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ENVIRONMENTAL POLICIES, UNCERTAINTY, AND GREEN TRANSITION

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Introduction:

The Paris Climate Agreement represents a significant advancement in the global initiative to address climate change and facilitate the transition towards a low-carbon economy. However, it is also acknowledged that achieving the commitments set forth in the agreement will require considerable efforts (Den Elzen et al., 2016; Dovie and Lwasa, 2017; Tobin et al., 2018). The agreement foresees increasing investment in green technologies for mitigation and adaptation (Robbins, 2016; Green, 2017; Karlsson et al., 2018). Specifically, the second commitment outlines that countries pledge to adopt tangible actions against global warming, tailored to their individual local conditions, and using the 2030 objectives of the European Union and UNSE4ALL as a reference (a 40% cut in GHG emissions, a 40% enhancement in energy efficiency, and a 40% rise in renewable energy production, compared to 1990 levels). This perspective amplifies the relevance of environmental innovation and its ramifications on fulfilling emission reduction commitments at the regional, national, and international level (Ahmad, 2020). The widespread reliance on fossil fuels has led to the release of a substantial amount of emissions and pollutants, exerting immense pressure on the environment. Thus, innovation in green energy technology (GETI) has emerged as a pivotal strategy to address climate change and mitigate air pollution. Innovations in renewable energy technologies are a fundamental element in tackling environmental issues.

The global transition towards a sustainable future is riddled with complexities and challenges. At the heart of this transition lies the intricate dance between innovation, policy, and socio-economic outcomes. As nations grapple with the imperative of green innovation, the role of external factors, particularly uncertainty and policy interventions, becomes increasingly salient. This thesis delves into the nuanced relationships between uncertainty, environmental policies, green innovation, and income inequality, proposing a comprehensive exploration of such relationships.

An expanding body of literature highlights the inhibitive effects of uncertainty on green innovation. Uncertainty, in its many forms, casts a long shadow over the landscape of green innovation. Whether it emanates from shifting political landscapes, volatile economic conditions, or evolving regulatory frameworks, uncertainty introduces an element of risk that can deter both public and private actors from investing in green research and development. For example, uncertainty can discourage investments in research and development, particularly in sectors where the returns on innovation are expected to materializes in the long-term and are unpredictable, like in the renewable energy sector (Slawinski et al., 2017; Bernanke, 1983; Dixit et al., 1994; Bloom, 2009; Caggiano et al., 2017; Ahir et al., 2022). Furthermore, episodes of economic uncertainty, such as recessions or market crashes, can divert attention and resources away from long-term sustainable investments toward more immediate economic recovery measures (Bloom, 2009; Caggiano et al., 2017). Such uncertainties can stymie the momentum of green technological advancements, thereby impeding the global shift towards sustainable energy solutions.

Conversely, environmental policies, have been identified as stimulants for green innovation. By setting clear regulatory frameworks and incentivizing the adoption of green technologies, strict environmental policies can catalyze research, development, and deployment in the green sector (Nesta et al., 2014; Hille et al., 2020; Johnstone et al., 2010; Wang et al., 2022; Zhang et al., 2022). For instance, carbon pricing mechanisms, by internalizing the environmental costs of carbon emissions, can make renewable energy sources more competitive, thereby spurring innovation in green technologies (Johnstone et al., 2010; Wang et al., 2022). Similarly, direct subsidies or tax breaks for green research and development can lower the financial barriers to entry, encouraging more players to contribute to the green innovation ecosystem (Zhang et al., 2022). Such policies, by creating a favorable ecosystem for green innovation, can accelerate the shift toward an economy with lower levels of carbon emissions. However, the narrative becomes more nuanced when one considers the socio-economic ramifications of these environmental policies. While they foster green innovation, strict environmental policies may also affect income inequality (Markannen and Anger-Kraavi, 2019; Kanzig, 2023; Yu et al., 2021; Zhao et al., 2022; Soergel et al., 2021). The implementation of such policies can lead to short-term economic disruptions, including job losses and increased energy costs, which disproportionately affect lower-income groups. The challenge for policymakers, therefore, is to design and implement environmental policies that strike a balance between promoting green innovation and ensuring socio-economic equity.

The journey towards a sustainable future is fraught with complexities. While the imperatives of environmental stewardship and green innovation are clear, they are also intertwined with broader socio-economic and political dynamics. This thesis aims to unravel these complexities, drawing from a rich corpus of research, case studies, and empirical data and analysis. By examining the intricate relationships between uncertainty, environmental policies, green innovation, and income inequality, this research seeks to offer insights and recommendations that can guide policymakers, innovators, and stakeholders in their quest for a sustainable and equitable future.

Summary of the Chapters:

The first paper (Chapter 1) investigates the impact of economic and policy uncertainty on green innovation in renewable energy. The paper highlights the adverse effects of uncertainty on innovation. It intends to investigate how uncertainty affects green innovation and explore potential mediating factors that work as a transmission channel between uncertainty and green innovation. In this context, the paper provides evidence that uncertainty is a major obstacle to green innovation, as it reduces investment and makes it difficult for firms to plan the future. In addition, uncertainty is inversely related to investment, since rational investors choose to delay investment decisions when there is a lot of unpredictability. This line of reasoning is compatible with the real options hypothesis, which states that companies would put off making decisions that are difficult or expensive to reverse when facing uncertain situations.

The study uses a unique dataset from the International Renewable Energy Agency (IRENA) that includes information on renewable energy patents filed in various sectors and technologies across a sample of 64 economies from 2000-2021. The World Uncertainty Index (WUI) is employed to gauge economic and political uncertainty in a diverse array of both developed and developing countries.

Empirically, we investigate the impact of economic and policy uncertainty on green innovation. We employ two distinct, but complementary, econometric approaches for our analysis. Initially, we adopt the linear version of the local projection method introduced by Jorda (2005) a technique similarly utilized by Auerbach and Gorodnichenko, (2013); Ramey and Zubairy, (2018); Alesina et al., (2020) among others. This method allows the direct estimation of Impulse Response Functions (IRFs) based on local projections of renewable energy patents to uncertainty shocks. In the next step, we consider the significance of the role of economic conditions and policy support influencing the trajectory of innovation in the field of renewable energy patents in the aftermath of uncertainty shocks. We adopt the methodology suggested by Auerbach and Gorodnichenko (2013), because it allows a direct test of whether the effect of economic uncertainty varies across different regimes, such as recessions vs.

expansions. In order to address the potential influence of unobserved factors on the relationship between new renewable energy patents and economic or policy uncertainty, an Instrumental Variable (IV) approach is employed. The IV approach uses an instrument called the World Uncertainty Spillover Index (WUSI) developed by Ahir et al., (2022) to enhance the robustness of the analysis. This index measures uncertainty spillovers from major economies, including the G7 countries and China. Uncertainty in systemic economies is an important driver of uncertainty around the world, and it is assumed to be exogenous since such uncertainty spillovers are hardly related to green patents except through affecting countries' own uncertainty.

The research uncovers that uncertainty shocks have a significant negative effect on green innovation, as measured by the number of renewable energy patents. A one-standard-deviation increase in the world uncertainty index leads to a reduction in green patents by about 40 percent five years after the shock. The negative impact of uncertainty on green innovation is observed across different sectors and technologies. The power and building sectors, as well as wind and solar energy technologies, experience larger and more persistent declines in innovation in response to uncertainty shocks. We also conduct robustness checks to validate the results, including controlling for GDP growth, inflation, oil price growth, and financial stress. These checks confirm the robustness of the baseline findings. The results for the instrumental variable (IV) reveal that the instrument is "strong", statistically significant, and shows the expected sign. The results indicate that a one standard deviation increase in uncertainty generates a contemporaneous decrease of about 12 percent in the number of new renewable energy patents that increases over the medium term to about 80 percent. The results from state-dependent effects of uncertainty shocks on economic conditions reveal that the impact of uncertainty shocks is notably more negative and significant on the number of green patents during periods of weak demand and higher financial stress. However, the negative effect of uncertainty on the number of green patents can be reduced if a country adopts strict environmental policies.

In the subsequent section (Chapter 2), we broaden the scope of our analysis. and investigate the impact of Climate Change Policies (CCPs) on green innovation, for a sample of 40 OECD economies and 5 economic sectors, during the period 2000-2021.

The paper emphasizes the global importance of addressing Climate Change Policies and transitioning to green energy sources. However, the transition to green energy is hindered by the high costs associated with renewable energy production compared to conventional fossil-based energy. In this regard, technological advancements are crucial to reducing these costs and facilitating the adoption of green energy worldwide. We use the Environmental Policy Stringency Index (EPS), provided by the OECD, to determine the extent to which countries implement CCPs in terms of green innovation, that in turn, is measured by the number of new patents for green technologies.

The approach that is used in the paper to estimate the dynamic response of green innovation to a change in the degree of stringency of the environmental policy is the local projection approach proposed by Jorda (2005) and it is equivalent to the one adopted in the first paper (Chapter 1). To address potential endogeneity issues, we then used an instrumental variable (IV) approach following Furceri et al., (2022) in which we identify as instrument, the interaction between a time-varying global term and a constant country-specific term (following Nunn and Qian, 2014). The time-varying global term used as a proxy of the policy pressure due to weather-related shocks is the number of flood events. Because preferences toward CCPs change after major natural disasters, the country-specific term used to proxy with "vulnerability of a country towards climate change", is the length of the coastline. Therefore, our instrument is the interaction between the number of global flood events in a year and the length of the coastline of a country. These two factors are likely to influence the adoption of climate change policies but are not directly responsible for driving or influencing the level of green innovation. During the third stage of our analysis, we employ a local projection smooth transition methodology (Auerbach and Gorodnichenko, 2013) to investigate if the response of green innovation to CCPs depends on the states of the economy, varies among countries, and is affected by the prevailing economic conditions and policies. In the last part, we employed the difference-in-differences approach to examine sectoral heterogeneity. This approach was chosen based on the theoretical assumption that the impact of CCPs on promoting green innovation is less pronounced in sectors that encounter more stringent financial constraints (Bloom, 2009). In order to assess the extent of financial constraints, we adopt the methodology proposed by Rajan and Zingales, (1998) and create a measure of external financial dependence (EFD). This measure is defined as the proportion of total capital expenditure deducted by current cash flow, relative to the total capital expenditures. A higher EFD indicates that the sector heavily relies on external financing, while a lower EFD means that the cash flow generated by (firms belonging to) the sector is sufficient to cover its capital expenditures.

The findings we obtain indicate that CCPs enhanced the frequency of green patents, with the effect having a ripple effect that gradually becomes more pronounced over time. We found that an increase of one standard deviation in the EPS index increased the number of new green patents by around 4 percent one year after the policy was introduced and by 18 percent in the medium term, which is defined as five years after. This effect, on the other hand, differs depending on the type of CCP being considered, and it is positive and statistically significant only in the case of non-market-based policies, such as emission limitations and R&D subsidy programs. The results are robust to several tests, such as the inclusion of additional controls (GDP growth, an index of financial stress, and oil prices), changing the lag structure, and control for the lagged stock of patents at the country level. In addition, the effect of CCPs on green innovation is found to be higher, when employing the IV approach, thus corroborating the idea that the OLS baseline estimates are biased towards zero. Furthermore, environmental policy helps to foster green innovation at a time when financial stress is lower, uncertainty is lower, and GDP growth is higher. In the final section, the results for sectoral heterogeneity demonstrate that the effects of CCPs on the number of green patents are greater for industries that are subject to lower financial constraints. This indicates that an increase in EPS has a greater impact on the growth of green patents in industries with low financial dependence relative to those with high financial dependence.

While CCPs can increase innovation and spur economic growth in the medium term, they may also lead to distributional costs. Indeed, as will be discussed in the third chapter (Chapter 3), CCPs may have some negative effects —e.g., job losses, and higher costs of energy— that are unevenly distributed among different income groups and may increase income inequality. For example, when a carbon tax is imposed on dirty energy production, it can lead to an increase in energy prices and reduce employment specially for low-skilled workers, thus increasing poverty and inequality. Our aim is to look at the medium-term effect of CCPs on several measures of income inequality—Gini, Palma ratio, P90/P10, S80/S20, and P50/P10, retrieved from the OECD database. The use of alternative measures of income inequality allows us to provide a more comprehensive characterization of how CCPs affect income distribution, given the different information provided by each indicator. For instance, the Gini index offers a comprehensive overview of the income distribution as a whole, with a particular emphasis on changes occurring in the middle of the distribution. On the other hand, the P90/P10 ratio primarily focuses on the extremes of the distribution.

