023]	[0.0024]	[0.0030]	[0.0032]
Log of Oil Prices	0.3470***	0.5936***	0.8886***	1.1347***	1.2726***	0.9822***
	[0.0270]	[0.0399]	[0.0554]	[0.0665]	[0.0829]	[0.1063]
Lag 1 - Policy Count Shock	-0.0048***	0.0004	-0.0017	-0.0004	0.0031	0.0084***
	[0.0012]	[0.0015]	[0.0017]	[0.0022]	[0.0025]	[0.0031]
Lag 2 - Policy Count Shock	0.0035***	0.0054**	0.0059**	0.0072***	0.0112***	0.0233***
	[0.0012]	[0.0023]	[0.0024]	[0.0025]	[0.0030]	[0.0050]
Lag 2 - Log Green Patent Filings pc	0.1802***	0.1374	-0.0926	-0.2686*	-0.4112***	-0.5613***
	[0.0650]	[0.1102]	[0.1146]	[0.1389]	[0.1022]	[0.1393]
Lag 3 - Log Green Patent Filings pc	-0.0952*	-0.1106	-0.0346	-0.0419	-0.0580	-0.0710
	[0.0554]	[0.0786]	[0.0787]	[0.1060]	[0.0910]	[0.0983]
year	-0.0445***	-0.0756***	-0.1031***	-0.1316***	-0.1609***	-0.1541***
	[0.0032]	[0.0057]	[0.0074]	[0.0084]	[0.0110]	[0.0161]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification investigating the effect of policy count shock on log green patents per capita on the horizon considered. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table C16: Baseline Effect of a Climate Policy Count Shock on Total Patent Filings

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Policy Count Shock	-0.0002	-0.0026	0.0023	0.0049**	0.0085***	0.0085**
	[0.0023]	[0.0027]	[0.0026]	[0.0024]	[0.0029]	[0.0033]
Log of Oil Prices	0.3574***	0.5819***	0.8378***	1.0311***	1.1351***	0.7698***
	[0.0337]	[0.0528]	[0.0729]	[0.0950]	[0.1255]	[0.1352]
Lag 1 - Policy Count Shock	-0.0047***	-0.0017	-0.0028	-0.0012	-0.0018	0.0042
	[0.0013]	[0.0020]	[0.0023]	[0.0030]	[0.0038]	[0.0032]
Lag 2 - Policy Count Shock	0.0020	0.0048*	0.0054*	0.0028	0.0072***	0.0185***
	[0.0015]	[0.0026]	[0.0028]	[0.0031]	[0.0027]	[0.0044]
Lag 2 - Log Total Patent Filings pc	-0.0572	-0.1412	-0.5384***	-0.7795***	-0.8409***	-0.8742***
	[0.1162]	[0.1663]	[0.1248]	[0.1553]	[0.1469]	[0.1289]
Lag 3 - Log Total Patent Filings pc	-0.0483	-0.1649	0.0123	0.1404	0.1762	0.1760
	[0.0693]	[0.1468]	[0.1483]	[0.1588]	[0.1573]	[0.1460]
year	-0.0405***	-0.0668***	-0.0925***	-0.1191***	-0.1510***	-0.1418***
	[0.0034]	[0.0062]	[0.0088]	[0.0112]	[0.0151]	[0.0204]
N	894	854	814	774	734	694

Notes: This table presents the results of a specification investigating the effect of policy count shock on log total patents per capita on the horizon considered. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

