INTERNATIONAL MONETARY FUND

Environmental Policies and Innovation in Renewable Energy

Luca Bettarelli, Davide Furceri, Pietro Pizzuto, and Nadia Shakoor

WORKING PAPER

2023
SEP

WP/23/180

IMF Working Paper

Asia and Pacific Department

Environmental Policies and Innovation in Renewable Energy[*]

Prepared by **Luca Bettarelli**[∂]**, Davide Furceri**[+]**, Pietro Pizzuto**[≈]**, and Nadia Shakoor**[÷]

Authorized for distribution by **Paulo Medas**

September 2023

Abstract:

This paper investigates the effect of Climate Change Policies (CCPs) on green innovation, for a sample of 40 advanced and emerging market economies and 5 economic sectors, during the period 2000-2021. Our results suggest that CCPs increase green patents, with the effect increasing gradually over time. The effect is larger for non-market-based policies—such as R&D subsidies—and technology-support instruments, in countries with greater competitiveness and during periods of stronger economic activity—that is, higher GDP growth, lower uncertainty and financial stress. The results based on a difference-in-differences approach suggest that the positive effect of stricter CCPs on green innovation is stronger in sectors with limited financial constraints.

JEL Classification Numbers:	O31; O32; E0.
Keywords:	green patents; climate change policy; diff-in-diff approach; innovation.
Author's E-Mail Address:	luca.bettarelli@unipa.it; dfuceri@imf.org; pietro.pizzuto02@unipa.it; nadia.shakoor@unipa.it

Environmental Policies and Innovation in Renewable Energy

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1. Introduction

The fight against climate change is a key global priority to ensure a healthy planet and guarantee a sustainable future. Countries must commit to drastically reduce emissions to stabilize global temperatures and ease the green transition, as put forward by numerous international agreements. In the path towards a greener economy, a key role is played by innovation, as technological advancements may reduce the cost of renewable energy production and facilitate the adoption of green energy worldwide (UNEP, 2011; World Bank, 2021). In addition, green innovation and diversification of energy sources may help economies to better cope with shocks due to climate change, thus favoring economic resilience.

However, innovation is both money- and time-expensive. It requires investing in projects with unpredictable returns, particularly in sectors where benefits tend to materialize over time, such as the renewable energy sector (Slawinski et al., 2017). As established in the literature, innovation responds to different drivers, such as the existence of localized competences (Storper, 1997), specialized human capital (Davies, 1996), the ability of firms to exploit changing market conditions (Porter, 1996). Government regulations and policies may also affect the production of innovation (Ashford, 2000; Acemoglu et al., 2012), even though the overall effect that policies may exert on the creation of new knowledge is ambiguous. One the one hand, environmental regulations may impose additional burdens on firms and weaken the incentives of economic agents to invest and innovate (Dechezleprêtre and Sato, 2017). On the other hand, public policies may positively affect innovation, both when interventions are directly targeted to foster innovative activities, e.g., credit and subsidies to R&D, and indirectly when they aim to reduce detrimental production's techniques, thus stimulating a firms' willingness to change and innovate. Moreover, as noted by Popp (2010), environmental policies may increase the demand

for clean energy that further incentivizes firms to invest in green technologies, as expected returns from green innovation would exceed investment' costs.

The empirical evidence on the role of policies in facilitating green innovation is so far limited. Nesta et al. (2014), Hille et al. (2020), Johnstone et al. (2010) and Wang et al. (2022) show that renewable energy policies may contribute to stimulate technological advancements in different green sectors, such as solar and wind in the US, Europe and some other OECD economies. Zhang et al. (2022) extend this finding to a larger set of 33 OECD and non-OECD economies. Our paper contributes to this literature by investigating the dynamic response of green innovation to climate change policies (CCPs), for a sample of 40 countries, over the period 2000-2021. We use the Environmental Policy Stringency Index (EPS), provided by the OECD, to measure the extent to which countries implement CCPs. In terms of green innovation, we consider the number of new patents related to green technologies—classified by country, year, and sector of application (industry, building, power, transport and waste)—using the IRENA (2022) database.[1] As a result, our final dataset is composed of 4,400 observations: 40 countries, 5 sectors, and 22 years.

Our empirical analysis consists of four main steps. In the first step, we analyze the dynamic macro-level response of green patents to an increase in the stringency of CCPs. In so doing, we employ the local projection approach, proposed by Jordà (2005), to estimate the evolution of green patent applications following an increase in the degree of stringency of CCPs. Our results show that CCPs increase green patents, with the effect that gradually increases over time. This effect, however, varies across types of CCPs and is positive and statistically significant only in case of non-market-based policies—such as emission limits and R&D subsidies—and

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[1] See Table A1 in the Appendix for more information about economic sectors.

technology-support policies.[2] In the next step, we try to address possible endogeneity issues due the reverse causality. Indeed, countries may be more prone to implement CCPs when green innovation is weak, implying that the OLS estimates would be biased towards zero and therefore underestimate the "true" effect of CCPs on green innovation. To address this issue, we follow Furceri et al. (2022) and use an instrumental variable (IV) strategy that exploits cross-sectional variation in the probability of a country to implement CCPs—due to its exposure to climate risks—and time-varying variation in climate-related events at the global level.

In the third step, we allow the response of green innovation to CCPs to be state-dependent and vary across countries and with economic conditions. In particular, the literature suggests that innovation is lower in countries with more limited product market competition and during periods of high economic uncertainty (Bloom et al., 2012), financial stress, and weak demand (Kopytov et al., 2018). Following this literature, we examine whether these characteristics also affect the response of green innovation to CCPs, using a local projection smooth transition approach (Auerbach and Gorodnichenko, 2013).

Finally, we extend the analysis at the sectoral level using a difference-in-differences approach (Rajan and Zingales, 1998) based on the theoretical assumption that CCPs have weaker effects in fostering innovation for sectors that face tighter financial constraints (Bloom, 2009; Alfaro et al. 2022). Our difference-in-differences approach includes a constellation of fixed effects, and therefore effectively control for country- and sector-specific time varying unobserved factors. In particular, country-time fixed effects absorb any unobserved cross-country heterogeneity in macroeconomic conditions that could be correlated with CCPs and

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[2] OECD distinguishes between market, non-market based and technology-support CCPs. For details about CCPs' classification see Botta and Koźluk (2014) and Kruse et al. (2022).

affect the innovation process in the same way across sectors. This would not be possible in a cross-country time-series setting, that would leave open the possibility that the impact attributed to CCPs could be due to other unobserved factors. Therefore, this approach further strengthens the identification of the causal effect of CCPs on innovation.

Our contribution to the literature is threefold. First, the use of a dynamic setting is a crucial improvement with respect to previous studies, as the production of innovation is expected to react to policy changes only gradually. Moreover, patenting activity, our proxy for innovation, requires technical time before being recognized by official data (Ascani et al., 2020). By analyzing the evolution of green patents over time, we account for the temporal gap between the adoption of CCPs and innovation output. Second, we show that the response of green innovation to policies is larger in countries with greater product market competition and it is magnified in periods of stronger economic activity. This result has important policy implications, as it highlights the importance of identifying the right timing to implement CCPs (that is, "fix the roof when the sun is shining") as well as the role of complementary policy to strengthen economic activity at the time of CCPs' implementation. In addition, the results also have implications for models analyzing the economic effect of CCPs and suggest that these models should generate a higher sensitivity in the response of green innovation during economic expansions. Finally, we strengthen the causal identification of CCPs using IV and sectoral difference-in-differences approaches.

The remaining of the paper is organized as follows. Section 2 presents an overview of the literature. Section 3 presents the data used in the empirical analysis. Section 4 examines the response of green innovation at the macro level. Section 5 focuses on the sectoral difference-in-

differences analysis. Section 6 concludes by summarizing the main results and the policy implications.

2. Literature review

In last decades, and particularly since 2000, many governments around the world have substantially expanded environmental regulation with the aim to reduce carbon emissions and facilitate the green transition (OECD, 2021). It is, therefore, not surprising that there has been a revival in the economic literature looking at the effect of CCPs on several measures of economic activity—such as productivity (Albrizio et al., 2017), employment (Dechezleprêtre et al., 2020) domestic investment (Dlugosch and Koźluk, 2017), foreign direct investment (Dlugosch and Koźluk, 2020), and international trade (Koźluk and Timiliotis, 2016).

The literature has also examined the effect of CCPs on innovation both theoretically and empirically. From a theoretical point of view, Xepapadeas and Zeeuw (1998) show that the net effect of green policies on innovation is ambiguous *a priori* and depends on the relative strength of two opposite channels: downsizing and modernization. The first channel suggests that environmental policies are likely to increase firms' input costs (e.g., energy) and, thereby, reduce investment including those related to innovation (Zhao et al., 2022). The second channel—based on the "Porter Hypothesis" (Porter and Van der Linde, 1995)—predicts that the associated increase in energy costs may induce firms to modernize their production techniques and switch to a more energy-efficient production process. Popp et al. (2010) show that, as demand for clean energy sources increases following CCPs adoption, green innovation is likely to expand due to higher investment returns.

From an empirical standpoint, Johnstone et al. (2010), based on a panel of OECD countries, find that public policy stimulates innovation in the renewable energy sectors, with the

effectiveness of different types of policy varying according to technologies, based on power generation costs. Nesta et al. (2014) analyze the interplay between green policy and market competition in a sample of 27 OECD countries, during the period 1976-2007, showing that energy policies generate a stronger effect on green innovation in case of more competitive energy markets. Hille et al. (2020) and Kim et al. (2017) focus on solar and wind technologies and differentiate between policy instruments. They find that policies incentivize technological advancements, particularly in case of R&D support programs and fiscal incentives. A recent study of Wang et al. (2022), focusing on China between 2008 and 2019, shows that different policies issued by the government significantly stimulate firms' green innovation. A positive effect of environmental regulation on green innovation is also found by Li and Shao (2021), who analyze OECD countries over the period 1990-2015. Bel and Joseph (2018) show a positive link between the enhancement of policy strictness and more green innovation in the European Union. Zhang et al. (2022) use the OECD environmental policy stringency index to evaluate the impact of environmental regulatory frameworks in 33 OECD and non-OECD countries and find that an increase in the stringency of CCPs positively affects green innovation, particularly for geothermal, hydro and marine energy, and in case non-marked based CCPs. Moreover, they find that the effects of policy are magnified in case of countries characterized by high innovation capacity, economic development and level of emissions. Few studies, particularly focusing on the US, have associated more stringent environmental policies to a downsizing effect and a reduction of green investment and innovation (Greenstone, 2002; Nelson et al., 1993).

We extend this literature in several ways. We extend the sample of analysis compared to previous studies, considering 40 advanced and merging market economies, and data up to 2021. We use a dynamic empirical setting that allows us to analyze the short- and medium-term

response of green innovation to stringent CCPs. More importantly, we extensively improve the identification strategy by using an IV-approach and a 3-dimensional setting including a comprehensive battery of fixed effects. Finally, we recognize that other factors may affect the production of new green technologies and mediate the link between environmental policies and innovation, particularly economic and financial conditions. Among drivers of investment and innovations, the literature has long recognized the role of political and economic uncertainty (Bernanke 1983; Dixit et al., 1994; Bloom, 2009; Caggiano et al., 2017; Ahir et al., 2022). In fact, uncertainty reduces investment, since rational agents hold back their investment decisions when uncertainty is high (Bloom, 2009). This argument is consistent with the real options theory (Myers, 1977), according to which firms postpone decisions that are costly to reverse under uncertain conditions (Dixit et al., 1994; Bernanke, 1983; Bloom, 2009; Bloom et al., 2012). In line with these arguments, we expect that the effect of CCPs on green innovation is larger during periods of low uncertainty, measured using the World Uncertainty Index by Ahir et al. (2022).