From a methodological point of view, to examine the impact of Climate Change Policies (CCPs) on income inequality, we have employed the same methodology adopted in the preceding chapters, that is the local projection approach proposed by Jorda (2005). In addition to the analysis based on the aggregate measure of Climate Change Policies (CCPs), we also investigate how different types of policies (i.e., market-based, non-market-based, and technology-based policies) can affect income inequality. Next, to address endogeneity issues, we use an instrumental variable (IV) strategy using the instrument described in the previous chapter, which is the interaction between the number of global flood events in a given year and the length of the coastline of a country. The rationale behind this instrument is that global weather-related shocks and coastline length are exogenous to income inequality, but they may influence the likelihood of countries adopting climate change policies. Finally, we use the smooth transition local projection approach (Auerbach and Gorodnichenko, 2013) to analyze the nonlinear response of income inequality to CCPs, depending on country-specific factors and economic conditions, related to the share of workers with low education and countries characterized by higher initial inequality, the state of the economy and the economic policies adopted.

The results show that CCPs cause distributional costs because income inequality keeps going up after the policy shock, that is 1 point increase in EPS increases income inequality by up to 5 percent. This effect is most noticeable in the medium term. Also, the effect is similar across all measures of income inequality, as each of them goes up after a strict climate policy is put in place. Moreover, CCPs have an effect especially in the case of market-based policies, such as pollution taxes. The implementation of such policies leads to rises in income inequality that are 50% higher across indicators than in the baseline scenario, while the effect is not statistically different from zero for non-market-based and technology support policies. We also check the validity of our baseline results through several robustness checks such as, adding additional controls, changing the lag structure, and including country-specific time trends. The results for the instrumental variable (IV) indicate that our instrument is strong and statistically significant, and coefficients are larger in the medium term, thus suggesting that failing to account for endogeneity may result in a downward bias in evaluating the impact of CCPs on income inequality. The results from the smooth transition local projection approach indicate that the impact of CCPs on income inequality is larger in countries with a high share of low-skilled workers and those characterized by higher initial levels of inequality. On the other hand, the consequences are less severe in countries that have comprehensive redistribution policies, as well as during periods of budgetary expansions and faster economic growth.

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Chapter 1

Uncertainty and Innovation in Renewable Energy

1.1. Introduction

The fight against climate change is a key global priority to ensure a healthy planet and to guarantee a sustainable future. By way of example, an increase of 1.1 degrees Celsius in global temperatures makes half of the global population face water insecurity at least one month per year. It is also crucial for economic reasons: extreme weather events cut annual economic growth by 1-2 percentage points per capita, as reported by IMF.[1]

Countries must commit to drastically reduce emissions in order to stabilize global temperatures and convert their economy to green energy, as put forward by the Paris Agreement. However, the transition to green energy is challenging due to high costs compared to production and consumption of conventional fossil-based energy (United Nations, 2021). This calls for rapid technological advancements aimed at reducing production costs of renewable energy and facilitating the adoption of green energy worldwide (World Bank, 2021).

But innovation is both money- and time-expensive. It requires investing in the future, with unpredictable returns, particularly in sectors where benefits tend to materialize over time, such as the renewable energy sector (Slawinski et al., 2017). Uncertainty can have profound effects on investment decisions and economic outcomes. However, Global uncertainty can significantly impact investment in green innovation, shaping the landscape of environmental progress and sustainable development. When uncertainty prevails on a global scale, investors

[1] https://www.imf.org/en/News/Articles/2022/03/28/sp033022-MD-remarks-MCD-adaptation-WGS.

and companies tend to become risk-averse, often hesitating to commit substantial capital to green projects that typically require long-term investment and offer returns that may be uncertain or delayed. Uncertainty and innovation are closely intertwined, with uncertainty serving as both a driver and a constraint on innovation. However, it's also noteworthy that global uncertainty can sometimes act as a catalyst for green innovation investment. In times of volatility, there can be a concerted push towards sustainability as a strategy to mitigate risks associated with climate change, resource scarcity, and geopolitical dependence on fossil fuels. This dual-edged impact of global uncertainty necessitates strategic foresight and supportive policy frameworks to ensure that the trajectory of green innovation investment contributes positively to sustainable and resilient economic growth.

The literature has long acknowledged that political and economic uncertainty reduce investment and innovation in general (Bernanke, 1983; Dixit et al., 1994; Bloom, 2009; Caggiano et al., 2017; Ahir et al., 2022) but little is known about the impact of uncertainty on green innovation, as well as the channels mediating such a relationship. Green innovation encompasses a broader set of goals and considerations compared to innovation in general, with a particular emphasis on environmental sustainability, resource efficiency, regulatory compliance, market demand, and collaborative approaches to addressing environmental challenges. Given the pressing need for sustainable development and environmental stewardship, exploring and investing in green innovation is essential for addressing global environmental issues and achieving a more sustainable future.

With this article, we aim to fill this gap and analyze the impact of uncertainty on innovation on green energy for a large set of advanced and developing economies. To this end, we measure innovation by the number of patents related to green energy. Though not perfect, patents are usually considered as the best proxy for innovation output (Jaffe et al., 1993; Aghion et al., 2015; Ascani et al., 2020; Acs et al., 2002; Jaffe, 2000). Of course, not all inventions are patented, many patents have no commercial value, and not all innovation requires intellectual property protection. Despite these shortcomings, patent data have the advantage of being immediately available, measurable and comparable, both over time and across countries. Lastly, patented inventions present by definition minimal standards of novelty and originality to be considered as a good proxy for innovation. Our data for green patents data are taken from the International Renewable Energy Agency (IRENA) dataset, which provides figures for about 140 thousand patents filed for renewable energy worldwide, classified by economic sector and type of technology, for a sample of 64 economies since 2000. The focus on renewable energy is deliberate due to the sector's pivotal role in combating climate change. The renewable energy sector faces unique challenges and opportunities, and understanding how uncertainty affects this sector specifically provides valuable insights for policymakers and stakeholders.

To measure uncertainty, we use the World Uncertainty Index (WUI), developed by Ahir et al., (2022). It captures country-level uncertainty related to both economic and political events, for a large, unbalanced sample of 142 developed and developing countries from 1952. Compared to other measures of uncertainty developed in literature, the main advantage of the WUI is that it covers a larger of set of developed and developing economies, and the level of uncertainty is comparable across countries (see Ahir et al., 2022, for a detailed discussion). The concept of uncertainty in our work is multifaceted, encompassing economic and political dimensions. It's measured using the World Uncertainty Index (WUI), which aggregates the frequency of uncertainty-related terms in the Economist Intelligence Unit country reports. This index captures a broad spectrum of uncertainty, including near-term events like elections and long-term geopolitical tensions. The WUI is a comprehensive measure that allows for cross-country comparisons and has been validated in various studies.

We use the local projection approach proposed by Jordà (2005) to estimate the dynamic response of renewable energy patents to uncertainty shocks, and how it varies with economic conditions (such as the business cycle and the degree of financial stress) and policy support towards renewable (captured by the stringency of environment protection regulation). While uncertainty is indeed a perception influenced by various factors, focusing on sudden changes in the WUI, that we label as “uncertainty shocks”, allows us to understand the immediate and short- and medium-term impacts on green innovation. This focus provides valuable insights into how firms and economies react to rapid changes in the uncertainty landscape.

Our analysis highlights three important results. First, we show that uncertainty shocks have a negative and statistically significant effect on renewable energy patents. The effect is also economically significant: one standard deviation increase in the world uncertainty index leads to reduction in patents by about the 40 percent—that is, about 0.2 standard deviation of changes in patents—five years after the shock. To give a sense of the magnitude of the results, the estimates imply that the increase in uncertainty associated with COVID-19 could result in a medium-term decrease in energy renewable patents by about 70 percent. This negative effect holds across sectors and technologies, even though it is larger and more persistent for the power and building sectors and for enabling technologies, wind and solar energy.

Second, consistent with previous findings on the state-dependent effects of uncertainty shocks on economic activity (Bloom, 2014; Nodari, 2014; Caggiano et al., 2017; Alessandri and Mumtaz, 2019), we find that uncertainty shocks tend to have more negative effects on patents during periods of weak demand and higher financial stress—that is, those periods when firms have lower profits and are more financially constrained.

Finally, we provide evidence that policy support to shift to a greener economy (such as more stringent regulation on carbon emissions, or more investment in renewable including through public R&D expenditure) tends to reduce the negative effect of uncertainty on green innovation.

These results are robust to a wide range of robustness checks, alternative set of countries (advanced vs. developing economies), additional set of controls potentially correlated with uncertainty and affecting renewable energy patents (such as GDP growth, inflation, oil price growth and financial stress), and an Instrumental Variable (IV) approach, where we instrument uncertainty in each country with the uncertainty stemming from key economies, such as Group of 7(G7) and China.

The rest of the paper is organized as follows. The next section (1.2) provides a review of the literature on the link between uncertainty, investment and (green) innovation. In Section 1.3, we describe our data and the empirical approach. Section 1.4 discusses our results. Section 1.6 concludes summarizing the results and discussing policy implications.

1.2. Literature Review

Our analysis relates to the literature investigating the macroeconomic effect of uncertainty. As it is well-established in the literature, uncertainty reduces investment, since rational agents hold back their investments 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). Under uncertainty managers will tend to focus on short-term benefits, due to the unpredictability of the future, and avoid long-term value creating activities.

The literature about the effects of uncertainty has experienced a recent come-back, due to availability of data and new measures of uncertainty, as well as increasing uncertainty at global level (Great Recession, terrorism, Brexit, Covid-19 pandemic are few examples) (see

Bloom, 2014 for a review). Authors have looked at the effect of uncertainty on economic performance, measuring uncertainty by volatility of economy's structural shocks or stock market returns (VIX), or using broader indices, as the one proposed by Ludvogson et al., (2016) or the composite Economic Policy Uncertainty indexes of Baker et al., (2016) and Ahir et al., (2022). These studies have found a negative effect of uncertainty on economic growth (Bloom, 2009), investment (Pastor and Veronesi, 2013; Barrero et al., 2017) and employment (Gilchrist et al., 2014; Caggiano et al., 2017). As for the effect of uncertainty on innovation and R&D, Bhattacharya et al., (2017) examine whether policy uncertainty affects technological innovation in a sample of 43 countries. They find that innovation is significantly reduced during higher policy uncertainty, measured by national elections. Lin et al., (2021) confirm that uncertainty reduces both R&D expenditure and patent, for a sample 109 countries. We complement this literature by looking at green innovation, also taking into account different types of technologies, as well as economic sectors where these innovations are used. Another, much smaller, stream of the literature has looked at the effect of policy volatility and shocks to renewable innovation. Kalamova et al., (2012) show that the volatility of public expenditures on environmental R&D significantly reduces green innovation in a sample of 23 OECD countries, during 1986-2007. Zheng et al., (2021) find that terroristic attacks negatively affect green innovation. We differentiate from these studies by using a broader measure of economic and policy uncertainty such as the WUI, which allows us to extend previous analyses to both developed and developing countries, and to consider a broader set of events causing uncertainty.

Our analysis also relates to another strand of literature that analyzes the effect of uncertainty on CO_2 emissions and consumption. Romano and Fumagalli, (2018) finds that uncertainty negatively affects the environment, by increasing CO_2 emissions. The same findings are present in studies by Lee and Klassen, (2016) and Jiang et al., (2019). In a recent article, Atsu and Adams, (2021) analyze BRICS countries over the period 1984-2017 and find that CO_2 emissions are positively correlated to fossil fuel consumption and policy uncertainty, while negatively associated with renewable energy consumption and financial development. Shafiullah et al., (2021) finds uncertainty contributes to environmental deterioration by decreasing the consumption of renewable energy in the US. Adedoyin and Zakari, (2020) highlight a non-linear effect. The authors focus on the UK after Brexit and show that uncertainty is likely to yield positive effects on climate change in the short run, due to decreasing industrial activity, but detrimental effects in the long run, due to lack of investment. Our article differentiates from the above studies for its specific focus on green innovation, which is an input for both the production of renewable energy and the reduction of emissions.