C.2 Breakdown into Policy Subcategories

Table C17: Breaking Down Neutral Policies into Regulations and Non-Regulations

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Regulations Count Shock	0.0098*	0.0223***	0.0249***	0.0190***	0.0190**	-0.0155
	[0.0054]	[0.0069]	[0.0068]	[0.0070]	[0.0086]	[0.0123]
Other Neutral Policies Count Shock	-0.0029	-0.0089	0.0086	-0.0011	0.0029	0.0320***
	[0.0040]	[0.0055]	[0.0061]	[0.0059]	[0.0077]	[0.0096]
Revenue Policies Count Shock	0.0171	0.0182	-0.0451*	0.0223	0.0312	0.0507
	[0.0118]	[0.0188]	[0.0234]	[0.0184]	[0.0217]	[0.0363]
Expense Policies Count Shock	-0.0049	-0.0134**	-0.0108*	-0.0014	-0.0069	-0.0075
	[0.0037]	[0.0057]	[0.0064]	[0.0059]	[0.0073]	[0.0110]
Log of Oil Prices	0.3463***	0.5885***	0.8859***	1.1300***	1.2188***	0.8563***
	[0.0291]	[0.0428]	[0.0566]	[0.0680]	[0.0890]	[0.1156]
Lag 1 - Regulations Count Shock	0.0056	0.0129**	0.0123**	0.0089	-0.0201**	-0.0485***
	[0.0037]	[0.0055]	[0.0060]	[0.0069]	[0.0102]	[0.0154]
Lag 2 - Regulations Count Shock	0.0188***	0.0264***	0.0216***	-0.0056	-0.0255**	0.0145
	[0.0046]	[0.0069]	[0.0074]	[0.0084]	[0.0114]	[0.0128]
Lag 1 - Other Neutral Policies Count Shock	-0.0084**	0.0067	-0.0145***	-0.0143**	0.0041	0.0197
	[0.0036]	[0.0062]	[0.0054]	[0.0065]	[0.0084]	[0.0121]
Lag 2 - Other Neutral Policies Count Shock	0.0025	-0.0064	0.0041	0.0232***	0.0322***	0.0289***
	[0.0038]	[0.0052]	[0.0058]	[0.0062]	[0.0080]	[0.0097]
Lag 1 - Revenue Policies Count Shock	-0.0048	-0.0612***	0.0216	0.0422**	0.0788***	0.0958**
	[0.0117]	[0.0232]	[0.0170]	[0.0184]	[0.0302]	[0.0425]
Lag 2 - Revenue Policies Count Shock	-0.0330**	0.0093	-0.0190	0.0038	0.0110	-0.0520
	[0.0165]	[0.0160]	[0.0203]	[0.0258]	[0.0368]	[0.0376]
Lag 1 - Expense Policies Count Shock	-0.0016	-0.0011	0.0023	-0.0007	0.0018	0.0189*
	[0.0034]	[0.0058]	[0.0060]	[0.0061]	[0.0091]	[0.0111]
Lag 2 - Expense Policies Count Shock	-0.0028	0.0022	0.0015	-0.0010	0.0159**	0.0194*
	[0.0041]	[0.0064]	[0.0054]	[0.0067]	[0.0074]	[0.0107]
Lag 2 - Log Green Patent Filings pc	0.1572**	0.1075	-0.1163	-0.2756**	-0.4050***	-0.5586***
	[0.0650]	[0.1095]	[0.1153]	[0.1384]	[0.1007]	[0.1385]
Lag 3 - Log Green Patent Filings pc	-0.0821	-0.0947	-0.0226	-0.0361	-0.0532	-0.0604
	[0.0543]	[0.0766]	[0.0802]	[0.1051]	[0.0895]	[0.0967]
year	-0.0461***	-0.0776***	-0.1053***	-0.1318***	-0.1526***	-0.1324***
	[0.0032]	[0.0057]	[0.0073]	[0.0085]	[0.0113]	[0.0162]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification investigating the subcategories of neutral policies (regulations vs. non-regulatory neutral) on log green patents per capita on the horizon considered, while controlling for revenue and expenditure measures. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table C18: Breaking Down Revenue Policies into Price-based and Quantity-based

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Price-based Revenue Policies Count Shock	0.0126	-0.0280	-0.1408***	-0.0405	-0.0755*	-0.0941
	[0.0171]	[0.0272]	[0.0423]	[0.0321]	[0.0444]	[0.0665]
Quantity-based Revenue Policies Count Shock	0.0171	0.0455**	0.0636**	0.0809***	0.1000***	0.0942**
	[0.0124]	[0.0201]	[0.0265]	[0.0261]	[0.0321]	[0.0385]
Neutral Policies Count Shock	0.0009	0.0021	0.0112***	0.0071*	0.0134***	0.0186***
	[0.0031]	[0.0038]	[0.0041]	[0.0039]	[0.0051]	[0.0061]
Expense Policies Count Shock	-0.0048	-0.0097*	-0.0096	-0.0023	-0.0050	0.0003
	[0.0036]	[0.0052]	[0.0059]	[0.0060]	[0.0072]	[0.0098]
Log of Oil Prices	0.3356***	0.5805***	0.8928***	1.1647***	1.3294***	1.0705***
	[0.0276]	[0.0418]	[0.0561]	[0.0683]	[0.0856]	[0.1153]
Lag 1 - Price-based Revenue Policies Count Shock	-0.0301	-0.1374***	-0.0192	-0.0313	-0.0588	-0.0824
	[0.0188]	[0.0414]	[0.0278]	[0.0365]	[0.0588]	[0.0835]
Lag 2 - Price-based Revenue Policies Count Shock	-0.0670***	-0.0033	-0.0174	-0.0348	-0.0772	-0.0973**
	[0.0252]	[0.0233]	[0.0317]	[0.0417]	[0.0613]	[0.0488]
Lag 1 - Quantity-based Revenue Policies Count Shock	0.0223*	0.0354*	0.0669***	0.0918***	0.1432***	0.1801***
	[0.0119]	[0.0212]	[0.0211]	[0.0261]	[0.0277]	[0.0360]
Lag 2 - Quantity-based Revenue Policies Count Shock	0.0021	0.0096	-0.0100	0.0124	0.0293	0.0199
	[0.0175]	[0.0187]	[0.0259]	[0.0219]	[0.0276]	[0.0354]
Lag 1 - Neutral Policies Count Shock	-0.0045**	0.0029	-0.0072**	-0.0064*	-0.0056	-0.0025
	[0.0020]	[0.0032]	[0.0028]	[0.0034]	[0.0042]	[0.0055]
Lag 2 - Neutral Policies Count Shock	0.0065***	0.0043	0.0065**	0.0082**	0.0105**	0.0284***
	[0.0023]	[0.0031]	[0.0033]	[0.0035]	[0.0044]	[0.0071]
Lag 1 - Expense Policies Count Shock	0.0002	0.0014	0.0069	0.0064	0.0115	0.0171*
	[0.0033]	[0.0056]	[0.0060]	[0.0059]	[0.0082]	[0.0097]
Lag 2 - Expense Policies Count Shock	0.0000	0.0044	0.0019	0.0014	0.0119*	0.0078
	[0.0038]	[0.0059]	[0.0050]	[0.0067]	[0.0072]	[0.0100]
Lag 2 - Log Green Patent Filings pc	0.1730***	0.1310	-0.1071	-0.2641*	-0.3922***	-0.5441***
	[0.0653]	[0.1102]	[0.1152]	[0.1403]	[0.1020]	[0.1395]
Lag 3 - Log Green Patent Filings pc	-0.0939*	-0.1139	-0.0300	-0.0498	-0.0812	-0.0937
	[0.0557]	[0.0793]	[0.0799]	[0.1066]	[0.0910]	[0.0955]
year	-0.0432***	-0.0726***	-0.1008***	-0.1322***	-0.1635***	-0.1603***
	[0.0032]	[0.0056]	[0.0071]	[0.0084]	[0.0110]	[0.0165]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification investigating the subcategories of revenue policies (price-based vs. quantity-based) on log green patents per capita on the horizon considered, while controlling for neutral and expenditure measures. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table C19: Breaking Down Neutral Expenditure Policies into FITs & Subsidies and Other