Another aspect identified by the literature as relevant for investment and innovation is the health of the financial system. In fact, access to finance represents one of the most serious barriers to firms' innovative activity and growth (Choi et al. 2018). A rise in the cost of intermediation (i.e., episodes of financial distress) reduces the capacity of financial institutions to extend loans, the supply of credit and may negatively affect investment in green innovations that are characterized by extremely uncertain and skewed returns (Cecere et al., 2020). We use the Romer and Romer (2017) measure of financial stress to proxy the health of the financial system of countries.

Similarly, investment in innovation is expected to be procyclical, with expenditures in R&D (and then patents) increasing during macroeconomic booms and decreasing during

recessions (Griliches 1990, Geroski and Walters 1995, Fatas 2000, Comin and Gertler 2006, Kopytov et al., 2018). Thus, we expect that the effect of CCPs is larger during periods of economic expansions.

Finally, there exists a long-standing debate in the literature linking innovation to economic competition (Schumpeter, 1942), even if theoretical predictions about the effect of the latter on the former are mixed. On the one hand, competition may be detrimental for innovation, as monopolistic firms face less market uncertainty and are more prone to invest in innovative activities (Cohen and Levin, 1989). On the other hand, high competition forces firms to invest and innovate in order to survive (Aghion and Howitt, 1998). In fact, when product market competition between firms is intense, the incentive of firms to increase their technological lead over rivals is higher (Autor et al., 2020). Recent empirical studies mostly disclose a positive effect of competition on both investments and innovation (Ahn, 2002; Aghion et al., 2022; Cappelli et al., 2023). We consider an indicator of product market regulation as a potential factor mediating the effect of CCPs on green innovation. The indicator—that we expect to positively mediate the effect of CCPs—identifies country-level real sector reforms affecting pro-competition regulation in the markets for goods and services (Alesina et al., 2023).

3. Data

This section describes the data used to measure green innovation and the stringency of Climate Change Policies (CCPs). The Annex provides additional information regarding the coverage (i.e., time, country and sector), as well as descriptive statistics of all the variables employed in the empirical analysis (Tables A1-A4).

3.1. Green innovation

We measure green innovation by counting the number of new patents related to green technologies, classified by country, sector and year. Though not perfect, patents are usually considered as the best proxy for innovation output, as patented inventions possess adequate standards of originality to be considered as a good proxy for innovation (Jaffe et al., 1993; Aghion et al., 2015; Ascani et al., 2020; Acs et al., 2002; Jaffe, 2000).

Our green patents data are retrieved from the International Renewable Energy Agency (IRENA) dataset, which provides information about 140 thousand patents filed for renewable energy worldwide, classified by 6 economic sectors, for a sample of 64 economies during the period 2000-21.[3] We restrict the sample to the 40 countries for which we also have information about CCPs, and to the 5 sectors that can be associated with NAICS codes, i.e., Industry, Transport, Building, Waste and Power.[4]

In the period under analysis (2000-2021), the overall number of new patents has grown by five times, from about 50 to 250 thousand, experiencing a sudden stop due to the COVID-19 crisis. Prior to the crisis, the most dynamic sector in term of new patents was the power sector, accounting for about a half of total new patents, followed by the transport sector. Marginal and with similar evolution are the number of new patents in the other sectors such as Building, Industry, and Waste.

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[3] The IRENA dataset collects information on patents related to renewable energy and filed to the European Patent Office (EPO). Data refers to published patents and are provided to EPO by national statistical offices. Sectors of application of patents are retrieved from the Climate Change Mitigation Technologies (Y02) classification, provided by EPO, and reported in the IRENA dataset. Patents are assigned to countries according to the residence of inventors. Thus, a patent could be allocated to more than one country at the same time.

[4] See Table A1, in the Appendix, for details about the way we assign a NAICS code to IRENA sectors. We exclude the CCUS (Carbon Capture, Usage and Storage) sector because it does not directly correspond to NAICS classification. However, that sector accounts for less than the 1% of green patenting activity of countries, across our sample.

Figure 1 shows the dynamic evolution of new renewable energy patents' shares (computed using total patents for the countries included in our sample) for the top 10 countries with higher average shares over 2000-2021. Three key facts emerge. First, the top 10 innovator countries account for more than 90 percent of the total number of the new patents, with the share of "all other countries" shrinking year-by year. Second, the relative importance of China skyrocketed in the latest years prior to COVID-19. China's share increased from about 6 percent in 2000 to about 65 percent in 2019, while that of Japan steadily dropped to about 7 percent in 2019 (declining 30 percentage points from 2000). Third, the relative importance of the US and Korea has remained quite constant, with values in the range of 15-20 percent and 6-10 percent, respectively.

3.2.Climate change policies (CCPs)

To evaluate the degree of stringency of environmental regulation at the country level, we use the OECD Environmental Policy Stringency Index (EPS): a composite index that measures the degree of stringency of environmental regulation, defined as higher costs (explicit or implicit) imposed by the regulation on polluting or other harmful activities (Botta and Koźluk, 2014; Kruse et al., 2022). It varies year-by-year at the country level, with higher values corresponding to more stringent regulations. This structure allows comparisons across years and countries.

The EPS index is available for 40 countries during the period 1990-2020. Figure 2 shows the evolution of the EPS, and of the 25th and 75th percentiles of its distribution, across countries over time, with an average change of about 0.09, bounded between -.84 (minimum change over the period) and 1.5 (maximum change over the period). The figure also shows that the index increases rapidly since 2000 following a wave of regulations for the energy sector and tightening of emissions regulations and R&D subsidies. By way of example, when the European Union

Emissions Trading System (EU ETS) entered into force in 2005, the median change in EPS index was about 0.47, which is 11.75 times the sample median. A similar impact on EPS resulted from the adoption of the Kyoto Protocol. Figure 3, panel A, shows the average yearly change of EPS for each country in the sample, ranging from approximately 0.03 in New Zealand to 1.6 in France. Figure 3, panel B, shows the distribution of the average EPS across countries in the last year available (i.e., 2020), and unmasks important heterogeneity with the index ranging from 0.83 in New Zealand to 4.89 in France.

The OECD database also provides disaggregated climate stringency indices classified in market-based instruments (such as taxes on emissions), non-market-based instruments (such as emission limit) and technology-support instruments (such as low-carbon R&D expenditures). In the empirical analysis, we will show that this distinction is key to better understand the dynamic response of green innovation to CCPs. Figure A1, in the Appendix, shows the breakdown by country of each sub-component of EPS.

4. Macro-level analysis

4.1. Baseline estimates

We estimate the dynamic response of green innovation at the country/sector/year-level to a change in the degree of stringency of the environmental regulation. In detail, we follow Jordà (2005) to estimate impulse-response functions of renewable energy patents to environmental policy shocks (Auerbach and Gorodnichenko, 2013; Ramey and Zubairy, 2018; Alesina et al., 2020). The regression equation takes the following form:

$$y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \, \Delta y_{i,s,t-l} + \sum_l \delta_l^k \, \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k} \qquad (1)$$

where, $y_{i,t}$ is the (log of the) number of renewable energy patents for country i, sector s, in time t; $y_{i,s,t+k} - y_{i,s,t}$ indicates the percent change of green patents between t and $t+k$; $time_{is,t}^k$ represents country-sector specific time trends—that is, country fixed effects*sector fixed effects* a time trend; $\Delta CCP_{i,t}$ measures the yearly variation in the degree of environmental policy stringency in country i, between years t and $t-1$. The specification also includes 2 lags (i.e., l=0,1,2) of the dependent variable and of $\Delta CCP_{i,t}$ to account for serial correlation in the patent growth and in the stringency index. Equation (1) is estimated for a balanced panel of 40 countries, across 5 sectors, over the period 2000-2021, for each horizon (year) k=1,..,5, with robust standard errors clustered at the country/sector level.[5]

Baseline results

Figure 4 reports the evolution of the (percent) number of patents following a 1 standard deviation increase in the EPS indicator (roughly corresponding to a yearly change of EPS of 0.24 point)—that is, the estimated β^k coefficients from equation (1). The results indicate that an increase in the stringency of environmental policy significantly contributes to the production of green innovation (patents). Moreover, the positive impact of the policy gradually increases over time, thus further validating our dynamic modelling choice. In particular, we find that a 1 standard deviation increase in the EPS index increases the number of new green patents by about 4 percent, one year after the introduction of the policy, and by 18 percent in the medium term—that is, five years after. The effects are strongly statistically significant as indicated by the narrow confidence bands, and large in magnitude. Taking these effects at the face value and translating it to major reforms (corresponding to changes in EPS at the 99th percentile of the distribution in our sample—that is, about 0.91), such as the big wave of new policy instruments introduced under

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[5] Results are robust to clustering the standard errors at the country-level.

the EU ETS system (around 2005) or the Canadian Action Plan in early 2000s, it implies an increase in green patenting of about 65 percent.

In addition, our results suggest that previous estimates based on a static framework may underestimate the "true" medium-term effect of CCPs on innovation. The results are also consistent with previous findings of the literature. For example, Zhang et al. (2022) find that a 1-point increase in EPS increases green innovation by about 57 percent, that is approximately equal to the average effect that we estimate across the time horizons we consider.[6]

While we keep our baseline equation very parsimonious in terms of number of regressors, we test the robustness of baseline results to the inclusion of additional controls, potentially affecting the production of (green) innovation and correlated with changes in climate policies. In particular, we extend the baseline regression to include GDP growth, an index of financial stress, and oil prices (see Table A3 in the Annex for data sources). Figure 5 presents results when controls are first included one at the time and then all together—the effect of CCPs on green innovation does not qualitatively change with respect to Figure 4. As additional robustness checks, we perform the following exercises: first, we change the number of lags in equation (1), from 2 (i.e., l=2) to 3 and 4; second, we estimate the model accounting also for contemporaneous effects of EPS changes on the dependent variable; third, we exclude potential outliers by cutting top and bottom 1 and 5 percent of the distribution of the dependent variable; fourth, we exclude one country and one year at time; fifth, we control for the lagged stock of patents at the country

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[6] Zhang et al. (2022) analyze the effect of CCPs (using the same EPS index as we do) on green innovation, employing a static panel fixed effects model, on a sample of 33 countries, during the period 1990-2015. Their estimated coefficient shows that 1-point increase in the EPS index raise the number of green patents by 101.6 (they scale the coefficient dividing it by 100). As the average number of green patents in their sample is 176.9, then the percent average effect is equal to: (101.6/176.9) *100=57.4%. If we translate our results in terms of 1 point increase in EPS, instead of 1 standard deviation, we find that the short-term effect of green patenting activity would be approximately equal to 16 percent, and the medium-term effect (5-years after the shock) equal to 80 percent.

level as the increase in patents is typically lower when the initial stock is higher (Eugster, 2021). The results reported in the Annex (Figures A2a-A2g) are qualitatively similar to the baseline one.

As discussed in the literature, alternative types of climate change policies may produce different effects on green innovation. To test this hypothesis, we follow Zhang et al., (2022) and distinguish between market-based, non-market-based and technology-support policies. Market-based policies use a market signal like taxes on emissions to contrast the impact of economy on environment; differently, non-market-based policies pose direct pressure on firms to introduce green practices, by mandating emission limits and standards; finally, technology-support policies directly incentivize firms to adopt environmentally friendly technologies. The latter, being specifically aimed to support green innovation, are expected to significantly foster the production of new patents. Moreover, non-market-based policies, as a form of institutional and social pressure, may stimulate firms to adopt clean production techniques (Ren et al., 2018; Zhang et al., 2022).