Finally, we contribute to the literature that has looked at the role of mediating factors—such as business and financial conditions, the level of economic and financial development, and policy support—in affecting the relation between uncertainty and economic activity as well as between uncertainty and green growth. For example, Caggiano et al., (2017) and Fernandez-Villaverde et al., (2015) show that the negative effect of uncertainty is magnified in periods when monetary policy is at the Zero-Lower-Bound. Alessandri and Mumtaz, (2019) analyze how the impact of uncertainty on economic performance is higher during periods of financial stress. Caggiano et al., (2014) and Caggiano et al., (2017) examine the effects of uncertainty shocks conditional on the business cycle, showing that recessions amplify the negative effects on uncertainty. Brem et al., (2020) emphasize the role of financial development in the reduction of emissions, since financial institutions support firms in the adoption of green innovations. Shaikh et al., (2018), studying the case of China, find that economic growth and financial development promote the environmental quality. Popp (2006, 2010) claims that innovative activity responds to government policies, such as tax and subsidiaries. In the same vein, Kalamova et al., (2012) recognize that government support for

R&D increases innovation. Romano and Fumagalli, (2018) confirm the importance of policy interventions to promote the green transition. We differentiate form these by focusing on green innovation and by considering these aspects using the same empirical framework.

1.3. Data and methodology

This section describes the main data and the empirical framework used in the paper to estimate the effect of economic and policy uncertainty on renewable energy patents.

1.3.1. Renewable Energy Patents

Previous studies on innovation traditionally rely on sources such as the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), PATSTAT , and the World Intellectual Property Organization (WIPO) to analyze patent activity and technological innovation. These databases provide comprehensive patent data to track trends, assess technological developments, and measure innovation outputs. In this study we used data from the International Renewable Energy Agency (IRENA). This dataset contains information on the number of renewable energy patents, and offers a distinct perspective on innovations in renewable energy which might not be fully represented in conventional patent databases.

Additionally, this dataset provides data on patents by sectors (Building, Carbon Capture, Usage and Storage (CCUS), Industry, Power, Transport and Waste) and technology (Bioenergy, Enabling Technologies, Hydropower, Geothermal, Ocean, Solar and Wind Energy , allowing for more precise analysis of trends and patterns in this critical area.

The sectors included in the analysis are critical in the context of green innovation due to their significant energy consumption and potential for emission reductions. Each sector has unique characteristics and challenges in adopting renewable energy technologies, making them pertinent for analysis. Innovation in these sectors often involves the development and implementation of new technologies or processes that can significantly reduce emissions and improve energy efficiency. For example, innovation in the power sector helps in reducing the carbon footprint of electricity generation and in making renewable energy more reliable and cost-effective. The building sector includes residential, commercial, and industrial buildings, and innovations in this sector also involve designing buildings with optimal thermal properties and the ability to generate their own renewable energy. Innovations in transportation sector also involve improving the efficiency of vehicles, developing advanced public transportation systems, and creating infrastructure for EV charging. Innovation in the industry sector involves improving energy efficiency and reducing emissions through cleaner production processes. The waste sector focuses on waste reduction, recycling, and energy recovery, with aim to minimize landfill use and turn waste into a resource. Innovation in CCUS is also crucial for mitigating climate change, it involves improving the efficiency and reducing the costs of capture technologies, developing secure and long-term storage solutions, and finding new uses for captured carbon.

Our database covers an unbalanced panel of 64 countries over the period 2000–2021. Table 1.A1 provides the list of countries included in the analysis as well as key descriptive statistics regarding the number of renewable energy patents. Figure 1.1 presents the evolution of the number of patents by sectors and technologies. The figure shows that the overall number of new patents has grown by five times in the period 2000-2019 (from about 50 to 250 thousand) experiencing a sudden stop due to the COVID-19 crisis. Prior to such 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, CCUS, Industry, and Waste. The sectors in the analysis are important for green innovation due to their high energy consumption and emission reduction potential. Each industry has unique characteristics and problems in implementing renewable energy technology, making them worth analyzing. The rising trends in the number of patents in technologies that enable further growth of renewable energy is the most evident, together with that of new patents in solar energy technologies. Instead, the growth of new patents in the ocean, geothermal energy and hydropower technologies has been negligible. Innovation in these sectors often involves the development and implementation of new technologies or processes that can significantly reduce emissions and improve energy efficiency.

Figure 1.2 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. Several key facts emerge. First, top 10 country innovators 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 moved 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 with respect to 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.

1.3.2. World Uncertainty Index (WUI)

To measure uncertainty, we rely on the new index proposed by Ahir et al., (2022). They build a new country uncertainty index for 143 countries using the Economist Intelligence Unit (EIU) country reports. This uncertainty index is the first effort to construct a panel index of uncertainty for a large set of developed and developing countries.[2] The index captures uncertainty related to economic and political developments, regarding both near-term (e.g.,

[2] See the website https://worlduncertaintyindex.com/ for further details.

uncertainty associated with elections) and long-term concerns (e.g., uncertainty engendered by the impending withdrawal of international forces in Afghanistan, or tensions between North and South Korea). The World Uncertainty Index (WUI) typically aggregates data from various sources to provide a composite measure of uncertainty at the global level. While it offers a broad indicator of overall uncertainty, it does not currently provide explicit information on the individual components or sources of uncertainty, such as political, economic, social, financial, or military factors, although the authors are developing some specific sub-indices (see for example the World Uncertainty Spillover Index – WUSI, or the World Pandemic Uncertainty Index – WPUI.

The approach to construct the WUI is to count the number of times uncertainty is mentioned in the EIU country reports. Specifically, for each country and quarter, the authors search through the EIU country reports for the words "uncertain", "uncertainty", and "uncertainties". To make the WUI comparable across countries, the raw counts of uncertainty (and its variants) are scaled by the total number of words in each report (specifically, thousands of words). As shown in Figure 1.3, the global GDP-weighted WUI spikes near the 9/11 attacks, the SARS outbreak, the Gulf War II, the failure of Lehman Brothers, the Euro debt crisis, El Niño, Europe border-control crisis, the UK's referendum vote in favor of Brexit, the 2016 US presidential elections, the US-China trade tensions and the COVID-19 pandemic. Table 1.A2 in the Appendix presents some key descriptive statistics on the WUI for the countries included in our sample.

The authors also construct an index that measures the extent of "uncertainty spillovers" from key systemic economies—the Group of 7 (G7) countries plus China—to the rest of the world. Specifically, uncertainty spillovers from each of the systemic economies are measured by the frequency that the word "uncertainty" is mentioned in the reports in proximity to a word related to the respective systemic-economy country such as the country's name, name of presidents, name of the central bank, name of central bank governors, and selected country's major events (such as Brexit). We use this measure of uncertainty spillovers as an instrument for domestic uncertainty.

1.3.3. Methodology

To investigate the effect of uncertainty on green innovation in renewable energy, we use two empirical specifications. The first consists of tracing-out the average response of the number of renewable energy patents to the effect of economic uncertainty. The second allows this response to vary across countries according to their economic conditions (such as the busyness and financial cycle) and policy factors (such as the stringency of the environmental policy).

We follow Jordà (2005) to estimate impulse-response functions of renewable energy patents to uncertainty shocks, a methodology used also by Auerbach and Gorodnichenko, (2013); Ramey and Zubairy, (2018); and Alesina et al., (2021) among others. This procedure does not impose the dynamic restrictions embedded in vector autoregression specifications and is particularly suited—as in our case—to estimating nonlinearities in the dynamic response. The first regression we estimate is:

$$y_{i,t+k} - y_{i,t-1} = time_{it}^{k} + \beta^{k} WUI_{i,t} + \theta^{k} X_{i,t} + \varepsilon_{i,t+k} \qquad (1.1)$$

where, $y_{i,t}$ is the number of renewable energy patents (log of) for country *i* in time *t*; $time_{it}^{k}$ represents country-specific time trends; $WUI_{i,t}$ is the World Uncertainty Index for country *i* in year *t*; $X_{i,t}$ is a vector that includes two lags of the dependent variable and of the WUI. To keep the baseline parsimonious, we do not include other controls. But as we show in the section of robustness checks the results are unchanged when we expand the set of controls to include macroeconomic factors correlated with uncertainty and potentially affecting renewable energy patents (such as GDP growth, inflation, oil price growth, financial stress).

Equation (1.1) is estimated for an unbalanced panel of 64 countries over the period 2000-2021, for each horizon (year) k=0,..,5. Impulse response functions are computed using the estimated coefficients β^k, and the confidence bands associated with the estimated impulse-response functions are obtained using the estimated standard errors of the coefficients β^k, based on robust standard errors clustered at the country level.

The second specification examines the role of mediating factors in shaping the response of innovation in renewable energy to economic uncertainty. In particular, following the approach proposed by Auerbach and Gorodnichenko, (2013) we extend the baseline specification as follows:

$$y_{i,t+k} - y_{i,t-1} = time_{it}^k + F(z_{it})\left[\beta_L^k D_{i,t}\right] + \left(1 - F(z_{it})\right)\left[\beta_H^k D_{i,t}\right] + \theta^k X_{i,t} + \varepsilon_{i,t+k} \qquad (1.2)$$

$$\text{with } F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1+exp^{-\gamma z_{it}})}, \quad \gamma = 1.5$$

in which z is alternatively an indicator of the position in the business cycle (GDP growth), financial stress (as measured by Romer and Romer, 2017) or change in the stringency of the environmental policy (the OECD's Environmental Policy Stringency Index – EPS), normalized to have zero mean and unit variance. $F(z_{it})$ is the corresponding smooth transition function. Since the indexes of financial stress and EPS have the same scale across countries, we exploit both within and cross-country variation in the normalization, that is we use $z_{it} = \frac{s_{it}-\bar{s}}{sd(s_{it})}$. Instead, since average GDP growth varies widely across countries we exploit only within-country variation and we construct:

$z_{it} = \frac{s_{it}-\bar{s_i}}{sd(s_i)}$.

The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(.)$, so that $F(z_{it})$ can be interpreted as the probability of being in a given state of the economy. The coefficient β_L^k is the coefficient in the case of very low output growth (or alternatively, lower financial stress or smaller changes in the environmental policy stringency) 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 output growth (or alternatively, higher financial stress or larger changes in the environmental policy stringency) that is when $(1 - F(z_{it})) \approx 1$ and *z* goes to plus infinity. This approach to model interaction is equivalent to the smooth transition model developed by Granger and Teravistra, (1993). Its advantages are threefold. First, compared with a model in which each dependent variable is interacted with each factor, it permits a direct test of whether the effect of economic uncertainty varies across different regimes, such as recessions vs. expansions. Second, compared to a linear interaction model, it allows the magnitude of the effect of economic uncertainty to vary non-linearly as a function of the different factors. Third, compared with estimating structural vector autoregressions for each regime it allows the effect of economic uncertainty to change smoothly between regimes by considering a continuum of states to compute the impulse response functions, thus making the response more stable and precise.

1.4. Results

1.4.1. Baseline

Figure 1.4 shows the estimated dynamic response of the number of new renewable energy patents to uncertainty over the five-year period following the shock, together with the 90 percent confidence interval around the point estimate. Table 1.1 reports the associated estimation results. One-standard deviation increase in uncertainty lead to a contemporaneous decrease in the number of green patents of about 10 percent. The impact is long-lasting with a peak effect of about -40 percent—about 0.2 standard deviation of changes in patents—five years after the shock. As noted above, these estimates imply that the increase in uncertainty associated with COVID-19 could result in a medium-term decrease in energy renewable patents by about 70 percent.

The fall is larger and more persistent for the power and building sectors, while it tends to stabilize and eventually recover for the waste, transport and carbon capture, usage and storage sectors (Figure 1.5). The impact is also heterogeneous across types of renewable energy. In line with previous literature (Zheng et al., 2021), the geothermal energy is less affected by increasing uncertainty, while green innovation in wind and solar energy as well as in enabling technologies tend to experience larger and longer-lasting negative effects (Figure 1.6). These findings may be related to the difference in cost structure and maturity of the different energy types. Indeed, geothermal energy is considered in a mature stage while wind and solar energy as well as enabling technologies have experienced an intensive patenting activity over the past years (see also Figure 1.2), and therefore are mostly exposed to increasing uncertainty.