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Subsidies & FITs Policies Count Shock	-0.0147**	-0.0081	0.0136	0.0241**	0.0400***	0.0404**
	[0.0066]	[0.0113]	[0.0095]	[0.0098]	[0.0124]	[0.0162]
Other Expense Policies Count Shock	0.0042	-0.0088	-0.0160	-0.0109	-0.0262**	-0.0045
	[0.0058]	[0.0081]	[0.0106]	[0.0095]	[0.0102]	[0.0131]
Neutral Policies Count Shock	0.0001	0.0013	0.0133***	0.0084**	0.0141***	0.0146***
	[0.0031]	[0.0039]	[0.0041]	[0.0039]	[0.0048]	[0.0055]
Revenue Policies Count Shock	0.0213*	0.0209	-0.0506**	0.0138	0.0183	0.0243
	[0.0115]	[0.0194]	[0.0226]	[0.0186]	[0.0225]	[0.0371]
Log of Oil Prices	0.3441***	0.5747***	0.8625***	1.1337***	1.2903***	1.0286***
	[0.0285]	[0.0419]	[0.0555]	[0.0657]	[0.0854]	[0.1126]
Lag 1 - Subsidies & FITs Policies Count Shock	-0.0072	0.0053	0.0123	0.0263***	0.0279**	0.0194
	[0.0074]	[0.0089]	[0.0108]	[0.0096]	[0.0121]	[0.0173]
Lag 2 - Subsidies & FITs Policies Count Shock	0.0026	0.0172	0.0457***	0.0458***	0.0319**	0.0708***
	[0.0071]	[0.0147]	[0.0130]	[0.0146]	[0.0147]	[0.0213]
Lag 1 - Other Expense Policies Count Shock	0.0018	-0.0052	-0.0060	-0.0167*	-0.0113	0.0116
	[0.0059]	[0.0093]	[0.0088]	[0.0098]	[0.0112]	[0.0145]
Lag 2 - Other Expense Policies Count Shock	-0.0028	-0.0066	-0.0253***	-0.0271**	-0.0024	-0.0359**
	[0.0062]	[0.0085]	[0.0090]	[0.0106]	[0.0108]	[0.0173]
Lag 1 - Neutral Policies Count Shock	-0.0044**	0.0059*	-0.0049*	-0.0041	-0.0046	-0.0019
	[0.0020]	[0.0034]	[0.0028]	[0.0034]	[0.0041]	[0.0055]
Lag 2 - Neutral Policies Count Shock	0.0078***	0.0057*	0.0086**	0.0092**	0.0117**	0.0316***
	[0.0023]	[0.0032]	[0.0035]	[0.0037]	[0.0046]	[0.0072]
Lag 1 - Revenue Policies Count Shock	-0.0006	-0.0532**	0.0366**	0.0470**	0.0798**	0.0839*
	[0.0122]	[0.0232]	[0.0178]	[0.0213]	[0.0323]	[0.0442]
Lag 2 - Revenue Policies Count Shock	-0.0365**	0.0063	-0.0158	-0.0025	-0.0094	-0.0286
	[0.0157]	[0.0152]	[0.0195]	[0.0239]	[0.0327]	[0.0332]
Lag 2 - Log Green Patent Filings pc	0.1668**	0.1291	-0.1071	-0.2733*	-0.4065***	-0.5651***
	[0.0650]	[0.1109]	[0.1150]	[0.1401]	[0.1015]	[0.1390]
Lag 3 - Log Green Patent Filings pc	-0.0848	-0.1031	-0.0249	-0.0374	-0.0593	-0.0635
	[0.0555]	[0.0803]	[0.0793]	[0.1065]	[0.0910]	[0.0965]
year	-0.0443***	-0.0746***	-0.1021***	-0.1329***	-0.1640***	-0.1616***
	[0.0032]	[0.0056]	[0.0072]	[0.0083]	[0.0113]	[0.0166]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification investigating the subcategories of expenditure policies (subsidies & feed-in-tariffs vs. other expenditures) on log green patents per capita on the horizon considered, while controlling for neutral and revenue measures. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