The results obtained by estimating equation (1) with measures of market-, non-market-based, and technology-support CCPs are reported in Figure (6). In line with expectations, we observe that the effect of CCPs on green patents is positive and statistically significant in the case of non-market-based and technology support CCPs, while is not statistically different from zero for market-based policies.[7]

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[7] However, even if our findings indicate that market-based policies do not directly stimulate green patenting activity, it is worth noting that they play a key role in advancing the green transition in several other ways. For instance, as documented by an extensive literature, market-based policies efficiently reduce emissions by making dirty productions more expensive (Zhao et al., 2015; Chang and Han, 2020). Moreover, they generate resources that can be used to compensate for the costs associated with CCPs (Känzig, 2023). Overall, previous studies have highlighted that a right policy-mix, including both market- and non-market-based policies, efficiently fight climate change, while mitigating the economic and distributional costs of CCPs (Bettarelli and Yarveisi, 2023).

4.2. Instrumental Variable (IV) analysis

As previously discussed, the baseline estimates may suffer from reverse causality, as our indicator of environmental policy may be endogenously determined by the intensity of green innovation. If green innovation is weak, a country may have more incentives to adopt more stringent environmental policies, particularly those directly linked to green innovation (e.g., subsidies for R&D activities), to stimulate economic agents to invest in new green technologies. In these circumstances, the OLS estimated coefficients may be biased towards zero. Moreover, potential measurement errors cannot be excluded *a priori*, especially in case of policy reform indicators (Furceri et al., 2022). To address these concerns, we employ an instrumental variable (IV) approach. In particular, we instrument ΔCCP with the interaction between a time-varying global term and a constant country-specific term (Nunn and Quian, 2014). As for the former, we use a variable measuring the environmental pressure for policy actions at the global level due to actual weather-related shocks. In detail, we use an indicator on the number of flood events. The rationale for choosing this instrument is that preferences toward CCPs change after major natural disasters (Bird et al., 2014; Welsch and Biermann, 2014; Latré et al., 2017). Moreover, we believe that this global indicator is exogeneous to specific policy actions implemented in a single country (Furceri et al., 2022). With the country term, we identify the extent to which a country is exposed to climate-related events, thus making the adoption of CCPs more likely. To do it, we use geographical characteristics, since they can reasonably be assumed to be randomly distributed across countries and thus should not drive green innovation. In our preferred specification, we consider the length of the coastline.[8]

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[8] Note that IV results are qualitatively similar when we use alternative instruments, such as the number of major hurricanes multiplied by the minimum distance of a country's centroid to the coast, the number of people affected by earthquakes multiplied by the share of urban population and the number of wildfires around the globe per annum multiplied by the agricultural land (in km2) per capita.

The regression equation takes the following form:

$$y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \widehat{\Delta CCP}_{i,t} + \sum_l \rho_l^k \, \Delta y_{i,s,t-l} + \sum_l \delta_l^k \, \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$$

$$\Delta CCP_{i,t} = time_{is,t} + \varphi \, Z_{i,t-1} + \sum_l \theta_l \, \Delta y_{i,s,t-l} + \sum_l \lambda_l \, \Delta CCP_{i,t-1-l} + \eta_{i,s,t}; \qquad (2)$$

where Z is the instrument.[9]

The IV results are reported in Table 1 and Figure 7. Table 1 shows the first-stage estimates, which suggest that the instrument is "strong", statistically significant and exhibits the expected sign. The Kleibergen–Paap rk Wald F statistic ranges from 85.9 (for t=4) to 97.2 (for t=5), approximately 7 times the associated Stock-Yogo critical value for strong instruments (16.38) (Andrews et al., 2019). Figure 7 reports the second stage estimates and confirm that the effect of a 1 standard deviation increase in EPS on green innovation is larger when using the IV approach, thus corroborating the idea that the OLS baseline estimates are biased towards zero.

4.3. State-dependent effects

In this section, we examine whether the response of green innovation to CCPs is state-dependent and varies with the level of competition and economic conditions, such as the business cycle, the level of economic uncertainty, and financial stress. In terms of competition, we use an indicator from Alesina et al. (2023) identifying regulation in the markets for goods and services at the country level. In detail, the variable ranges from -1 to 1, with higher values indicating more liberalization (or more competition), and lower values tightening reforms (or less competition). As measures of the business cycle, we follow the literature on state-dependent fiscal multipliers (Auerbach and Gorodnichenko, 2013) and we consider GDP growth. For uncertainty, we use the World Uncertainty Index (WUI), developed by Ahir et al. (2022), which captures country-level

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[9] Consistently with baseline estimates, we standardize the predicted value of the endogenous variable in the second-stage.

uncertainty related to both economic and political events, for a large sample of developed and developing countries (see Ahir et al. 2022, for a detailed discussion). Finally, we use the Romer and Romer (2017) discrete measure of financial stress as a proxy of the health of the financial system.

To estimate the role of these factors in shaping the response of innovation in renewable energy to environmental policy, we follow the approach proposed by Auerbach and Gorodnichenko (2013) and extend the baseline specification as follows:

$$y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + F(z_{it})\left[\beta_L^k \Delta CCP_{i,t} + \sum_l \rho_{L,l}^k \Delta y_{i,s,t-l} + \sum_l \delta_{L,l}^k \Delta CCP_{i,t-1-l}\right] +$$

$$\left(1 - F(z_{it})\right)\left[\beta_H^k \Delta CCP_{i,t} + \sum_l \rho_{H,l}^k \Delta y_{i,s,t-l} + \sum_l \delta_{H,l}^k \Delta CCP_{i,t-1-l}\right] + \phi_l^k F(z_{it-1}) + \varepsilon_{i,s,t+k} \qquad (3)$$

$$\text{with } F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1+exp^{-\gamma z_{it}})}, \quad \gamma > 0;$$

in which z is alternatively an indicator of product market regulation, the business cycle (GDP growth), uncertainty, and financial stress, normalized to have zero mean and unit variance. For the variables that have the same scale across countries (uncertainty, product market regulation and financial stress), we exploit both within and cross-country variation in the normalization, that is we use $z_{it} = \frac{s_{it} - \bar{s}}{sd(s_{it})}$. Differently, GDP growth changes widely across countries; thus, we exploit the within-country variation, and construct $z_{it} = \frac{s_{it} - \bar{s_i}}{sd(s_i)}$. The weights assigned to the regimes vary between 0 and 1 according to the smooth transition function $F(.)$. The coefficient β_L^k is the coefficient in the case of very low output growth (low competition, uncertainty or financial stress)—that is, when $F(z_{it}) \approx 1$ and z goes to minus infinity. β_H^k is the coefficient in the case of very high output growth (high competition, uncertainty or financial stress)—that is, when $(1 - F(z_{it})) \approx 1$ and z goes to plus infinity. As in Auerbach and Gorodnichenko (2011), we do not

estimate the parameters of the smooth transition model and set $\gamma=5$ to give an intermediate degree of regime switching.[10]

This approach—which is similar in spirit to the smooth transition approach of Granger and Teravistra (1993)—presents two main advantages over traditional interaction models: (i) it allows us to directly test if the effect of CCPs changes across regimes, such as low vs. high uncertainty; (ii) differently from a linear interaction model or structural vector autoregressions, this method allows the effect of CCPs to vary non-linearly and smoothly between regimes, as a function of different economic variables.

The results obtained from estimating equation (3) are reported in Figures 8-11. All figures show on the left the results for the low regime—that is, low competition, low uncertainty, low financial constraints, and low economic growth—and on the right the results for the high regime—that is, high competition, high uncertainty, high financial constraints, and high economic growth. In Table 2, we report the F-test for the difference in the responses between the two regimes (e.g., recessions vs expansions), across all horizons.

Figure 8 reports the results for GDP growth as the state variable, which suggests that the positive effects that CCPs exert on the production of new green patents are larger during economic expansions. In particular, the effects are positive and statistically significant, and larger (about 1.5 times) in magnitude than the baseline results. The difference in the responses between low and high growth regimes is statistically significant for most of the horizons.

Figure 9 reports the results for uncertainty. In line with expectations, we see that environmental policy stimulates green innovation more intensively when uncertainty is low. This result corroborates the hypothesis that uncertainty negatively affects the innovation process by

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[10] Results do not change when varying the value of γ (e.g., $\gamma=2.5$ or $\gamma=7$).

reducing the willingness of firms to invest (Bloom et al., 2012). The difference in the responses between low and high uncertainty regimes is statistically significant across all horizons.

Figure 10 presents the results for financial stress as the mediating factor in the relationship between CCPs and green innovation. When financial stress is high, the impact of CCPs is not statistically significant, while it is large and precisely estimated in periods of no or low financial stress—in this case, the difference in the response is statistically significant in the medium term.

Finally, Figure 11 illustrates the results when we use the product market regulation index as the mediating factor, to proxy the degree of economic competition faced by firms. Results show that the effect of CCPs on the production of green patents is larger when competition is high. This indicates that firms that face high competition are more incentivized to invest in new technology in response to climate-related policy actions. The difference between low and high competition regimes is highly statistically significant across all horizons.

5. Sectoral analysis

In this last exercise, we exploit sectoral heterogeneity in the response of green patents to CCPs. We consider a difference-in-differences approach (Rajan and Zingales, 1998) based on the theoretical assumption that CCPs have weaker effects in fostering innovation for sectors that face tighter financial constraints (Bloom, 2009). This approach allows to control for a constellation of fixed effects, and country- and industry-specific time trends to account for unobserved factors. In particular, country-time fixed effects help to absorb unobserved cross-country heterogeneity in macroeconomic conditions that could be correlated with CCPs and that affect the innovation process in a similar way across industries. To measure financial constraints, we follow Rajan and Zingales (1998) and construct a measure of external financial dependence (EFD) defined as the

ratio of total capital expenditures minus current cash flow to total capital expenditures. To construct this sectoral variable, we use US firm-level data from Compustat (as in Samaniego and Sun, 2015), and we aggregate them at sector-level by computing the median score for each sector. To match firms and sectors we exploit information about NAICS codes.[11] The regression that we estimate reads as follows:

$$y_{i,s,t+k} - y_{i,s,t} = \alpha_{is}^k + \alpha_{it}^k + \alpha_{st}^k + \beta^k \Delta CCP_{i,t} * EFD_s + \sum_l \rho_l^k \Delta y_{i,s,t-l} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} * EFD_s + \varepsilon_{i,s,t+k} \tag{4}$$

where α_{is}^k are country-sector fixed effects included to controls for differences in sectoral comparative advantages across countries; α_{it}^k are country-time fixed effects which allows to control for aggregate macroeconomic shocks; and α_{st}^k are sector-time fixed effects to control for changes in common sectoral compositions across countries. β^k captures the differential impact of CCPs on green innovation between a sector with low financial constraints and sector with high financial constraints. The specification also includes 2 lags (i.e., l=0,1,2) of the dependent variable and of the interaction term $\Delta CCP_{i,t} * EFD_s$. Standard errors are clustered at the country-sector level. We include *EFD,* alternatively, as a ranking variable and as a continuous variable. In the former case, it takes values 1, …, 5, where 1 indicates that *EFD* has its lowest score in sector *s,* and 5 the highest score. Table A4, in the Appendix, reports the ranking by sector. As a continuous variable, *EFD* represents the median score for each sector of the average firm-level score. The results, reported in Figure 12 (continuous) and Figures A3 in the Appendix (ranking), provide similar results. Consistent with the macro results on the role of financial stress, we find that the effects of CCPs on green patent is higher for sectors that face low financial constraints.

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[11] See Table A1, in the Appendix, for further details.

In particular, results show that the gain in green patent growth from a 1 standard deviation increase in EPS for an industry with low external financial dependence (i.e., the 25th percentile of the distribution) is about 1.5 percentage points in the short term (one year after the policy change) and about 4 percentage points in the medium term (5 years after) higher than that for an industry with high external financial dependence (i.e., the 75th percentile).