1.4.2. Robustness check

We have carried out several robustness checks to test the validity of the baseline findings.

First, in order to mitigate omitted variable bias, we included several controls that could be related uncertainty and affect new renewable energy patents—such as GDP growth and inflation (from WDI's World Bank database), oil price growth (from BP Statistical Review of World Energy) and a proxy of financial stress (from Romer and Romer, 2017). Previous literature has shown that there is a strong relationship between oil price growth and volatility, and production/consumption of renewable energy (Davis and Owens, 2003). Moreover, oil price movements have been connected to episodes of uncertainty, such as recessions and inflation (Bloom, 2009; Colombo, 2013); GDP growth is generally positively associated with the production of renewable energy (Chen et al., 2021), regardless of the type of technology; and financial stress significantly reduces investment and the transition to green economy (Atsu and Adams, 2021). We estimated equation (1.1) separately for each control variable, also including all the controls at the same time. The results in Figure 1.7 are very close to those in Figure 1.4, thus confirming our baseline findings.

Second, since it is possible that the results may be sensitive to the presence of countries with extremely high and low levels of new green patents and outliers, we repeated our estimates by dropping, in turn, those observations in the upper and lower 1 percentile of the distribution and those in the upper and lower 5 percentile of the distribution. Again, the results presented in Figure 1.8 are broadly consistent with the baseline results.

Third, the presence of two large uncertainty and recessionary shocks (such as the Great Financial Crisis and COVID-19) in the period under scrutiny may bias the results. To check the robustness of our findings to such events, we re-estimated equation (1.1) dropping from the sample period the related years (i.e., 2008 and 2020). Reassuringly, the impulse response functions obtained in such restricted sample do not point to different results with respect to the baseline.

Fourth, we examined whether our baseline results were driven by the lag structure choice. Figure 1.10 shows that this is not the case: regardless of the number of the lags for the WUI and for the dependent variable, the results are very similar and broadly unchanged with respect to the baseline.

Finally, we checked the sensitivity of our results to different levels of development. Specifically, we re-estimated equation (1.1) by subsamples of high-income versus low- and middle-income economies (see Table 1.A1 for country classification). The results shown in Figure 1.11 suggest that the effects of uncertainty are quite similar across the two groups.

1.4.3. Instrumental variable estimations

While potential reverse causality is likely to not be an issue, since number of new renewable energy patents is not a direct driver of economic and policy uncertainty, it could still be the case that unobserved factors influencing the dynamics of new patents over time could affect uncertainty. While the inclusion in the regression of several factors affecting new patents mitigates this concern, to fully address this issue we also adopt an Instrumental Variable (IV) approach, in which we instrument the World Uncertainty Index with the World Uncertainty Spillover Index (WUSI) by Ahir et al., (2022). It measures uncertainty spillovers related to the G7 economies plus China on quarterly basis. The index is computed by counting the percent of word "uncertain" (or its variant) mentioned within a proximity to a word related to a specific country (i.e., the US) in the EIU country reports. We take the sum of all the eight country-specific WUSI rescaled on yearly basis, providing also robustness checks based on the WUSI computed for the US and US+UK (see tables 1.A3 and 1.A4 in the appendix). As shown in Ahir et al., (2022) uncertainty in systemic economies is an important driver of uncertainty around the world (see for example the uncertainty spillovers from the United States related to US 2016 elections and trade policies as well as those related to the United Kingdom in the case of Brexit). The changes in global uncertainty caused by these systemic economies are generally independent of renewable energy innovation, including green patents. This independence is essential for our instrumental variable approach's validity. Global uncertainty shocks may affect green patent activity via affecting countries' economies, not by directly affecting green patent innovation.

The first-stage estimates shown in the upper panel of Table 1.2 suggest that the instrument is "strong", statistically significant and exhibit the expected sign. The first-stage estimates suggest The Kleibergen–Paap rk Wald F-statistic—which is equivalent to the F-effective statistic for non-homoscedastic error in case of one endogenous variable and one instrument (Andrews et al., 2019)—is higher than the associated Stock-Yogo critical value (Table 1.2). The results that we obtain following this approach are shown in the bottom panel of Table 1.2 (and in Figure 1.12) and are very similar to and not statistically different from the baseline estimates of Figure 1.4—even though the point estimates are larger: one standard deviation increase in uncertainty generates a contemporaneous decrease of 12 percent (vs. 10 percent with OLS) in the number of new renewable energy patents that increases over the medium term to about 80 percent (vs. 40 percent with OLS). The larger point estimates suggest that the true effect of economic and policy uncertainty on green innovation may be more substantial than initially indicated by the baseline OLS estimates.

1.5. Role of economic conditions and policy support

As discussed in the previous sections, the average response of green patents to uncertainty may mask significant heterogeneity across states of the economy and policy support. To test for these hypotheses, we estimate equation (1.2) using alternatively, GDP growth, the Romer and Romer, (2017) measure of financial stress and changes in the stringency of environmental policies.

First, business cycle fluctuations may affect our average estimates since investments in innovation are likely procyclical, with expenditures in R&D (and then patents) increasing during macroeconomic booms and decreasing during recessions. Indeed, despite Schumpeter, (1939) claims that recessions are periods of "creative destruction" concentrating innovation that is useful for the long-term growth of the economy, previous empirical literature has shown that when typically measured by R&D expenditures and raw patent counts, innovative activities tend to be procyclical (Griliches, 1990; Geroski and Walters, 1995; Fatas, 2000; Comin and Gertler, 2006; Kopytov et al., 2018). [3] In addition, the previous literature has shown

[3] Manso et al., (2021) argue that such traditional measures do not capture shifts in firms' innovative search strategies and contemplating innovative search as a tension within firms between exploration (the pursuit of novel

that the effect of uncertainty shocks on economic activity tends to be larger during recessions (Caggiano et al., 2014; and Caggiano et al., 2017).

In line with this empirical literature, our results suggest that the short-term negative effects of uncertainty on new green patents are larger during period of slack. In particular, the effects are statistically significant and larger than the average effect shown in Figure 1.2 during periods of recessions (the contemporaneous effect is about -40 percent compared to -10 percent in the baseline), while they are mostly not significantly different from zero for episodes associated with higher growth (Figure 1.13 – upper panels).[4] Since uncertainty adversely affects also economic growth in the short term (Bloom, 2009) and investment decisions in green innovation activities may be costly to revert, firms may prefer to postpone such decisions until further information has become available or uncertainty about the future economic outlook has diminished.

Similarly, previous studies have shown the importance of financial constraints in the development of green innovations (Mina et al., 2013; Kerr and Nanda, 2015). Indeed, access to finance represents one of the most serious barriers to firms' innovative activity and growth. A rise in the cost of intermediation (i.e., episodes of financial distress as defined by Romer and Romer, 2017) makes it more costly for financial institutions to extend loans to firms and households, reduces the supply of credit and may negatively affect investments in green innovations that as known are characterized by extremely uncertain and skewed returns (Cecere et al., 2020). Moreover, the effect of uncertainty shocks on investment has been found to be amplified in periods of financial stress and in sectors/countries with higher financial constraints (Choi et al., 2018).

to the firm approaches) vs. exploitation (the refinement of existing technology that is known to the firm) they find that exploitation strategies are procyclical while exploration strategies are countercyclical.

[4] The difference is statistically significant in the short term but not in the medium term, given the very large confidence bands associated with the effect of uncertainty during periods of booms (Table 1.3).

To probe further, we re-estimate equation (1.2) using the financial distress index by Romer and Romer, (2017) as state variable to proxy the health of the financial system. We find that worsening in credit sector's conditions further dampen green innovation when uncertainty increase (Figure 1.13–middle panels). One-standard deviation increase in uncertainty lead to a contemporaneous decrease of about 50 percent in the number of new green patents when countries experience higher degree of financial stress. The effects are persistent, reaching a peak of -80 percent two years after the shock. Conversely, the effects are smaller and mostly not statistically significantly different from zero for uncertainty shocks associated with improvements in the financial markets.[5]

Moving to the role of policy, we first re-estimate equation (1.1) using the OECD Environmental Policy Stringency index as shock variable (instead of WUI) to understand the direct effect of such policies on green patenting. In a second stage, we investigate the presence of a non-linear relationship between uncertainty and green innovation according to the strictness of environmental policy regulations. In line with previous studies claiming that strict environmental regulation induces more innovation output (Porter and Van der Linde, 1995; Johnstone et al., 2010; Hille et al., 2020), we find that increases in the OECD EPS index generate substantial increases in patents. Specifically, an increase of one point in the OECD EPS index (i.e., more stringent policy) leads to a persistent increase in the number of new patents with a peak effect of 50 percent five years after the shock. (Figure 1.14). Next, we re-estimate equation (1.2) using the Environmental Policy Stringency index as state variable. Consistently with the effect of policy to spur green innovation, we find that more stringent environmental policies tend to cushion the negative effects of uncertainty on green patenting.

[5] As for growth, the difference is statistically significant in the short term but not in the medium term, given the very large confidence bands associated with the effect of uncertainty during periods of no financial stress (Table 1.3).

In particular, the negative effects of uncertainty on innovation are smaller and statistically not significant when the change in the OECD EPS index is larger (Figure 1.13 – bottom panels)[6].

1.6. Conclusions

Today, climate change represents (one of) the greatest human problem. 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. In this scenario, the transition to green energy is becoming key to ensure the sustainability of the planet. In order to facilitate the spread of renewable energy, green innovations must help reducing its production and distribution costs by introducing new technology (Zheng et al., 2021).

However, innovation requires massive investment, which in turn resent of uncertainty and irreversibility, as put forward by the real options literature (Dixit and Pindyck, 1994). With this article, we offer a novel analysis of the extent to which economic and policy uncertainty affects the production of green innovation. We make use of the World Uncertainty Index (Ahir et al., 2022) as a thermometer of the degree of uncertainty surrounding the globe, and data on patent filed for renewable energy to proxy green innovation. Our results indicate that the production of green innovation drastically drops when uncertainty increases. In detail, a one standard deviation increase in uncertainty reduces patent activity of about the 40 percent five years after the shock. We test the robustness of our findings using various techniques, including an IV approach to address potential endogeneity concerns.

Moreover, we show that the negative impact that uncertainty exerts on the production of green innovation may be nullified if a country adopts stringent environmental policy, as the

[6] The difference, however, is not statistically significant given the very large confidence bands associated with the effect of uncertainty during periods of reduction in the stringency of environmental protection legislation (Table 1.3).

latter may reduce uncertainty about future returns of innovation. The same result is achieved in case of countries experiencing positive economic growth or suffering less from financial stress.

Overall, our results provide novel insights into the debate about tools to stimulate the production of renewable energy, to fight climate change and to facilitate the transition to a greener economy. Moreover, we disclose useful recommendations for policy-makers in terms of drivers to stimulate green innovation. In this view, future research may be dedicated to further analyzing different policy instruments, e.g., subsidiaries to green R&D vs. tax to emissions, that may efficiently stimulate green innovation and contrast negative effects of uncertainty.