C.3 Robustness

C.3.1 Controlling for Growth Expectations

Table C20: Robustness to Baseline Effect of Policy Count Shock on Green Patent Filings by Including Growth Expectations

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Policy Count Shock	-0.0003	-0.0026	0.0036	0.0051**	0.0091***	0.0138***
	[0.0022]	[0.0027]	[0.0024]	[0.0024]	[0.0030]	[0.0032]
Growth Expectations	-0.0084**	-0.0213***	-0.0293***	-0.0258***	-0.0334***	-0.0312***
	[0.0036]	[0.0058]	[0.0053]	[0.0054]	[0.0065]	[0.0084]
Log of Oil Prices	0.3473***	0.5948***	0.8938***	1.1483***	1.3093***	1.0695***
	[0.0270]	[0.0400]	[0.0553]	[0.0667]	[0.0839]	[0.1169]
Lag 1 - Policy Count Shock	-0.0047***	0.0006	-0.0013	-0.0000	0.0036	0.0090***
	[0.0012]	[0.0015]	[0.0017]	[0.0022]	[0.0026]	[0.0031]
Lag 2 - Policy Count Shock	0.0032***	0.0046**	0.0049**	0.0065***	0.0104***	0.0224***
	[0.0012]	[0.0021]	[0.0022]	[0.0022]	[0.0027]	[0.0047]
Lag 2 - Log Green Patent Filings pc	0.1826***	0.1449	-0.0783	-0.2500*	-0.3839***	-0.5275***
	[0.0650]	[0.1101]	[0.1131]	[0.1367]	[0.1008]	[0.1378]
Lag 3 - Log Green Patent Filings pc	-0.1011*	-0.1273*	-0.0593	-0.0662	-0.0890	-0.1021
	[0.0553]	[0.0756]	[0.0768]	[0.1031]	[0.0884]	[0.0944]
year	-0.0448***	-0.0762***	-0.1048***	-0.1344***	-0.1669***	-0.1662***
	[0.0032]	[0.0056]	[0.0074]	[0.0085]	[0.0112]	[0.0175]
N	874	834	794	754	716	678

Notes: This table presents robustness for specification 4 investigating the effect of policy count shock on log green patents per capita on the horizon considered by controlling for growth expectations. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

C.3.2 Instrumental Variables Results

Table C21: Robustness to Baseline Effect of Domestic Policy Count Shock on Green Patent Filings via 2SLS

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Policy Count Shock	0.0296**	0.0928***	0.0705***	0.0889***	0.0739***	0.0584**
	[0.0137]	[0.0255]	[0.0220]	[0.0242]	[0.0218]	[0.0266]
Growth Expectations	-0.0044	-0.0084	-0.0177***	-0.0113	-0.0224***	-0.0264***
	[0.0038]	[0.0078]	[0.0062]	[0.0072]	[0.0066]	[0.0078]
Lag 1 - Policy Count Shock	-0.0103***	-0.0166*	-0.0132**	-0.0150*	-0.0077	0.0019
	[0.0038]	[0.0086]	[0.0067]	[0.0086]	[0.0071]	[0.0072]
Lag 2 - Policy Count Shock	-0.0012	-0.0100*	-0.0059	-0.0062	0.0005	0.0156**
	[0.0028]	[0.0057]	[0.0055]	[0.0051]	[0.0048]	[0.0064]
Lag 2 - Log Green Patent Filings pc	0.1823**	0.0940	-0.1680	-0.3661**	-0.4680***	-0.5751***
	[0.0865]	[0.2035]	[0.1673]	[0.1622]	[0.1407]	[0.1377]
Lag 3 - Log Green Patent Filings pc	-0.0712	-0.0095	0.0425	0.0680	0.0231	-0.0198
	[0.0641]	[0.1706]	[0.1458]	[0.1876]	[0.1577]	[0.1285]
Log of Oil Prices	0.2960***	0.4143***	0.7502***	0.9693***	1.1715***	1.0718***
	[0.0287]	[0.0669]	[0.0745]	[0.0947]	[0.1149]	[0.1253]
Observations	874	834	794	754	716	678
F-stat CDF	20.44	18.47	23.37	22.82	25.07	19.13
Kleibergen Paap rk Wald F	22.87	21.28	23.95	23.71	25.36	21.02

Notes: This table presents 2SLS results of the baseline specification of climate policy shock on green patent filings by instrumenting the domestic policy shock with number of climate disasters in the rest of the world. It also controls for growth expectations. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes two lags of the policy, three lags of the log of green patent filings, log of oil prices and a linear time trend. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