6. Conclusions

Climate change is (one of) the greatest challenge of our time. The use of conventional energy is the principal cause of global warming and climate change, leading to a series of issues for the society, such as natural disasters and weather extreme events. The transition to green energy is thus becoming key to ensure the sustainability of the planet. To stimulate the reduction of greenhouse emissions and ease the spread of renewable energy, most governments attempt to formulate and implement numerous environmental policies. However, the effect of CCPs on national economies may be ambiguous, as noted by several studies (see OECD, 2021, for a review). On the one side, CCPs may negatively affect the economy by imposing additional costs on firms. On the other side, they may stimulate the willingness of firms to invest and innovate (Porter, 1996).

With this article, we offer a dynamic analysis of the extent to which CCPs affects the production of green innovation. We make use of the Environmental Policy Stringency index, provided by the OECD, to measure the degree of environmental policies stringency and data on new patents filed for renewable energy to proxy green innovation. Our results show that the production of green innovation drastically increases when CCPs become more stringent. In detail, a 1-standard deviation increase in EPS positively fosters green patent activity by about the 18 percent, five years after the policy shock. To give a sense of the result, our estimates suggest

that major reforms like the introduction of the EU Emissions Trading System (ETS) in 2005,

increase green patenting by about the 69 percent in the medium term. These effects, however,

mask two important sources of heterogeneity that are key for policy design. First, not all CCPs

spur green innovation as the positive effects of CCPs are mostly related to non-market-based

policies (such as R&D subsidies). Second, the state of the economy at the time of CCPs

implementation matters: the effects are particularly strong in countries with more pro-

competitive regulation and when the economic environment is strong and characterized by low

uncertainty and financial stress. These results are important for policy design on how to

maximize the positive effects of CCPs on green innovation.

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Figures

Figure 1. Evolution of patents by country
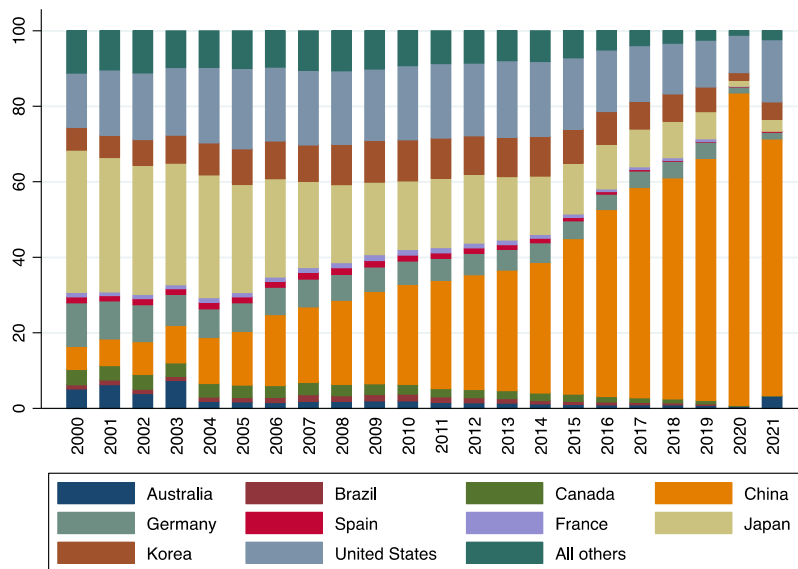
Notes: The chart shows the share of new renewable energy patents by country, for top 10 countries with higher average share over the period 2000-2021. All the other 30 countries in our sample are grouped together.

Figure 2: Evolution of the EPS index over time (median, 25th percentile, 75th percentile)
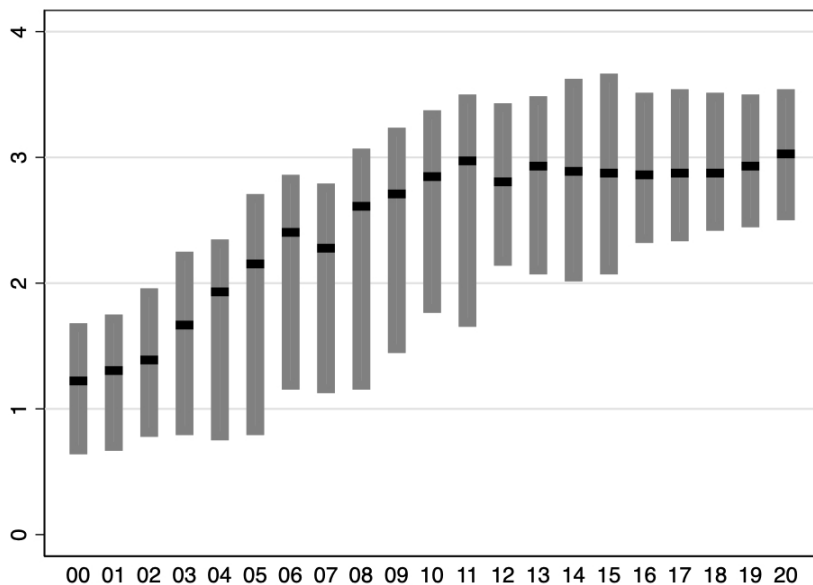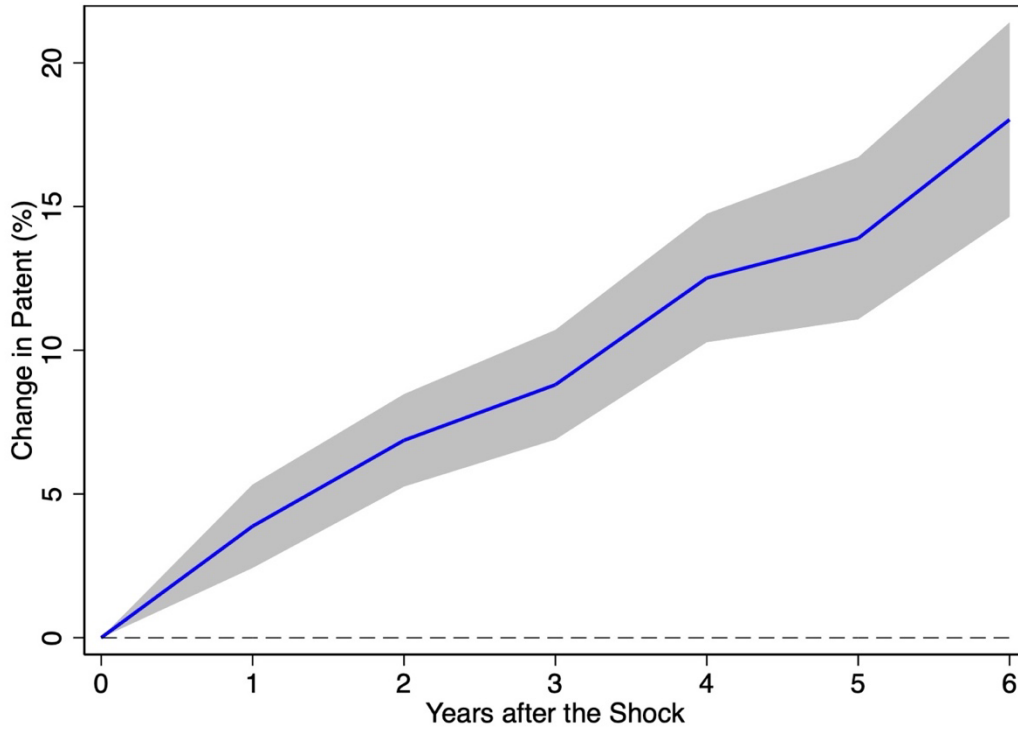

Notes: authors elaboration on OECD data. x-axis indicates years (from 2000 to 2020); y-axis indicates the EPS score, where the box refers to the 25th and 75th percentiles of the EPS distribution and the black line the median across countries.

Figure 3: average change of EPS index across countries (panel A), and distribution of EPS across countries in 2020 (panel B)
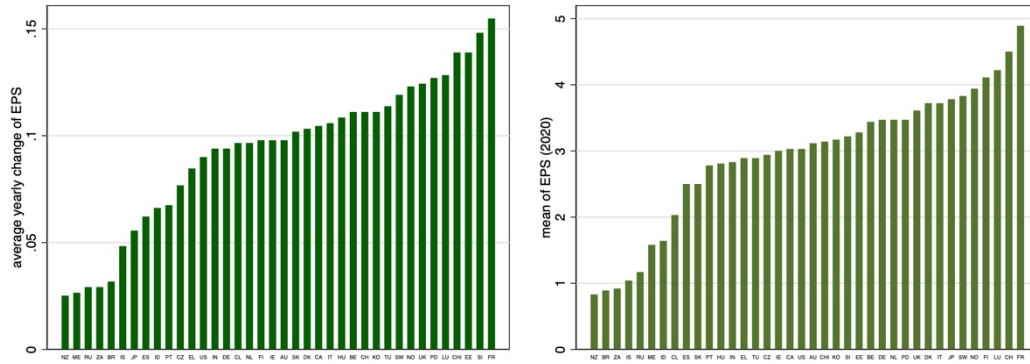
Notes: authors elaboration on OECD data. The charts reports the average yearly change of the EPS index and the average EPS score in 2020 for all countries in the dataset.

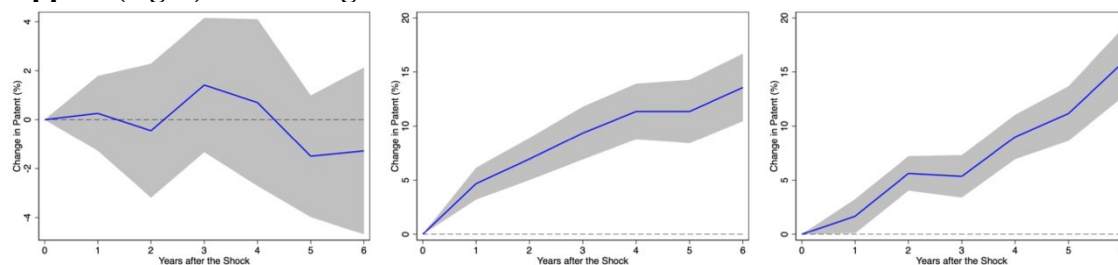**Figure 4: Impact of CCPs on green innovation**

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country *i*, sector *s*, between *t+k* and *t*, with *k=1, …,5*; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country *i*, between *t* and *t-1*. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level.

**Figure 5: Impact of CCPs on green innovation—robustness checks with additional controls**

(a) baseline with GDP growth

(b) baseline with financial stress

(c) baseline with oil price

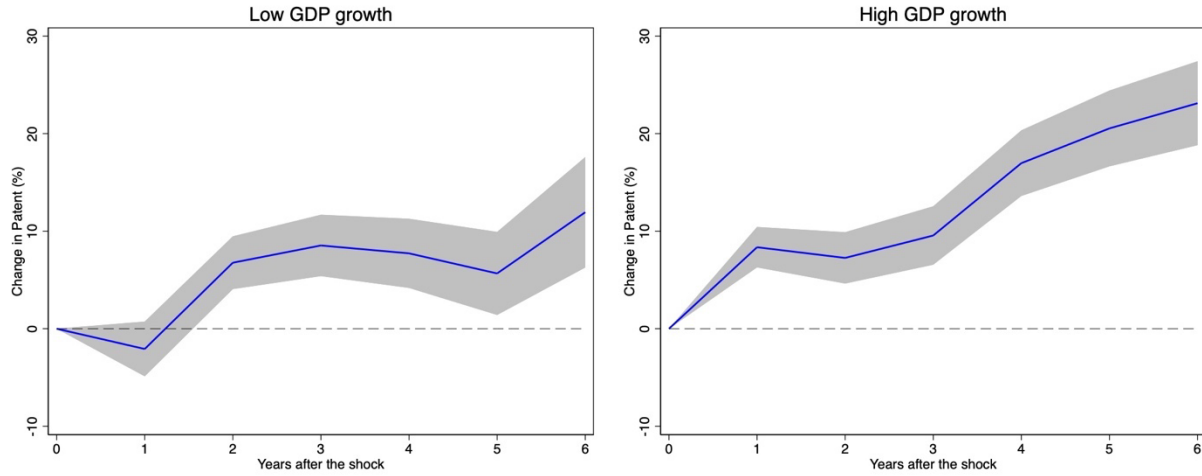(d) baseline with GDP growth, financial stress, oil price

Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-l} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, \ldots, 5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. Controls include 2 lags of the dependent variable and of the CCP shock. Additional controls have been included for robustness check: (a) GDP growth; (b) financial stress; (c) oil price; (d) GDP growth, financial stress, oil price. Standard errors are clustered at the country/sector level.