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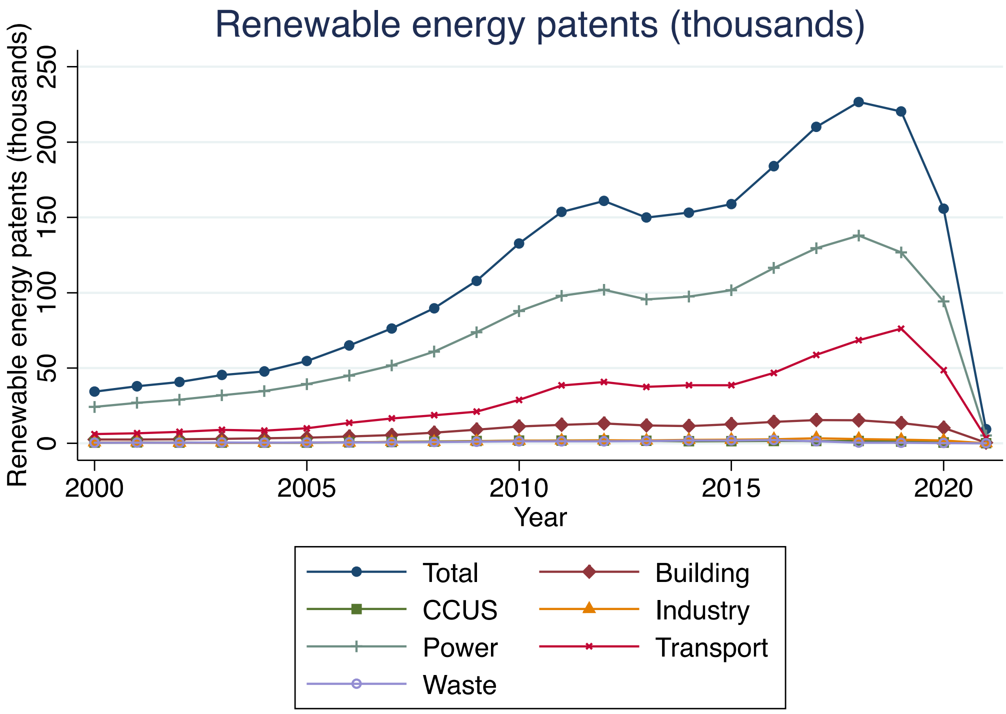
Figures

Figure 1.1. Evolution of patents by sectors and technologies



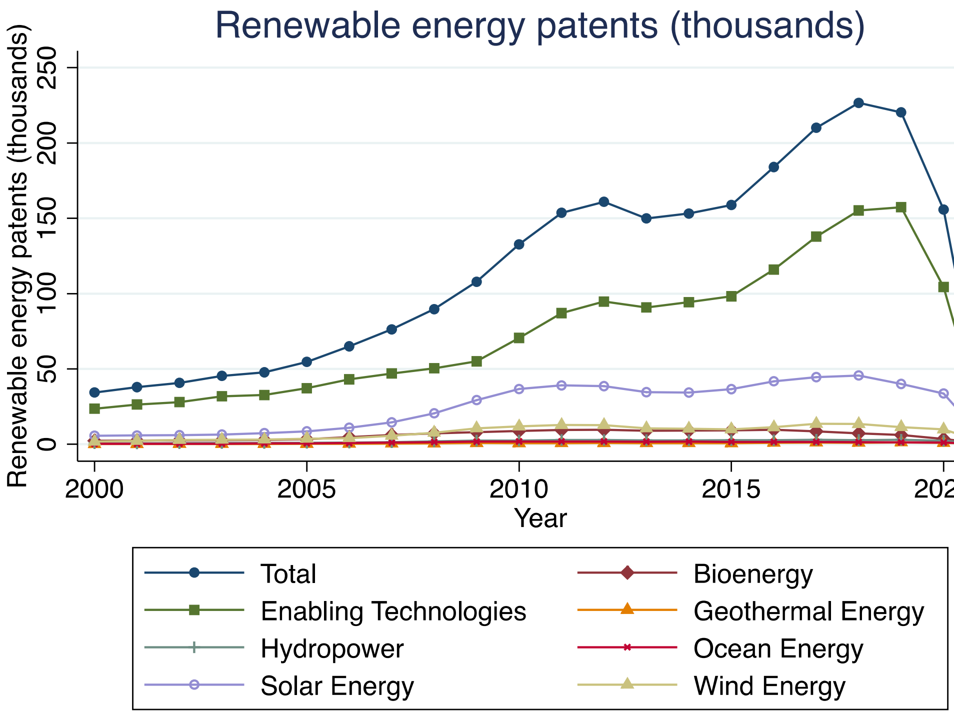
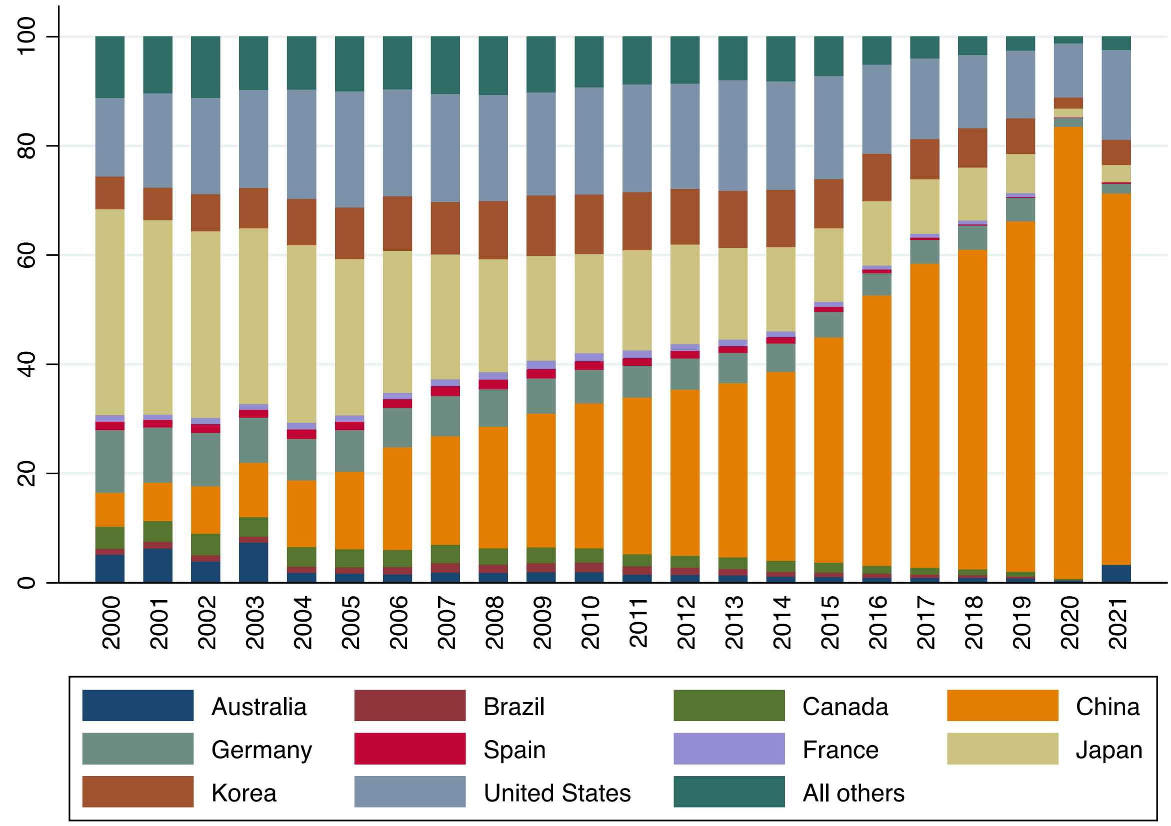
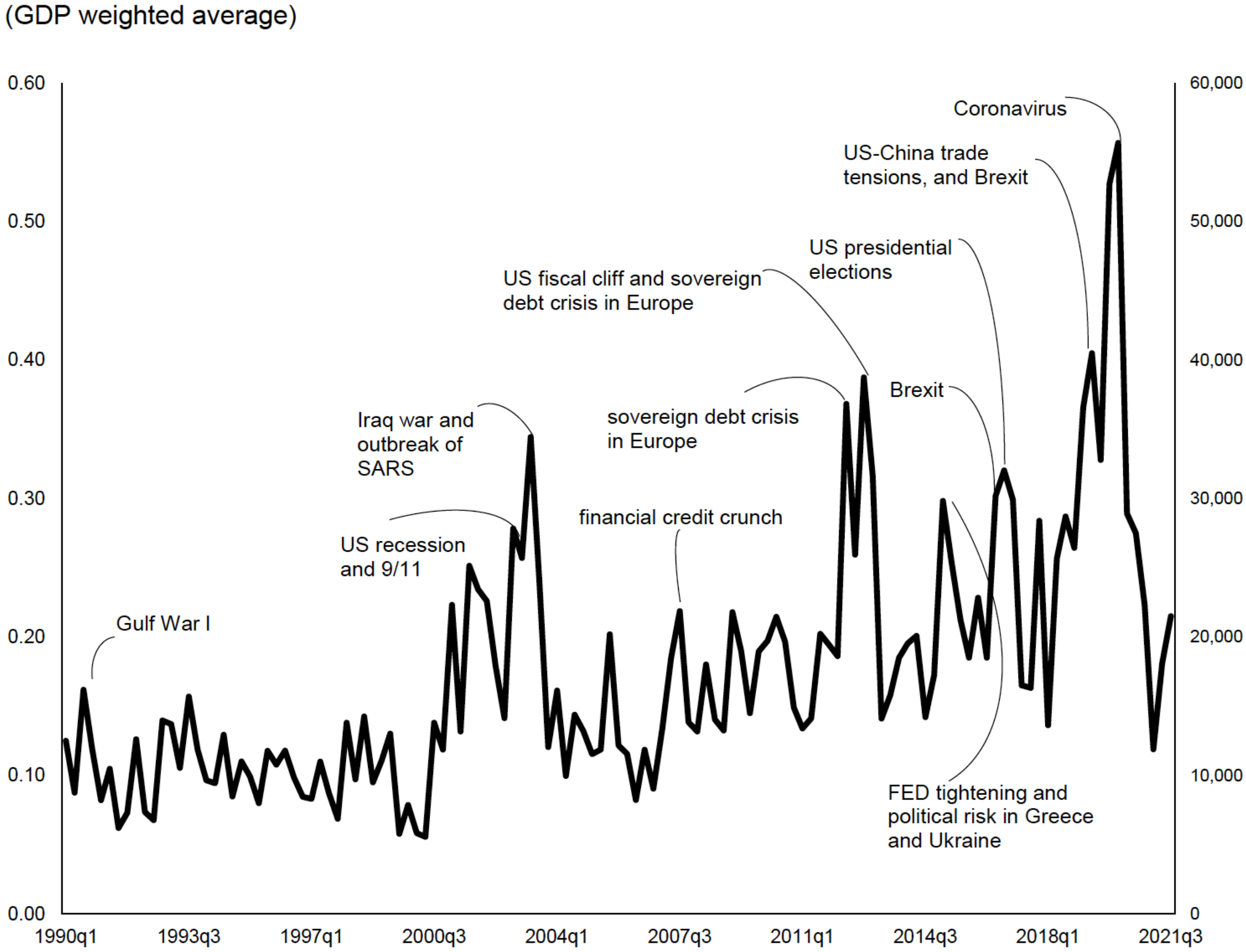


Figure 1.2 Evolution of patents by country



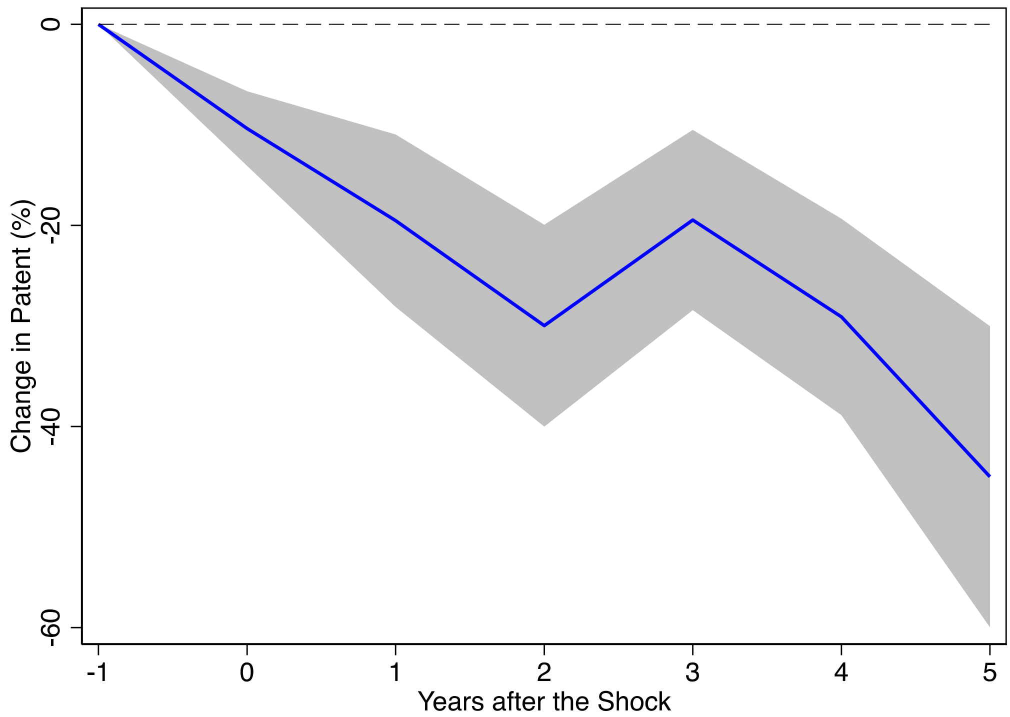
Notes: The chart show the share of new renewable energy patents by country for top 10 countries with higher average share over the 2000-2021. All the other 54 countries in our sample are grouped together.