C.4 Key Dates and Global Policies

Table C22: Effect of Policy Count Shock Around Key Climate Policy Dates

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Policy Count Shock	0.0022	0.0011	0.0046	0.0037	0.0066**	0.0100***
	[0.0029]	[0.0034]	[0.0030]	[0.0027]	[0.0030]	[0.0034]
Interaction of Policy Count Shock with Key Dates	-0.0047	-0.0070*	-0.0003	0.0052	0.0088*	0.0112*
	[0.0030]	[0.0040]	[0.0043]	[0.0044]	[0.0052]	[0.0063]
Key Global Climate Policy Dates	0.1809***	0.2904***	0.0876*	0.0479	-0.0083	-0.0652
	[0.0349]	[0.0501]	[0.0496]	[0.0500]	[0.0596]	[0.0802]
Log of Oil Prices	0.4246***	0.7420***	0.9458***	1.1857***	1.3007***	0.9895***
	[0.0319]	[0.0494]	[0.0615]	[0.0700]	[0.0847]	[0.0956]
Lag 1 - Policy Count Shock	-0.0045***	0.0004	-0.0017	-0.0009	0.0022	0.0074**
	[0.0012]	[0.0014]	[0.0017]	[0.0022]	[0.0024]	[0.0030]
Lag 2 - Policy Count Shock	0.0027***	0.0043**	0.0054**	0.0061***	0.0098***	0.0218***
	[0.0010]	[0.0019]	[0.0024]	[0.0023]	[0.0028]	[0.0050]
Lag 2 - Log Green Patent Filings pc	0.1358**	0.1011	-0.0881	-0.2625*	-0.4045***	-0.5553***
	[0.0629]	[0.1033]	[0.1144]	[0.1386]	[0.1020]	[0.1390]
Lag 3 - Log Green Patent Filings pc	-0.0734	-0.0872	-0.0358	-0.0469	-0.0652	-0.0785
	[0.0538]	[0.0748]	[0.0786]	[0.1061]	[0.0905]	[0.0975]
year	-0.0467***	-0.0831***	-0.1072***	-0.1349***	-0.1625***	-0.1546***
	[0.0031]	[0.0058]	[0.0076]	[0.0084]	[0.0107]	[0.0149]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification based on 4 and augmented with an interaction term of the main policy shock with key dates of climate policy. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table C23: Breaking Down Neutral Policies While Controlling for Global Policies

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Regulations Count Shock	0.0075	0.0224***	0.0172**	0.0092	0.0093	-0.0343***
	[0.0057]	[0.0075]	[0.0069]	[0.0072]	[0.0089]	[0.0106]
Other Neutral Policies Count Shock	-0.0054	-0.0206***	-0.0063	-0.0139**	-0.0143*	0.0051
	[0.0041]	[0.0058]	[0.0063]	[0.0058]	[0.0079]	[0.0085]
Revenue Policies Count Shock	0.0244**	0.0218	-0.0446*	0.0228	0.0275	0.0646*
	[0.0119]	[0.0190]	[0.0240]	[0.0184]	[0.0216]	[0.0337]
Expense Policies Count Shock	-0.0031	-0.0104*	-0.0063	0.0034	-0.0022	-0.0002
	[0.0040]	[0.0059]	[0.0063]	[0.0060]	[0.0067]	[0.0099]
Distance-Weighted Policies	0.0049	0.0552***	0.1263***	0.1219***	0.1708***	0.2281***
	[0.0139]	[0.0178]	[0.0207]	[0.0204]	[0.0259]	[0.0288]
Log of Oil Prices	0.2433***	0.2548***	0.5701***	0.8639***	0.9905***	0.3322***
	[0.0352]	[0.0493]	[0.0579]	[0.0679]	[0.0978]	[0.1220]
Lag 1 - Regulations Count Shock	0.0099**	0.0119*	0.0206***	0.0224***	-0.0005	-0.0173
	[0.0043]	[0.0062]	[0.0066]	[0.0072]	[0.0105]	[0.0152]
Lag 2 - Regulations Count Shock	0.0094**	0.0203***	0.0179**	-0.0101	-0.0218*	0.0213*
	[0.0045]	[0.0065]	[0.0071]	[0.0080]	[0.0111]	[0.0110]
Lag 1 - Other Neutral Policies Count Shock	-0.0124***	-0.0019	-0.0229***	-0.0254***	-0.0089	-0.0044
	[0.0036]	[0.0060]	[0.0051]	[0.0062]	[0.0079]	[0.0111]
Lag 2 - Other Neutral Policies Count Shock	-0.0002	-0.0164***	-0.0078	0.0121**	0.0188**	0.0026
	[0.0038]	[0.0051]	[0.0058]	[0.0058]	[0.0078]	[0.0089]
Lag 1 - Revenue Policies Count Shock	-0.0079	-0.0870***	-0.0221	0.0032	0.0157	-0.0103
	[0.0125]	[0.0245]	[0.0199]	[0.0190]	[0.0320]	[0.0411]
Lag 2 - Revenue Policies Count Shock	-0.0392**	-0.0115	-0.0323	-0.0179	-0.0072	-0.0984***
	[0.0168]	[0.0159]	[0.0200]	[0.0258]	[0.0356]	[0.0357]
Lag 1 - Expense Policies Count Shock	-0.0025	-0.0018	-0.0008	-0.0043	-0.0028	0.0160*
	[0.0033]	[0.0056]	[0.0058]	[0.0059]	[0.0086]	[0.0094]
Lag 2 - Expense Policies Count Shock	-0.0023	0.0004	0.0009	-0.0017	0.0128*	0.0116
	[0.0039]	[0.0055]	[0.0053]	[0.0066]	[0.0071]	[0.0091]
Lag 1 - Distance-Weighted Policies	0.0162	0.1405***	0.1009***	0.0757***	0.0955***	0.1698***
	[0.0122]	[0.0216]	[0.0223]	[0.0216]	[0.0256]	[0.0346]
Lag 2 - Distance-Weighted Policies	0.0906***	0.1438***	0.1364***	0.1535***	0.1336***	0.3001***
	[0.0123]	[0.0196]	[0.0233]	[0.0231]	[0.0258]	[0.0314]
Lag 2 - Log Green Patent Filings pc	0.1488**	0.1235	-0.0403	-0.1874	-0.3033***	-0.3993***
	[0.0632]	[0.1071]	[0.1077]	[0.1291]	[0.1076]	[0.1487]
Lag 3 - Log Green Patent Filings pc	-0.0690	-0.0719	-0.0309	-0.0515	-0.0754	-0.1053
	[0.0525]	[0.0726]	[0.0737]	[0.0993]	[0.0905]	[0.0925]
year	-0.0460***	-0.0767***	-0.1094***	-0.1407***	-0.1712***	-0.1506***
	[0.0031]	[0.0052]	[0.0071]	[0.0082]	[0.0115]	[0.0151]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification investigating the subcategories of domestic neutral policies (regulations vs. non-regulatory neutral) on log green patents per capita on the horizon considered, while controlling for domestic revenue and expenditure measures, as well as distance-weighted global measures. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table C24: Breaking Down Revenue Policies While Controlling for Global Policies