Figure 6: Impact of market based (left), non-marked based (center) and technology-support (right) CCPs on green innovation
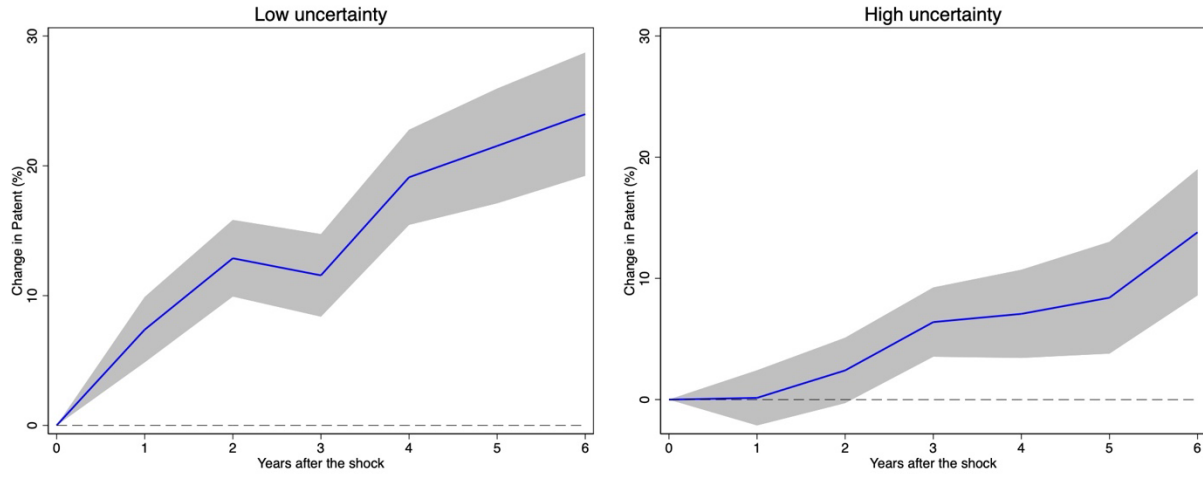

Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with k=1, …,5. In the left panel, $\Delta CCP_{i,t}$ indicates the market-based CCP shock, that is the yearly change in the market-based EPS index in country i, between t and $t-1$. In the right panel, $\Delta CCP_{i,t}$ indicates the technology-support CCP shock, which is the yearly change in technology-support EPS index in country i, between t and $t-1$ In the center panel, $\Delta CCP_{i,t}$ indicates the non-market-based CCP shock, which is the yearly change in the non-market-based EPS index in country i, between t and $t-1$. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level.

Figure 7: impact of CCPs on green innovation—IV approach
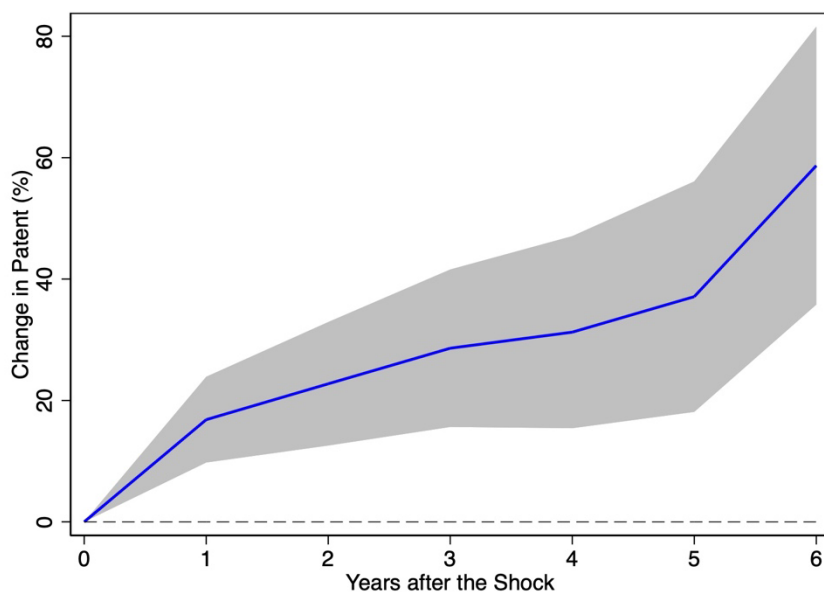
Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \widehat{\Delta CCP}_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with k=1, …,5; and $\widehat{\Delta CCP}_{i,t}$ is the predicted CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$, with the instrument being the number of floods at global level at time t, multiplied by the length of the coastline in country i. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level.
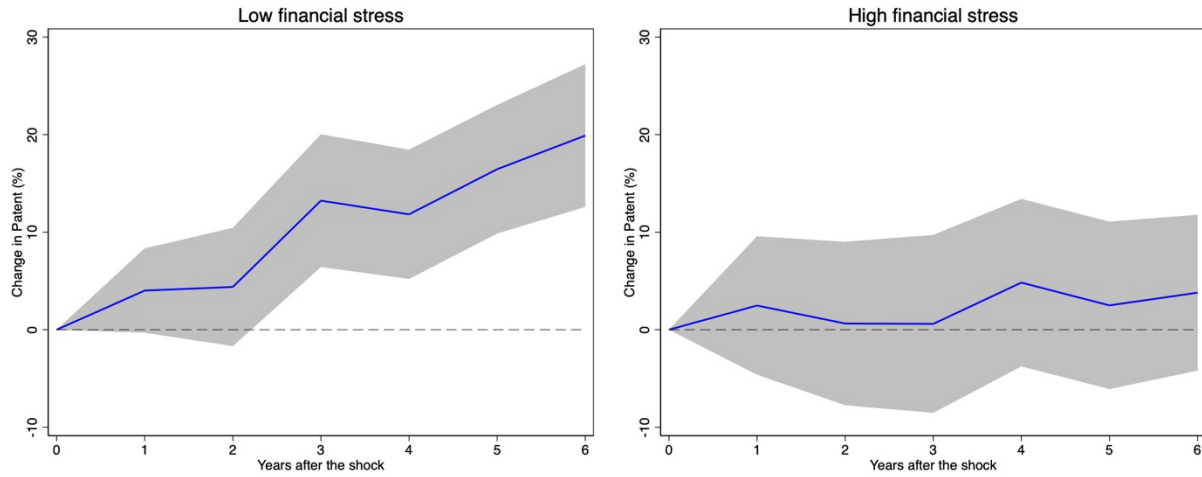
Figure 8: impact of CCPs on green innovation in case of economic recession or growth

Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (3): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + F(z_{it})[\beta_L^k \Delta CCP_{i,t} + \sum_l \rho_{L,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{L,l}^k \Delta CCP_{i,t-1-l}] + (1 - F(z_{it}))[\beta_H^k \Delta CCP_{i,t} + \sum_l \rho_{H,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{H,l}^k \Delta CCP_{i,t-1-l}] + \phi_l^k F(z_{it}) + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, \ldots, 5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level. $F(z_{it})$ is the smooth transition function that refers to the low regime, i.e., economic recession (left). $1-F(z_{it})$ is the smooth transition function that refers to the high regime, i.e., economic growth (right). Economic recession and growth are defined in terms of the GDP percent change in country i between t and $t-1$.

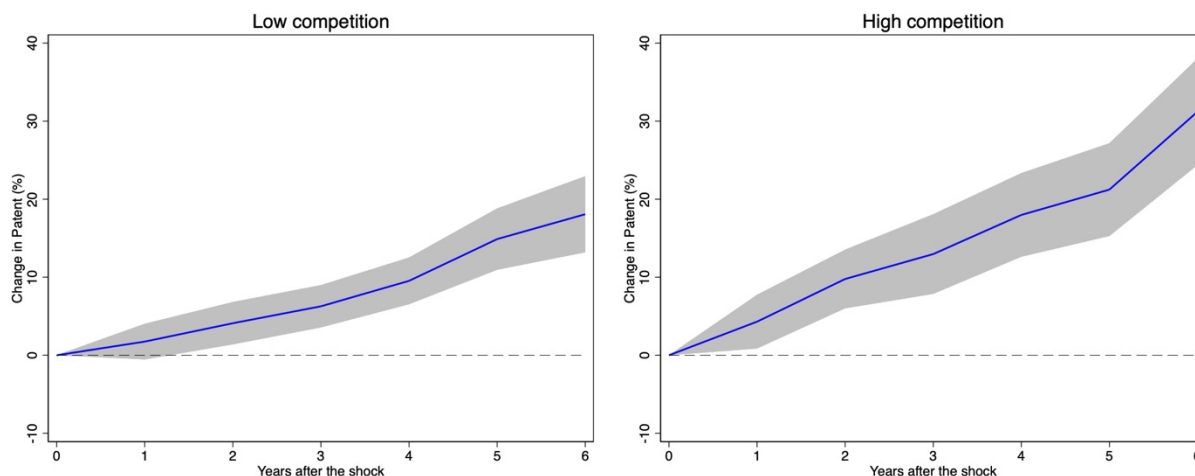**Figure 9: impact of CCPs on green innovation when uncertainty is low or high**

Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (3): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + F(z_{it})[\beta_L^k \Delta CCP_{i,t} + \sum_l \rho_{L,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{L,l}^k \Delta CCP_{i,t-1-l}] + (1 - F(z_{it}))[\beta_H^k \Delta CCP_{i,t} + \sum_l \rho_{H,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{H,l}^k \Delta CCP_{i,t-1-l}] + \phi_l^k F(z_{it}) + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country *i,* sector *s,* between *t+k* and *t,* with *k*=1, …,5; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country *i,* between *t* and *t-1.* Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level. $F(z_{it})$ is the smooth transition function that refers to the low regime, i.e., low uncertainty (left). 1-$F(z_{it})$ is the smooth transition function that refers to the high regime, i.e., high uncertainty (right). Uncertainty is the defined as the change in the World Uncertainty Index by Ahir et al. (2022), in country *i,* between *t* and *t-1.*

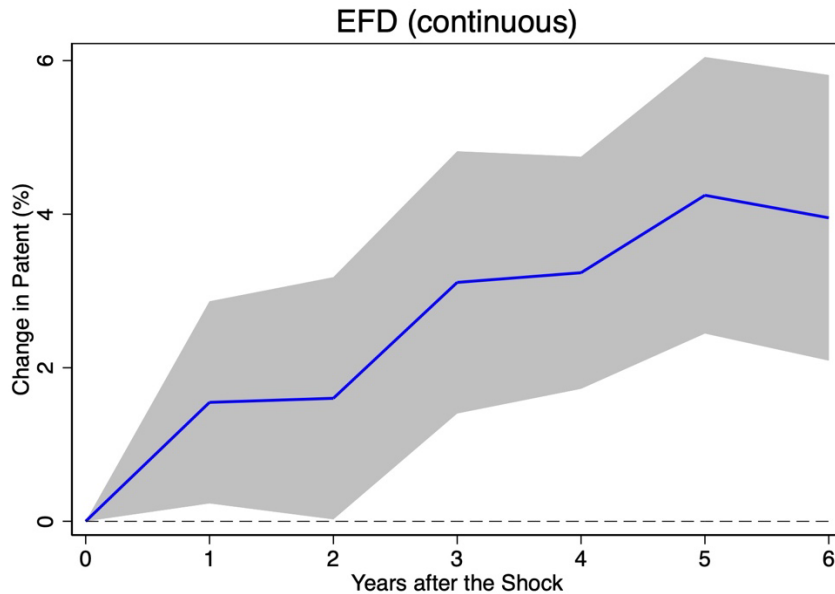**Figure 10: impact of CCPs on green innovation when financial constraints are low or high**

Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (3): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + F(z_{it})[\beta_L^k \Delta CCP_{i,t} + \sum_l \rho_{L,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{L,l}^k \Delta CCP_{i,t-1-l}] + (1 - F(z_{it}))[\beta_H^k \Delta CCP_{i,t} + \sum_l \rho_{H,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{H,l}^k \Delta CCP_{i,t-1-l}] + \phi_l^k F(z_{it}) + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country *i,* sector *s,* between *t+k* and *t,* with *k*=1, …,5; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country *i,* between *t* and *t-1.* Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level. $F(z_{it})$ is the smooth transition function that refers to the low regime, i.e., low financial stress (left). 1-$F(z_{it})$ is the smooth transition function that refers to the high regime, i.e., high financial stress (right). Financial stress is the defined as the change in the Romer and Romer (2017) index of financial distress, in country *i,* between *t* and *t-1*.