Figure 1.3. Global World Uncertainty Index (WUI) over time



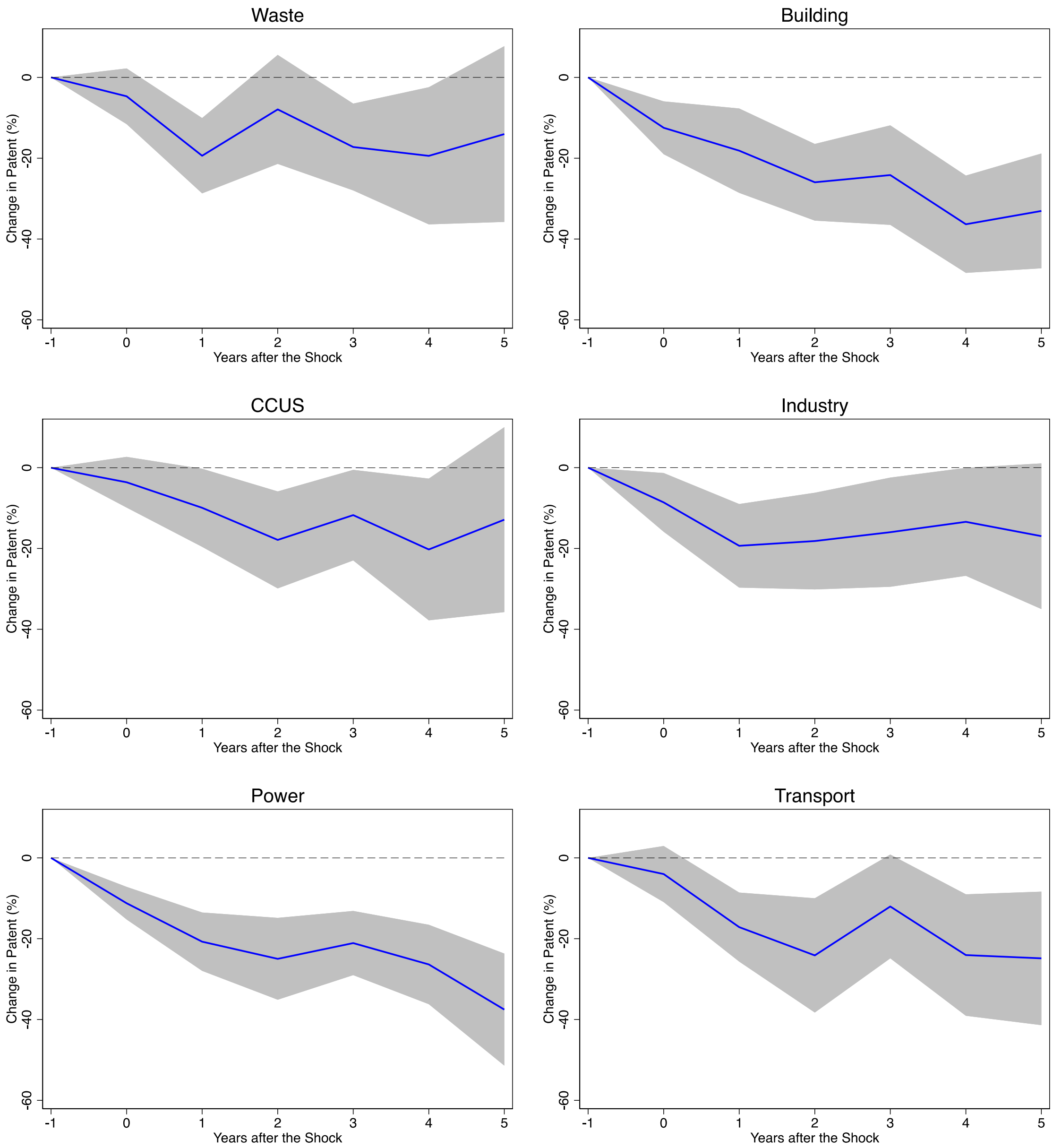
Source: Ahir et a., (2022). Note. Left scale: number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words. Right scale: number of times uncertain (or the variant) is mentioned in EIU country reports per thousand words multiplied by 100,000. A higher number means higher uncertainty and vice versa. see

Figure 1.4. The impact of uncertainty on renewable energy patents – baseline



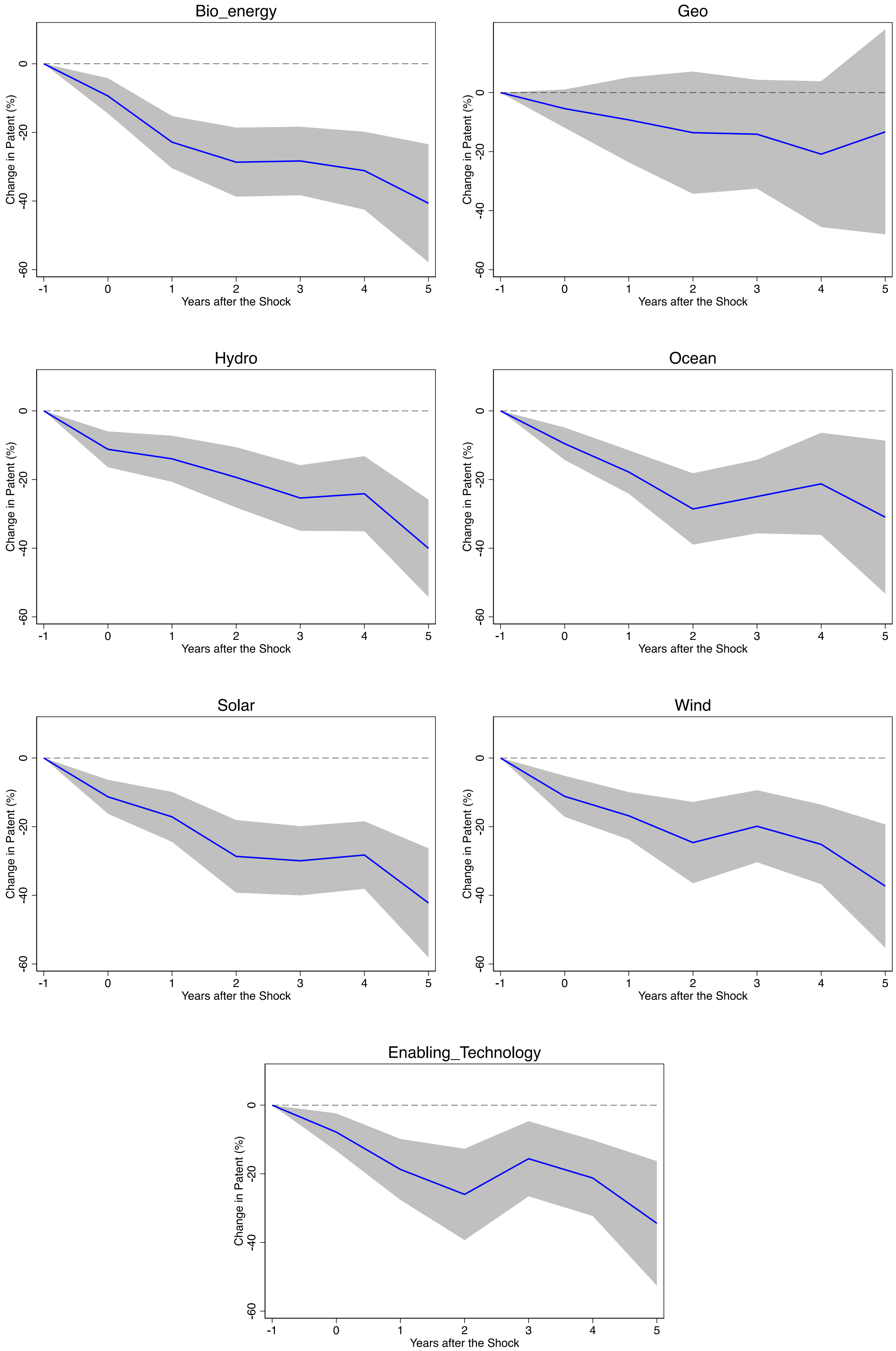
Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (*k*) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1).

Figure 1.5. The impact of uncertainty on renewable energy patents – by sectors



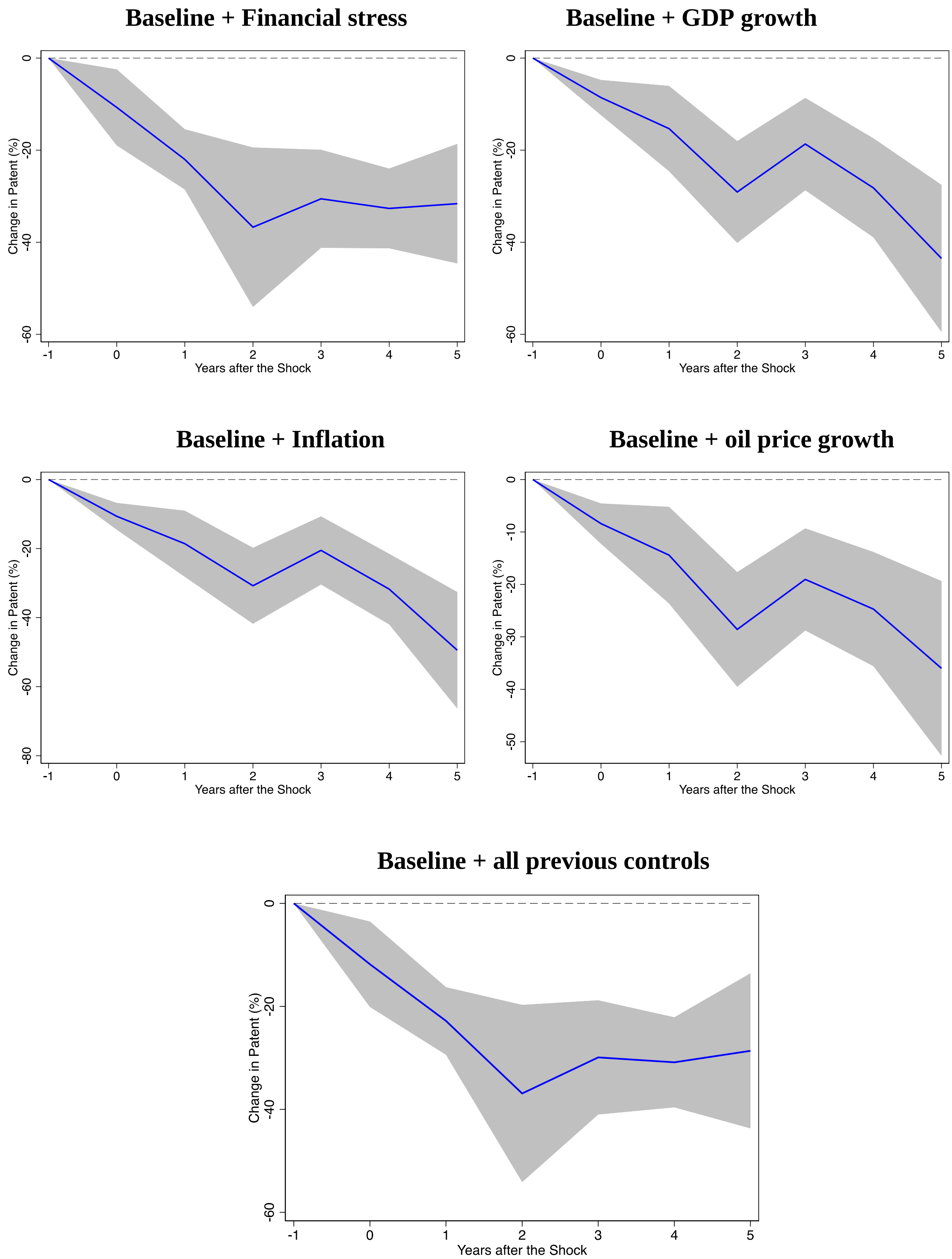
Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (*k*) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1) for each sector.