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Price-based Revenue Policies Count Shock	0.0215	-0.0069	-0.1279***	-0.0305	-0.0693	-0.0465
	[0.0174]	[0.0265]	[0.0416]	[0.0307]	[0.0440]	[0.0635]
Quantity-based Revenue Policies Count Shock	0.0300**	0.0530**	0.0705***	0.0895***	0.1066***	0.1190***
	[0.0128]	[0.0220]	[0.0266]	[0.0258]	[0.0304]	[0.0325]
Neutral Policies Count Shock	-0.0005	-0.0036	-0.0002	-0.0049	-0.0037	-0.0097**
	[0.0035]	[0.0044]	[0.0046]	[0.0041]	[0.0052]	[0.0049]
Expense Policies Count Shock	-0.0044	-0.0086	-0.0074	-0.0002	-0.0026	0.0028
	[0.0038]	[0.0054]	[0.0059]	[0.0057]	[0.0064]	[0.0090]
Distance-Weighted Policies	-0.0096	0.0286	0.1028***	0.1095***	0.1742***	0.2240***
	[0.0137]	[0.0179]	[0.0194]	[0.0201]	[0.0257]	[0.0274]
Log of Oil Prices	0.2663***	0.3117***	0.6324***	0.9198***	1.0592***	0.4334***
	[0.0350]	[0.0477]	[0.0594]	[0.0694]	[0.0957]	[0.1202]
Lag 1 - Price-based Revenue Policies Count Shock	-0.0237	-0.1314***	-0.0162	-0.0253	-0.0595	-0.0897
	[0.0186]	[0.0399]	[0.0263]	[0.0343]	[0.0538]	[0.0769]
Lag 2 - Price-based Revenue Policies Count Shock	-0.0770***	-0.0153	-0.0183	-0.0433	-0.0717	-0.1167**
	[0.0258]	[0.0225]	[0.0318]	[0.0439]	[0.0633]	[0.0464]
Lag 1 - Quantity-based Revenue Policies Count Shock	0.0150	0.0006	0.0105	0.0333	0.0559*	0.0333
	[0.0136]	[0.0245]	[0.0247]	[0.0276]	[0.0301]	[0.0348]
Lag 2 - Quantity-based Revenue Policies Count Shock	0.0006	-0.0198	-0.0272	-0.0054	0.0093	-0.0211
	[0.0188]	[0.0212]	[0.0258]	[0.0225]	[0.0275]	[0.0343]
Lag 1 - Neutral Policies Count Shock	-0.0042**	-0.0021	-0.0087***	-0.0076**	-0.0069*	-0.0053
	[0.0021]	[0.0033]	[0.0030]	[0.0035]	[0.0036]	[0.0044]
Lag 2 - Neutral Policies Count Shock	0.0008	-0.0040	-0.0026	-0.0013	0.0008	0.0088*
	[0.0022]	[0.0029]	[0.0035]	[0.0032]	[0.0040]	[0.0052]
Lag 1 - Expense Policies Count Shock	0.0003	0.0014	0.0043	0.0033	0.0069	0.0123
	[0.0033]	[0.0055]	[0.0057]	[0.0057]	[0.0079]	[0.0087]
Lag 2 - Expense Policies Count Shock	0.0012	0.0037	0.0030	0.0030	0.0130*	0.0067
	[0.0036]	[0.0053]	[0.0050]	[0.0065]	[0.0068]	[0.0094]
Lag 1 - Distance-Weighted Policies	0.0032	0.1102***	0.0735***	0.0669***	0.0906***	0.1656***
	[0.0129]	[0.0197]	[0.0211]	[0.0203]	[0.0231]	[0.0315]
Lag 2 - Distance-Weighted Policies	0.0869***	0.1391***	0.1263***	0.1342***	0.1241***	0.3052***
	[0.0124]	[0.0201]	[0.0230]	[0.0223]	[0.0246]	[0.0300]
Lag 2 - Log Green Patent Filings pc	0.1594**	0.1442	-0.0409	-0.1838	-0.2953***	-0.3839***
	[0.0637]	[0.1092]	[0.1101]	[0.1326]	[0.1080]	[0.1485]
Lag 3 - Log Green Patent Filings pc	-0.0798	-0.0905	-0.0339	-0.0592	-0.0938	-0.1182
	[0.0537]	[0.0758]	[0.0751]	[0.1023]	[0.0913]	[0.0897]
year	-0.0434***	-0.0723***	-0.1039***	-0.1381***	-0.1739***	-0.1630***
	[0.0031]	[0.0052]	[0.0069]	[0.0082]	[0.0112]	[0.0148]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification investigating the subcategories of domestic revenue policies (price-based vs. quantity-based) on log green patents per capita on the horizon considered, while controlling for domestic neutral and expenditure measures, as well as distance-weighted global measures. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table C25: Breaking Down Expense Policies While Controlling for Global Policies