Figure 11: impact of CCPs on green innovation when competition is low or high

Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (3): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + F(z_{it})[\beta_L^k \Delta CCP_{i,t} + \sum_l \rho_{L,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{L,l}^k \Delta CCP_{i,t-1-l}] + (1 - F(z_{it}))[\beta_H^k \Delta CCP_{i,t} + \sum_l \rho_{H,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{H,l}^k \Delta CCP_{i,t-1-l}] + \phi_l^k F(z_{it}) + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with k=1, …,5; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level. $F(z_{it})$ is the smooth transition function that refers to the low regime, i.e., low competition (left). $1-F(z_{it})$ is the smooth transition function that refers to the high regime, i.e., high competition (right). Competition is proxied by making use of the product market regulation index (PMR) by IMF, in country i, at time t.

Figure 12: Impact of CCPs on green innovation—sectoral analysis and interaction external finance dependence (EFD).

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (4): $y_{i,s,t+k} - y_{i,s,t} = \alpha_{is}^k + \alpha_{it}^k + \alpha_{st}^k + \beta^k \Delta CCP_{i,t} * \text{EFD}_s + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} * \text{EFD}_s + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, \ldots,5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. EFD indicates the index of external financial dependence, as in Rajan and Zingales (1998). Controls include 2 lags of the dependent variable and of the interaction between the CCP shock and the EFD index. Equation (4) also includes three batteries of fixed effects: country-year, country-sector, and sector-year. The EFD is included in equation (4) as a continuous variable. Standard errors are clustered at the country/sector level. The chart reports the percent difference in the effect that CCPs exert on green innovation between sectors where EFD is low (25th percentile) and high (75th percentile).

Table 1. The impact of uncertainty on renewable energy patents – Instrumental Variable. First stage

First stage	t=0	t=1	t=2	t=3	t=4	t=5
Flood_events*coastal_lenght	.00007***	.00008***	.00008***	.00008***	.00008***	.00008***
	(.00000)	(.00000)	(.00000)	(.00000)	(.00000)	(.00000)
Observations	2664	2664	2664	2646	2599	2418
KleibergenPaap_rk_Wald_F_statistic	96.2	95.0	91.2	92.6	85.9	97.2
Stock-Yogo weak ID test critical value for 10% maximal IV size: 16.38						

Note: The charts show the coefficient associated with the instrument Z, when estimating the following first-stage regression: $\Delta CCP_{i,t} = time_{is,t} + \varphi\, Z_{i,t-1} + \sum_l \theta_l\, \Delta y_{i,s,t-1} + \sum_l \lambda_l\, \Delta CCP_{i,t-1-l} + \eta_{i,s,t}$. Standard errors in parentheses are clustered at country/sector level. *** p<0.01, ** p<0.05, * p<0.1. The Table also reports the Kleibergen–Paap rk Wald F-statistic tests for weak identification.

Table 2. F-tests difference

	F-test difference					
	t=0	t=1	t=2	t=3	t=4	t=5
GDP growth	14.60***	0.03	0.00	3.30*	9.95***	1.75
Uncertainty	10.06***	14.35***	3.41*	11.89***	9.39***	5.36**
Financial stress	0.10	0.04	0.34	0.31	2.79*	4.03**
Competition	3.65*	11.29***	8.90***	10.44***	7.51***	17.48***

Notes: The Table reports the F-test of the difference between low and high regimes of the interaction variable between the CCP shock and the smooth transition functions $F(z_{it})$ and $1 - F(z_{it})$, from equation (3): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + F(z_{it})\big[\beta_L^k \Delta CCP_{i,t} + \sum_l \rho_{L,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{L,l}^k \Delta CCP_{i,t-1-l}\big] + (1 - F(z_{it}))\big[\beta_H^k \Delta CCP_{i,t} + \sum_l \rho_{H,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{H,l}^k \Delta CCP_{i,t-1-l}\big] + \phi_t^k F(z_{it}) + \varepsilon_{i,s,t+k}$. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Figure A1: Distribution of sub-components of EPS, by country.
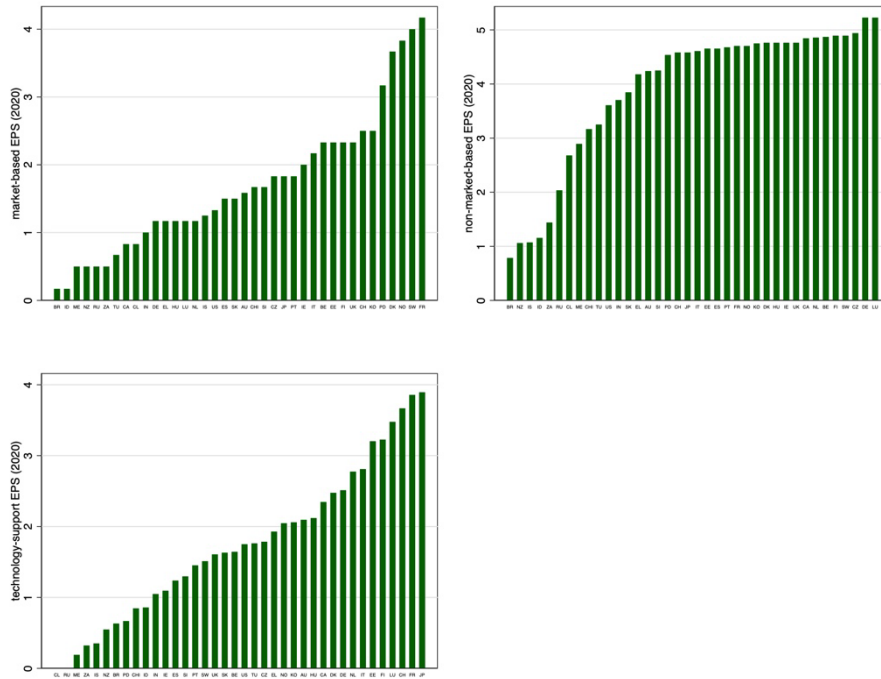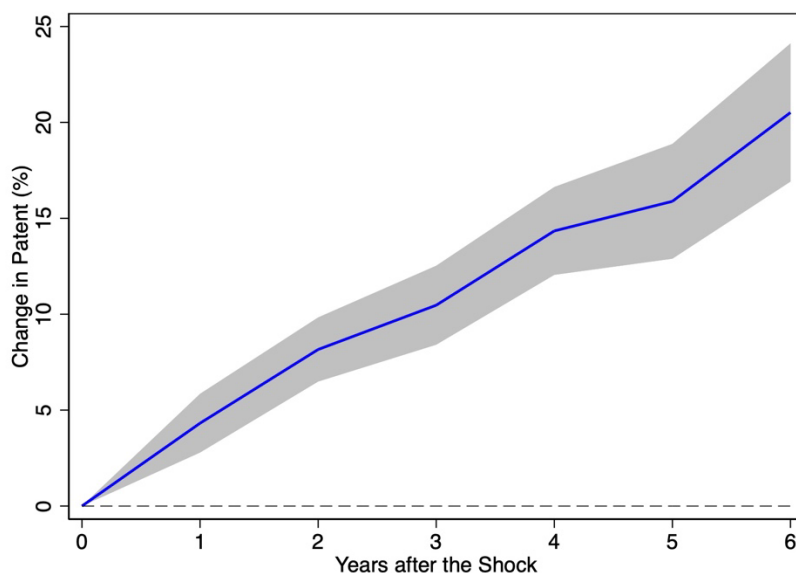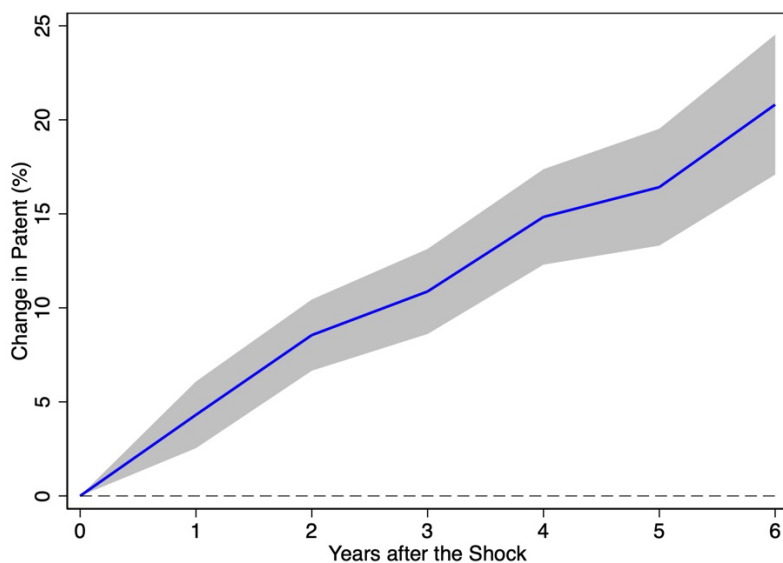
Figure A2: Impact of CCPs on green innovation—robustness checks.
**A2a—baseline with different lag structure, i.e., using 3 lags**

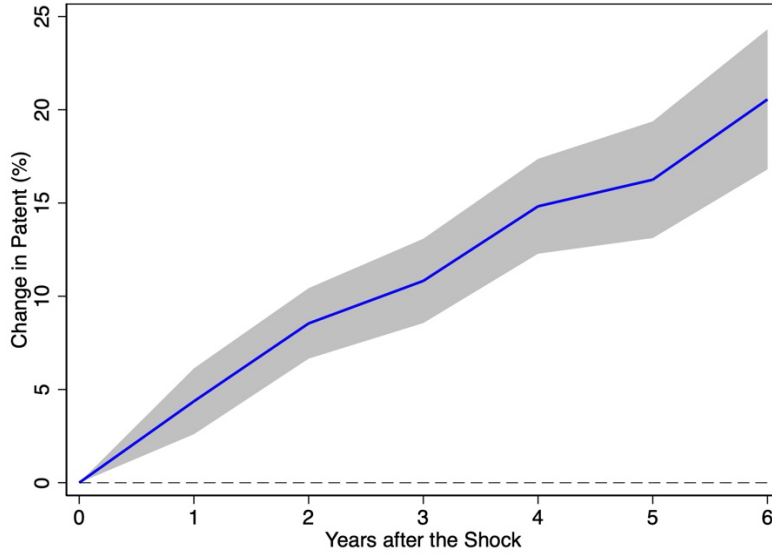**A2b—baseline with different lag structure, i.e., using 4 lags**

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, \ldots,5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. Controls include 4 and 4 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level.