Figure 1.6. The impact of uncertainty on renewable energy patents – by technologies



Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (*k*) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1) for each technology.

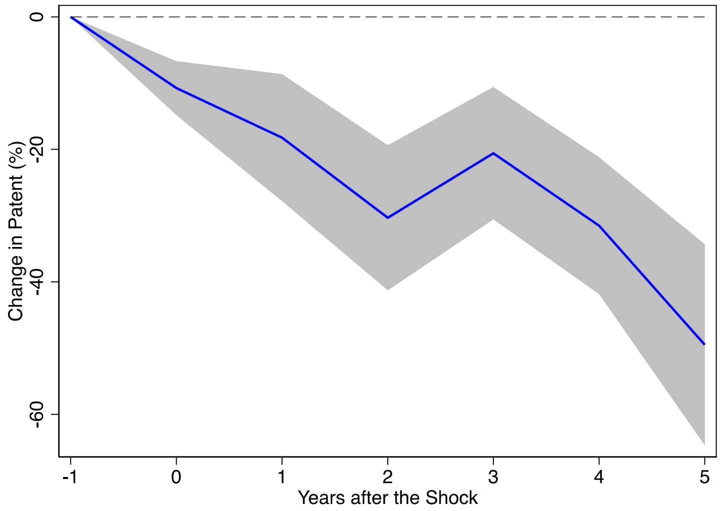
Figure 1.7. Robustness checks – additional controls



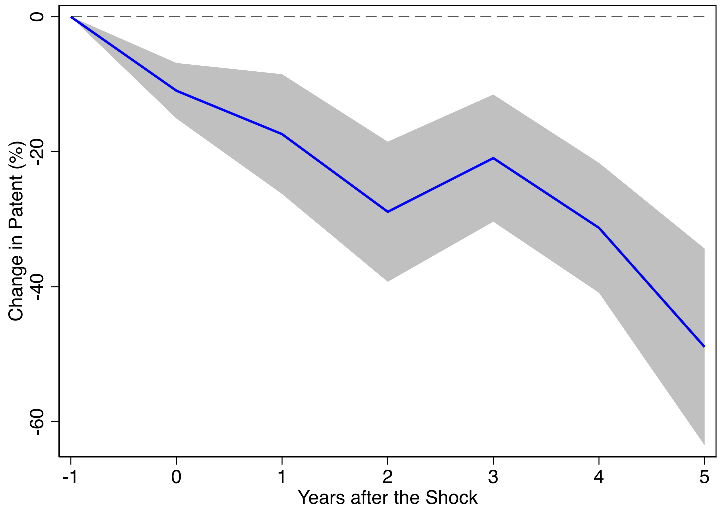
Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (*k*) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1) adding each control variable once at a time and all together.

Figure 1.8. Robustness checks – controlling for outliers

Excluding observations above the 99^{th} and below the 1^{st} percentile of renewable energy patents (log)

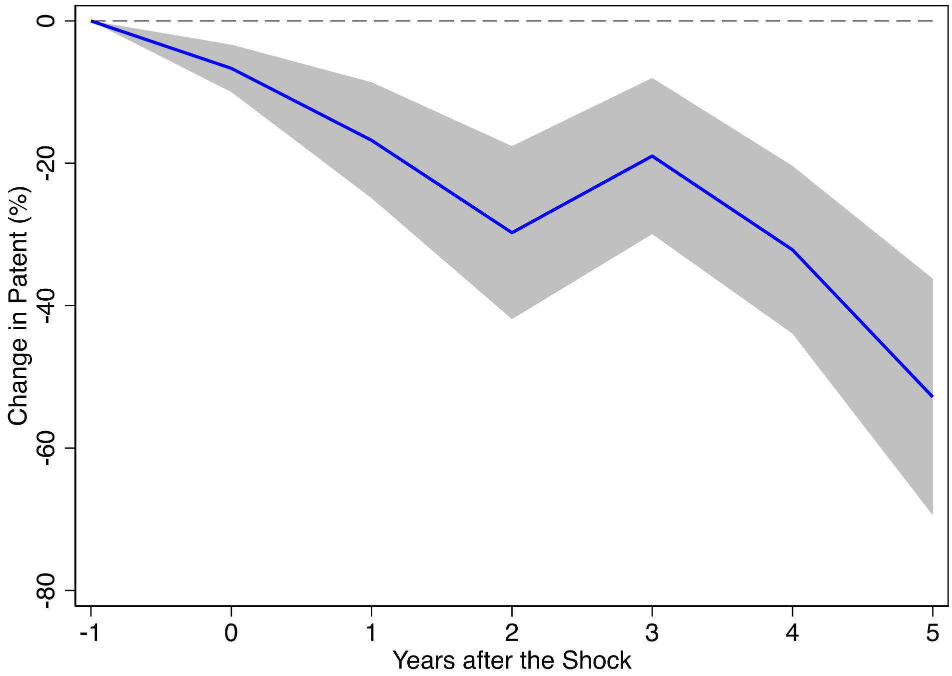


Excluding observations above the 95^{th} and below the 5^{th} percentile of renewable energy patents (log)



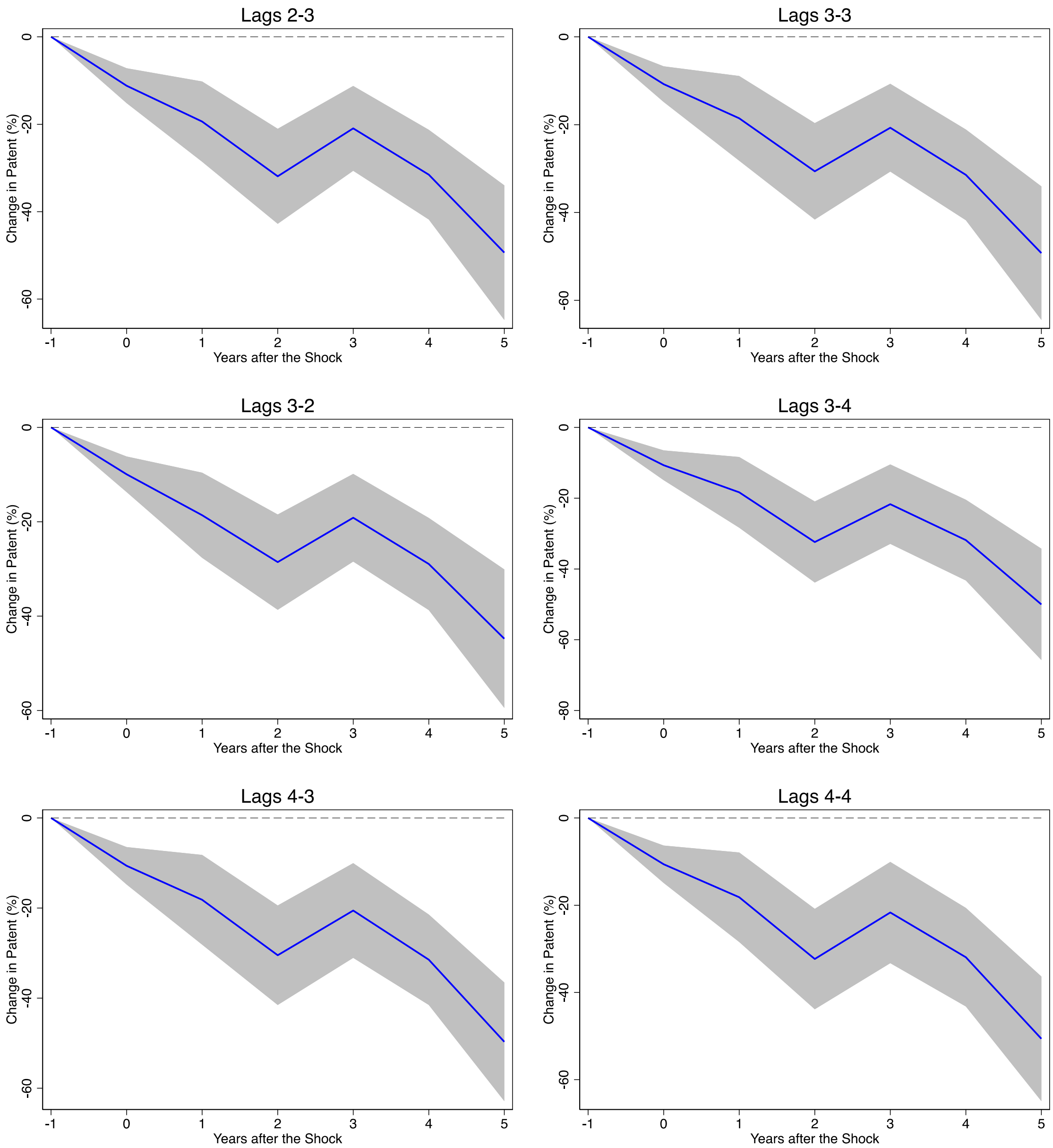
Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (*k*) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1) excluding, alternatively, observations above the 99^{th} (95^{th}) and below the 1st (5^{th}) percentile of renewable energy patents (log).

Figure 1.9. Robustness checks – excluding GFC and COVID-19



Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (*k*) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1) excluding 2008 and 2020 from the estimation period.

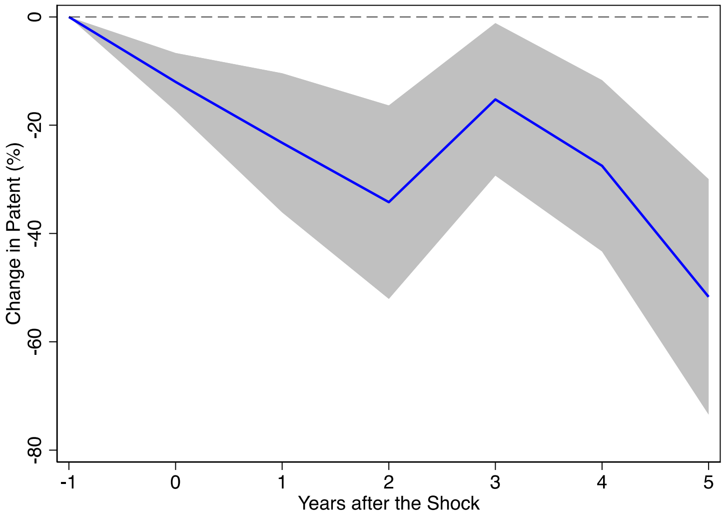
Figure 1.10. Robustness checks – different lag structure



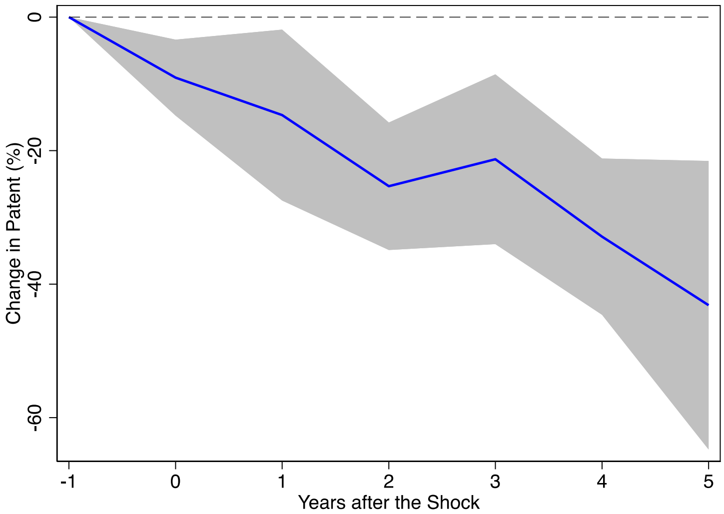
Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (k) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1) using three lags of the dependent variable and the WUI as controls.

Figure 1.11. The impact of uncertainty on renewable energy patents by levels of development

High-Income economies (HI)



Low- and Middle-income economies (LMI)



Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (*k*) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1) for subsamples of High-Income vs Low- and Middle-income economies. See Table 1.A1 in the Appendix for country group classification.