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Subsidies & FITs Policies Count Shock	-0.0100	0.0003	0.0193**	0.0295***	0.0436***	0.0502***
	[0.0068]	[0.0109]	[0.0093]	[0.0101]	[0.0115]	[0.0150]
Other Expense Policies Count Shock	0.0015	-0.0127	-0.0177	-0.0122	-0.0262**	-0.0120
	[0.0062]	[0.0088]	[0.0114]	[0.0102]	[0.0102]	[0.0144]
Neutral Policies Count Shock	-0.0013	-0.0049	0.0026	-0.0033	-0.0027	-0.0118**
	[0.0035]	[0.0044]	[0.0045]	[0.0039]	[0.0050]	[0.0047]
Revenue Policies Count Shock	0.0313***	0.0329*	-0.0423*	0.0214	0.0215	0.0506
	[0.0119]	[0.0200]	[0.0229]	[0.0186]	[0.0221]	[0.0335]
Distance-Weighted Policies	-0.0054	0.0372**	0.0997***	0.1100***	0.1781***	0.2245***
	[0.0133]	[0.0168]	[0.0188]	[0.0196]	[0.0258]	[0.0266]
Log of Oil Prices	0.2666***	0.2903***	0.5958***	0.8814***	0.9980***	0.3747***
	[0.0359]	[0.0477]	[0.0580]	[0.0682]	[0.0960]	[0.1199]
Lag 1 - Subsidies & FITs Policies Count Shock	-0.0059	0.0080	0.0127	0.0259***	0.0275**	0.0159
	[0.0070]	[0.0084]	[0.0107]	[0.0097]	[0.0116]	[0.0153]
Lag 2 - Subsidies & FITs Policies Count Shock	0.0011	0.0097	0.0371***	0.0379***	0.0228*	0.0440**
	[0.0064]	[0.0126]	[0.0110]	[0.0123]	[0.0125]	[0.0185]
Lag 1 - Other Expense Policies Count Shock	0.0008	-0.0061	-0.0085	-0.0196**	-0.0169	0.0063
	[0.0055]	[0.0091]	[0.0084]	[0.0098]	[0.0111]	[0.0130]
Lag 2 - Other Expense Policies Count Shock	0.0001	-0.0019	-0.0185**	-0.0200*	0.0035	-0.0239
	[0.0061]	[0.0079]	[0.0089]	[0.0104]	[0.0099]	[0.0177]
Lag 1 - Neutral Policies Count Shock	-0.0046**	0.0003	-0.0074***	-0.0062*	-0.0066*	-0.0060
	[0.0021]	[0.0034]	[0.0028]	[0.0034]	[0.0037]	[0.0046]
Lag 2 - Neutral Policies Count Shock	0.0022	-0.0037	-0.0006	-0.0005	0.0016	0.0111**
	[0.0023]	[0.0029]	[0.0036]	[0.0034]	[0.0043]	[0.0054]
Lag 1 - Revenue Policies Count Shock	0.0000	-0.0687***	0.0073	0.0178	0.0262	-0.0005
	[0.0128]	[0.0230]	[0.0182]	[0.0206]	[0.0329]	[0.0409]
Lag 2 - Revenue Policies Count Shock	-0.0430***	-0.0142	-0.0264	-0.0159	-0.0180	-0.0581*
	[0.0160]	[0.0154]	[0.0192]	[0.0246]	[0.0328]	[0.0320]
Lag 1 - Distance-Weighted Policies	0.0081	0.1122***	0.0814***	0.0722***	0.1025***	0.1764***
	[0.0121]	[0.0194]	[0.0209]	[0.0206]	[0.0229]	[0.0315]
Lag 2 - Distance-Weighted Policies	0.0857***	0.1457***	0.1259***	0.1348***	0.1287***	0.3102***
	[0.0122]	[0.0202]	[0.0231]	[0.0221]	[0.0249]	[0.0304]
Lag 2 - Log Green Patent Filings pc	0.1564**	0.1467	-0.0356	-0.1867	-0.2982***	-0.3929***
	[0.0636]	[0.1100]	[0.1101]	[0.1323]	[0.1081]	[0.1482]
Lag 3 - Log Green Patent Filings pc	-0.0719	-0.0840	-0.0339	-0.0525	-0.0797	-0.0989
	[0.0536]	[0.0771]	[0.0745]	[0.1018]	[0.0918]	[0.0907]
year	-0.0445***	-0.0738***	-0.1047***	-0.1383***	-0.1738***	-0.1628***
	[0.0031]	[0.0052]	[0.0071]	[0.0082]	[0.0113]	[0.0149]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification investigating the subcategories of domestic expenditure policies (subsidies & feed-in-tariffs vs. other expenditures) on log green patents per capita on the horizon considered, while controlling for domestic neutral and revenue measures, as well as distance-weighted global measures. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.