A2c—baseline with contemporaneous CCP shock, instead of 1-period lagged
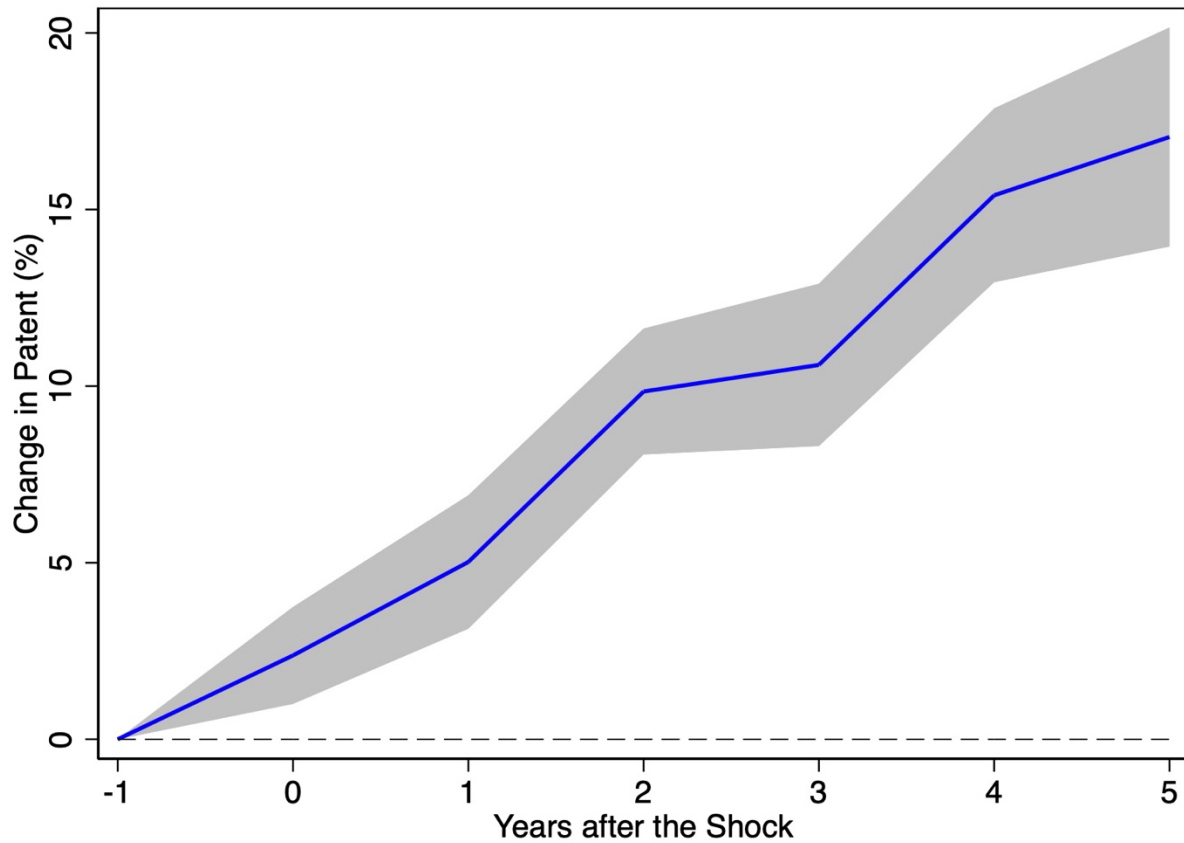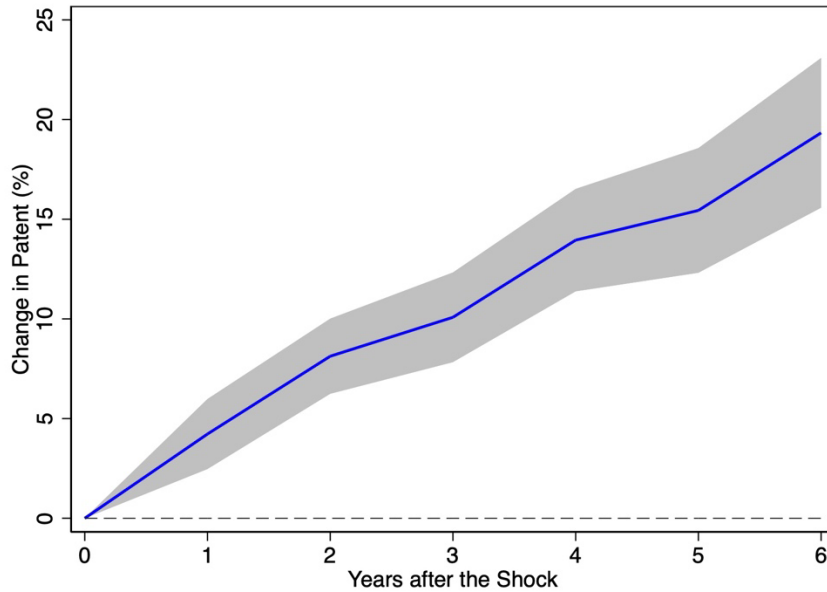

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, \ldots, 5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between $t+1$ and t. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level.

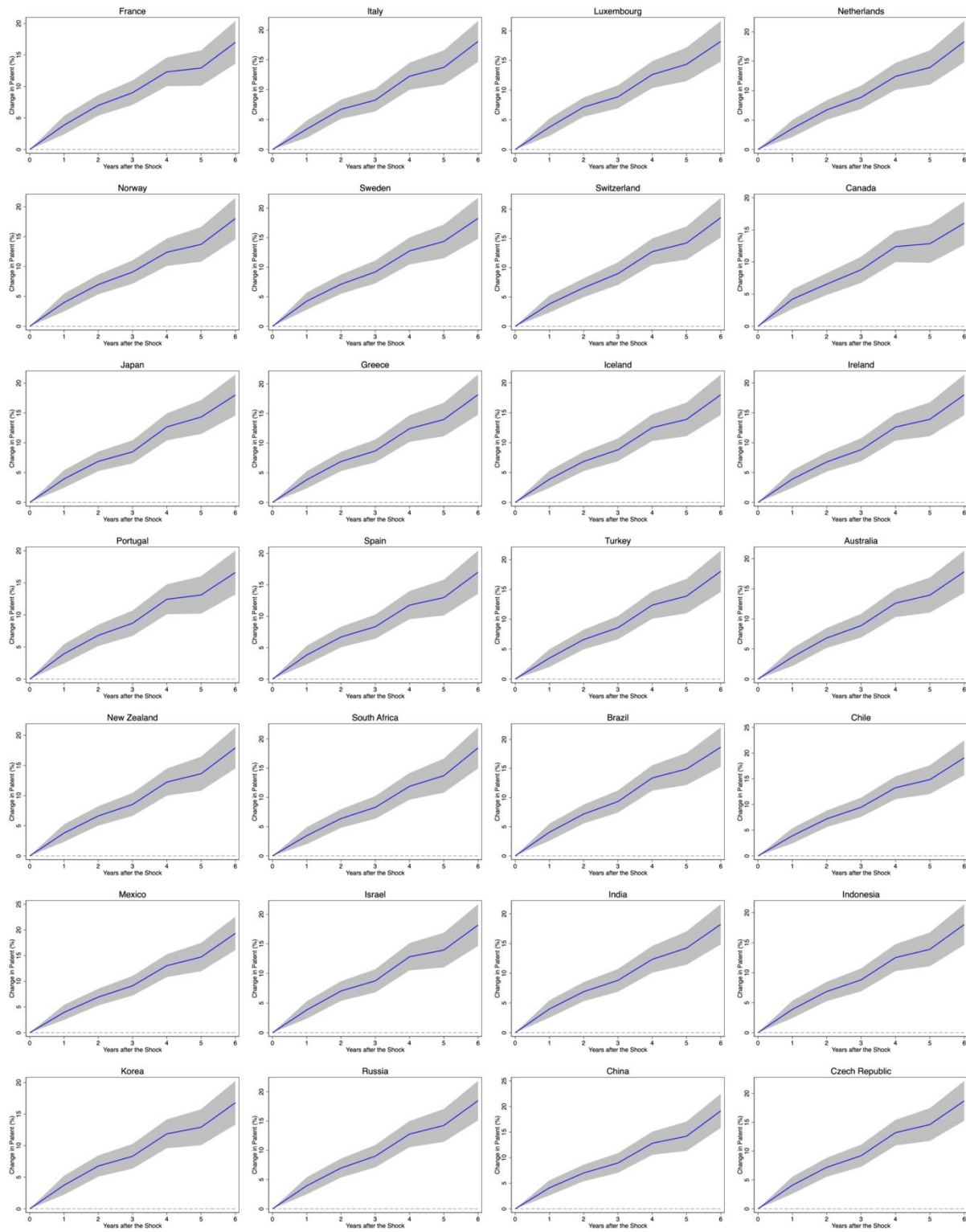**A2d—baseline excluding top and bottom 1% percent of the distribution of the dependent variable**

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, \ldots, 5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. We exclude top and bottom 1% of the distribution of the dependent variable. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level.
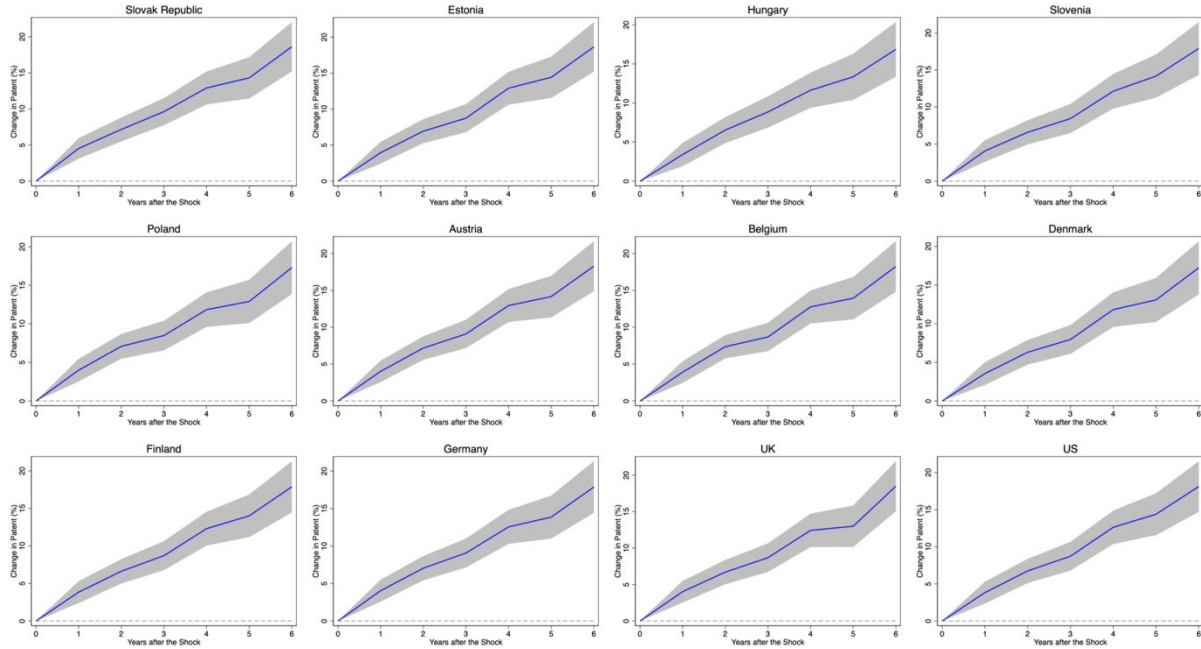
A2e— baseline excluding top and bottom 5% percent of the distribution of the dependent variable

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, …,5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. We exclude top and bottom 5% of the distribution of the dependent variable. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level.
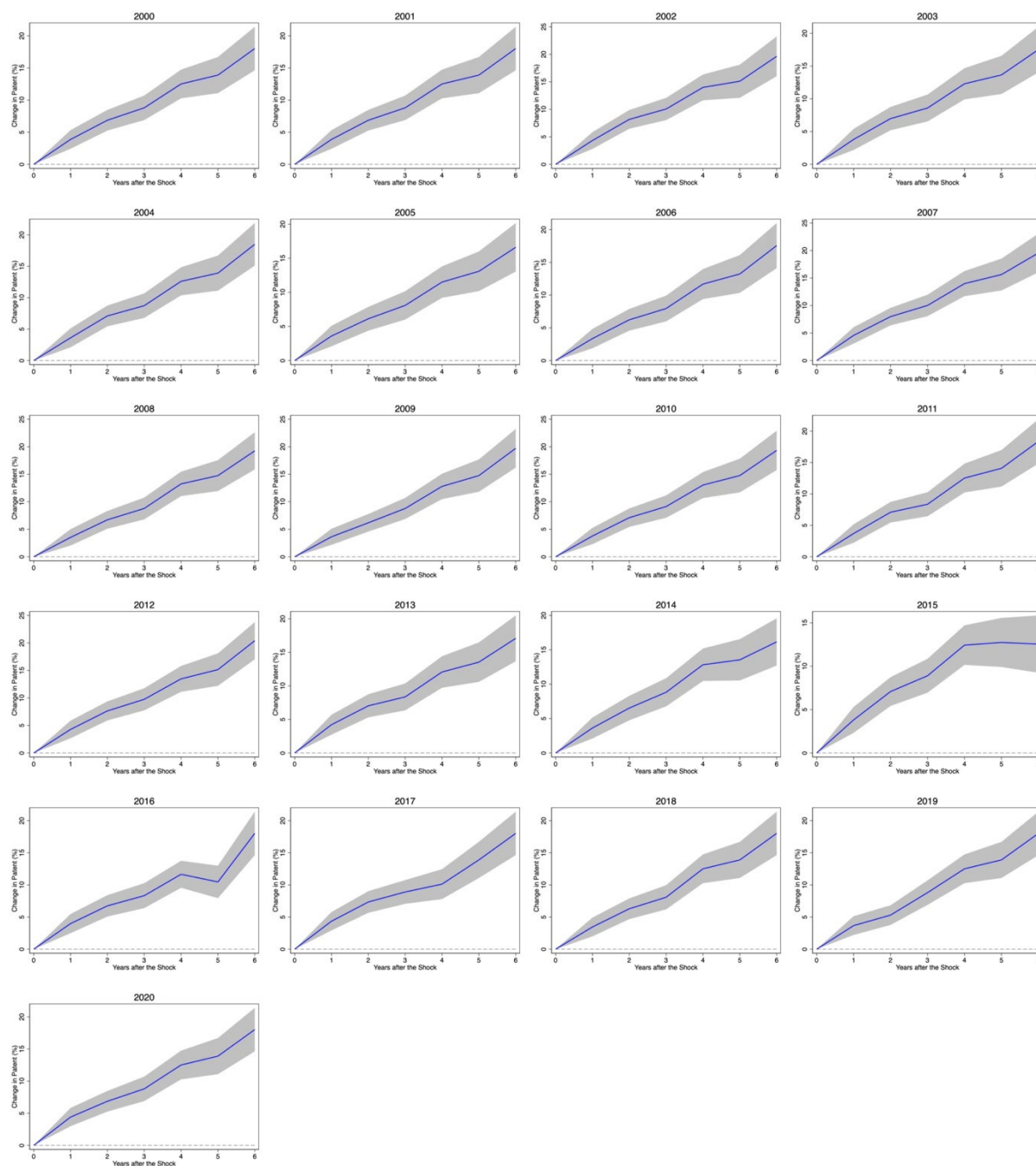
Figure A2f—baseline excluding a country at time (reported in chart's caption)

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, …,5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level. Each chart excludes a country in the sample, as reported in the caption.

Figure A2g—baseline excluding a year at time (reported in chart's caption)
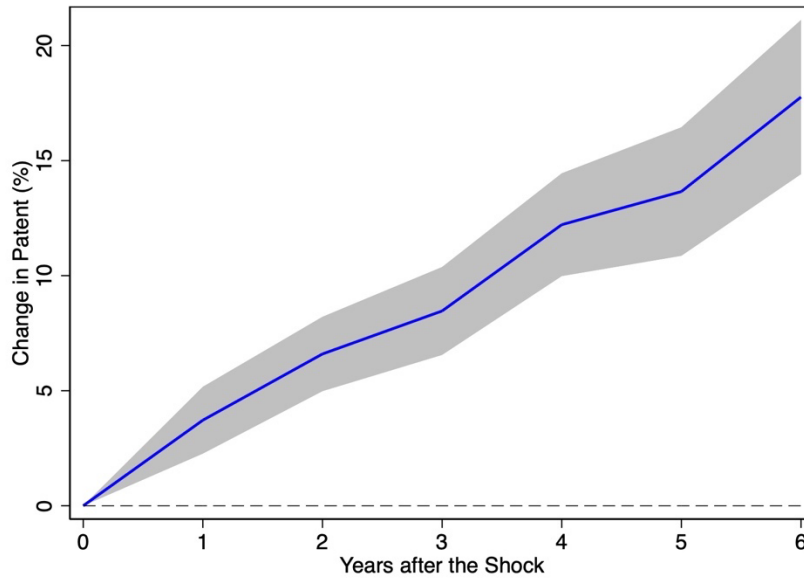

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, …,5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. Controls include 2 lags of the dependent variable and of the CCP shock. Standard errors are clustered at the country/sector level. Each chart excludes a year in the sample, as reported in the caption.

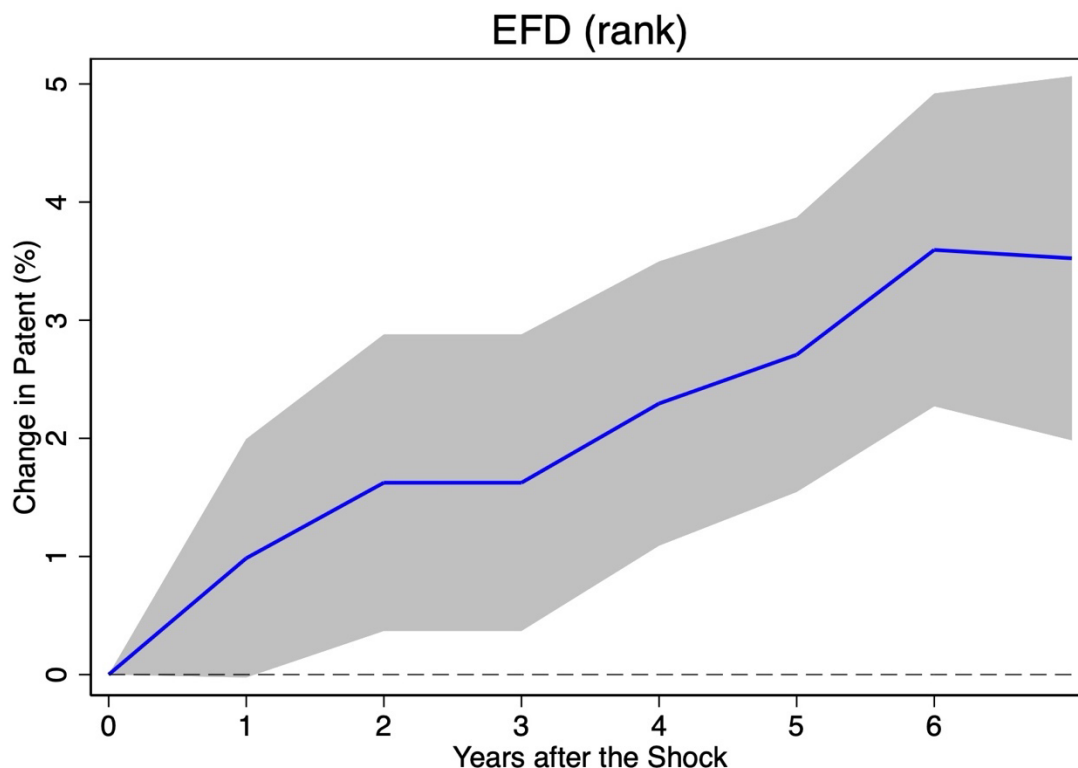**Figure A2h—baseline controlling for the lagged stock of patents**

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^k + \beta^k \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-l} + \sum_l \delta_l^k \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country *i*, sector *s*, between *t+k* and *t*, with *k*=1, …,5; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country *i*, between *t* and *t-1*. Controls include 2 lags of the dependent variable and of the CCP shock, and the lagged stock of patents (i.e., the cumulative sum of patents) at country level. Standard errors are clustered at the country/sector level.

Figure A3: Impact of CCPs on green innovation—sectoral analysis and interaction with external finance dependence.

Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (4): $y_{i,s,t+k} - y_{i,s,t} = \alpha_{is}^k + \alpha_{it}^k + \alpha_{st}^k + \beta^k \Delta CCP_{i,t} * \text{EFD}_s + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1} * \text{EFD}_s + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country i, sector s, between $t+k$ and t, with $k=1, \ldots, 5$; and $\Delta CCP_{i,t}$ is the CCP shock, that is the yearly change in the EPS index in country i, between t and $t-1$. EFD indicates the index of external financial dependence, as in Rajan and Zingales (1998). Controls include 2 lags of the dependent variable and of the interaction between the CCP shock and the EFD index. Equation (4) also includes three batteries of fixed effects: country-year, country-sector, and sector-year. The EFD is included in equation (4) as a ranking variable, which takes the value 1 in the sector where EFD has its lowest score across sectors (with $s=5$), and 5 when EFD has its highest score. Standard errors are clustered at the country/sector level. The chart reports the percent difference in the effect that CCPs exert on green innovation between sectors where EFD is low (25th percentile) and high (75th percentile).

Table A1: Economic sectors used in the analysis and associated Naics codes

SECTORS	NAICS CODES
Building	23
Industry	31-33
Power	22
Transport	48
Waste	562

Table A2: List of countries included in the analysis

List of countries			
Australia	Finland	Italy	Russia
Austria	France	Japan	Slovak Republic
Belgium	Germany	Korea	Slovenia
Brazil	Greece	Luxembourg	South Africa
Canada	Hungary	Mexico	Spain
Chile	Iceland	Netherlands	Sweden
China	India	New Zealand	Switzerland
Czech Republic	Indonesia	Norway	Turkey
Denmark	Ireland	Poland	United Kingdom
Estonia	Israel	Portugal	United States

Table A3: Descriptive statistics of all variables used in the analysis

Variable	Obs.	Mean	Std. Dev.	Min	Max	Source
Patent	4782	544.859	3652.181	0	100429	IRENA
Patent (log)	4782	2.887	2.372	0	11.517	IRENA
CCP	4782	2.3	1.101	0	4.889	OECD
ΔCCP	4782	.093	.249	-.833	1.5	OECD
CCP_mkt	4782	1.183	.861	0	4.167	OECD
CCP_non_mkt	4782	3.943	1.689	0	6	OECD
ΔCCP_mkt	4782	.046	.244	-1.333	1.5	OECD
ΔCCP_non_mkt	4782	.164	.502	0	4	OECD
Gdp_growth	4782	2.476	3.37	-14.629	25.176	OECD
Financial stress	1830	1.428	2.401	0	11.5	Romer & Romer, 2017
Oil Price	4782	63.818	28.233	24.444	111.67	BP Statistical Review of World Energy
WUI	4476	.214	.167	0	1.343	Ahir et al., 2022

PMR index	3324	.186	.398	-1	1	Alesina et al., 2023
EFD	3489	-.430	.463	-.961	.232	Compustat
Intangibility	3489	.0533	.0421	0	.112	Compustat

Table A4: Ranking of sectors in terms of External Financial Dependence (EFD)

Sector	N	Rank
Power	4134	1
Transport	4134	2
Waste	4134	3
Industry	4134	4
Building	4134	5

Source: Authors' elaboration based on Compustat data