Table C26: Breaking Down Policies into Main Subcategories While Controlling for Global Policies

	Impact	Year 1	Year 2	Year 3	Year 4	Year 5
Neutral Policies Count Shock	-0.0007	-0.0050	0.0020	-0.0047	-0.0037	-0.0108**
	[0.0035]	[0.0044]	[0.0047]	[0.0041]	[0.0053]	[0.0047]
Revenue Policies Count Shock	0.0314***	0.0355*	-0.0330	0.0359**	0.0313	0.0564*
	[0.0119]	[0.0197]	[0.0225]	[0.0180]	[0.0216]	[0.0337]
Expense Policies Count Shock	-0.0051	-0.0110**	-0.0095	-0.0016	-0.0048	0.0014
	[0.0037]	[0.0054]	[0.0060]	[0.0054]	[0.0063]	[0.0092]
Distance-Weighted Policies	-0.0063	0.0379**	0.1034***	0.1132***	0.1816***	0.2305***
	[0.0133]	[0.0167]	[0.0189]	[0.0200]	[0.0263]	[0.0270]
Log of Oil Prices	0.2631***	0.2943***	0.6042***	0.8954***	1.0179***	0.3664***
	[0.0350]	[0.0475]	[0.0576]	[0.0685]	[0.0959]	[0.1170]
Lag 1 - Neutral Policies Count Shock	-0.0047**	-0.0001	-0.0085***	-0.0076**	-0.0071*	-0.0057
	[0.0021]	[0.0035]	[0.0029]	[0.0034]	[0.0036]	[0.0044]
Lag 2 - Neutral Policies Count Shock	0.0020	-0.0036	-0.0009	-0.0003	0.0025	0.0106*
	[0.0024]	[0.0030]	[0.0037]	[0.0035]	[0.0043]	[0.0057]
Lag 1 - Revenue Policies Count Shock	0.0014	-0.0698***	0.0011	0.0090	0.0096	-0.0183
	[0.0128]	[0.0221]	[0.0175]	[0.0195]	[0.0313]	[0.0392]
Lag 2 - Revenue Policies Count Shock	-0.0413***	-0.0176	-0.0312*	-0.0261	-0.0327	-0.0702**
	[0.0153]	[0.0150]	[0.0187]	[0.0235]	[0.0320]	[0.0306]
Lag 1 - Expense Policies Count Shock	-0.0014	0.0000	0.0013	0.0009	0.0031	0.0094
	[0.0033]	[0.0055]	[0.0056]	[0.0059]	[0.0082]	[0.0089]
Lag 2 - Expense Policies Count Shock	0.0004	0.0033	0.0063	0.0041	0.0146**	0.0092
	[0.0038]	[0.0055]	[0.0049]	[0.0063]	[0.0069]	[0.0094]
Lag 1 - Distance-Weighted Policies	0.0088	0.1127***	0.0830***	0.0745***	0.1026***	0.1780***
	[0.0119]	[0.0194]	[0.0209]	[0.0203]	[0.0227]	[0.0311]
Lag 2 - Distance-Weighted Policies	0.0872***	0.1450***	0.1258***	0.1341***	0.1234***	0.3078***
	[0.0122]	[0.0203]	[0.0234]	[0.0227]	[0.0252]	[0.0307]
Lag 2 - Log Green Patent Filings pc	0.1577**	0.1487	-0.0285	-0.1844	-0.3019***	-0.3941***
	[0.0636]	[0.1096]	[0.1101]	[0.1320]	[0.1085]	[0.1485]
Lag 3 - Log Green Patent Filings pc	-0.0720	-0.0835	-0.0362	-0.0540	-0.0805	-0.1024
	[0.0537]	[0.0771]	[0.0749]	[0.1017]	[0.0921]	[0.0908]
year	-0.0446***	-0.0738***	-0.1047***	-0.1380***	-0.1735***	-0.1598***
	[0.0031]	[0.0052]	[0.0071]	[0.0083]	[0.0113]	[0.0147]
N	874	834	794	754	716	678

Notes: This table presents the results of a specification investigating the effects of distance-weighted global policies on log green patents per capita on the horizon considered, while controlling for domestic neutral, revenue, and expenditure measures. In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate column. Each column includes logarithm of oil prices, time trend, two lags of the policy shock and the second and third lags of the dependent variable. Each regression includes state fixed effects. Robust standard errors are in brackets below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes OECD countries, as well as Brazil, China, Russia and South Africa, for years 1990-2019. N counts the number of country-year observations in each horizon.