Figure 1.12. The impact of uncertainty on renewable energy patents – Instrumental variable results

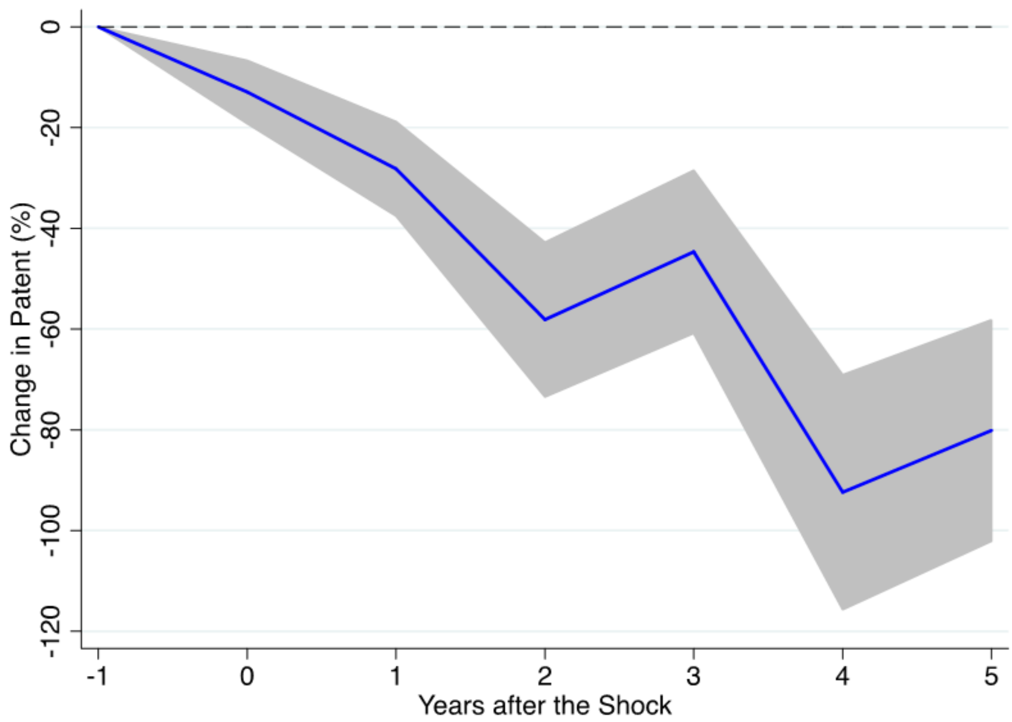
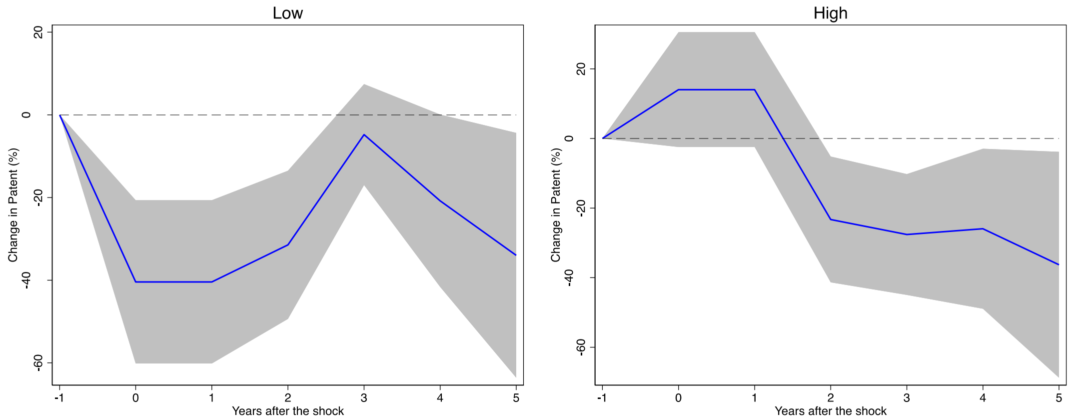
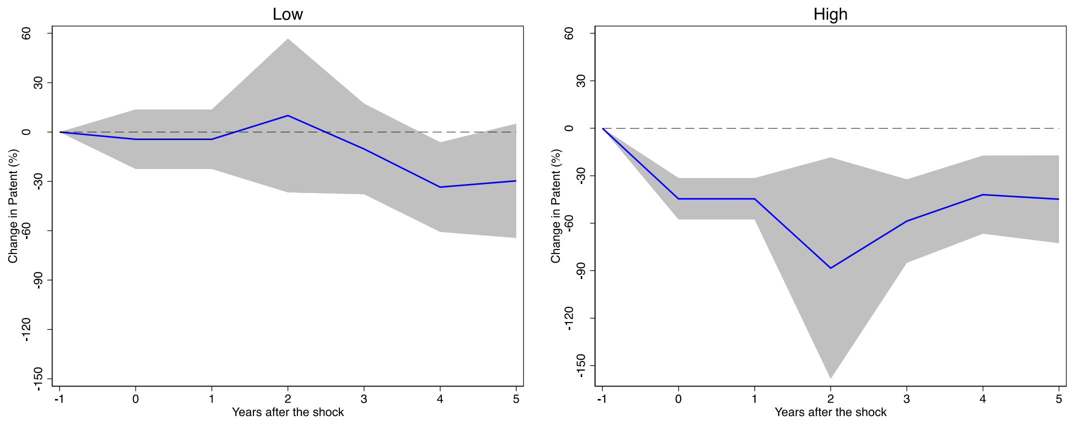


Figure 1.13. The impact of uncertainty on renewable energy patents – non-linear effects

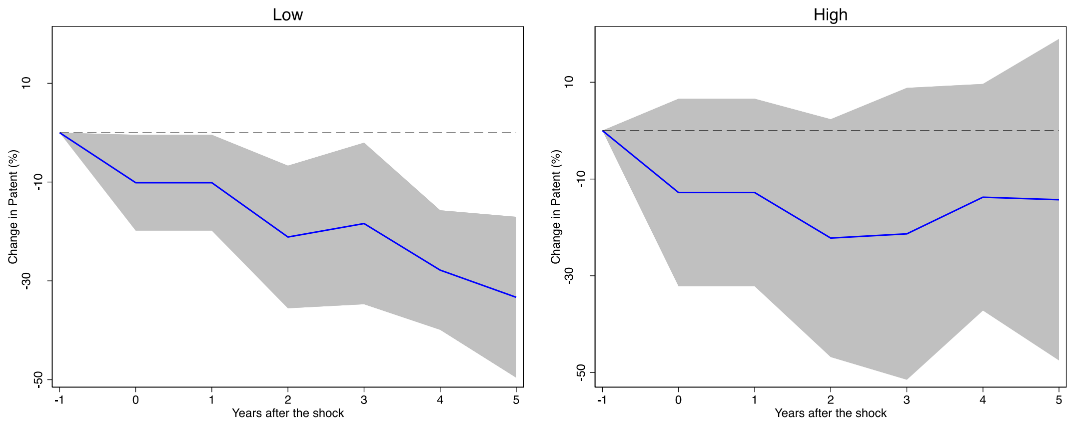
GDP Growth



Financial Stress

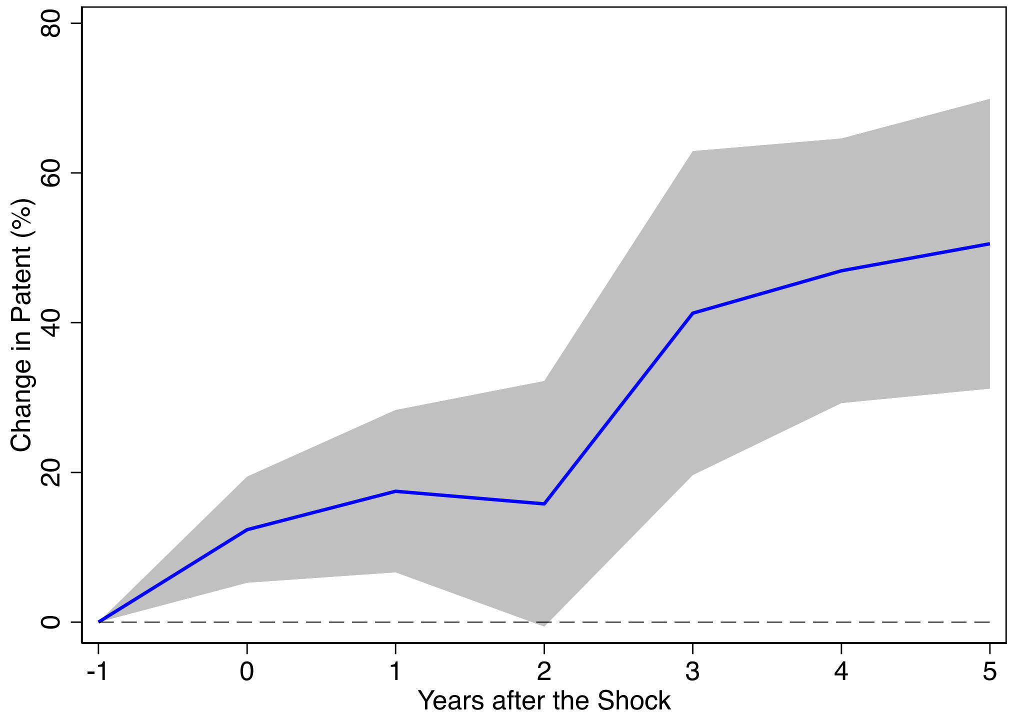


Environmental Policy stringency



Notes: The graph shows the response of the number of new renewable energy patents (in %) to one-standard deviation increase in uncertainty and 90 percent confidence bands. Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The x-axis shows years (k) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.2) using Environmental Policy stringency index, GDP growth and financial stress as state variable.

Figure 1.14. The impact of the OECD environmental stringency index on renewable energy patents



Notes: Impulse response functions are estimated using a sample of 64 countries over the period 2000-2021. The graph shows the response and 90 percent confidence bands. The x-axis shows years (*k*) after the shock; t = 0 is the year of the shock. Estimates based on equation (1.1) using the change in the OECD environmental stringency index as shock variable 3nstead of WUI.

Tables

Table 1.1. The impact of uncertainty on renewable energy patents – baseline

	k=0	k=1	k=2	k=3	k=4	k=5
WUI_{it}	-10.37***	-19.538***	-29.968***	-19.475***	-29.105***	-45.005***
	(2.249)	(5.208)	(6.096)	(5.443)	(5.933)	(9.096)
WUI_{it-1}	-8.11***	-15.78***	-2.046	-16.267***	-27.258***	-12.472*
	(2.882)	(5.591)	(4.922)	(4.289)	(6.855)	(7.349)
WUI_{it-2}	-1.764	-5.001	-18.999***	-23.386***	-10.619	-10.559
	(3.395)	(4.093)	(6.563)	(7.871)	(7.944)	(8.798)
ΔPatents (log)$_{it-1}$	-.248***	-.248***	-.257***	-.211*	-.449**	-.349***
	(.07)	(.08)	(.091)	(.114)	(.171)	(.105)
ΔPatents (log)$_{it-2}$	-.065	-.013	.066	-.125	-.122	-.122
	(.053)	(.068)	(.087)	(.138)	(.114)	(.105)
Observations	1008	964	901	842	780	717
R-squared	0.106	0.142	0.15	0.159	0.200	0.214

Note: k=0 is the year of the shock. k=1,2,3,4,5 are the years after the shock. Estimates based on equation (1.1). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Country-specific time trends included but not reported.

Table 1.2. The impact of uncertainty on renewable energy patents – Instrumental Variable

First stage	k=0	k=1	k=2	k=3	k=4	k=5
Instrument	0.366***	0.357***	0.377***	0.437***	0.445***	0.627***
	(0.026)	(0.027)	(0.035)	(0.042)	(0.048)	(0.067)

IV results	k=0	k=1	k=2	k=3	k=4	k=5
WUI_{it}	-12.951***	-28.198***	-58.128***	-44.661***	-92.376***	-80.137***
	(3.802)	(5.684)	(9.321)	(9.832)	(14.151)	(13.345)
WUI_{it-1}	-0.682	3.564	18.655***	5.608	19.728**	13.242*
	(2.390)	(3.574)	(5.516)	(5.834)	(8.237)	(7.300)
WUI_{it-2}	-1.060	-4.272	-11.845***	-14.047***	-6.985	-9.573*
	(1.833)	(2.755)	(3.643)	(3.990)	(5.405)	(5.396)
ΔPatents (log)$_{it-1}$	-0.250***	-0.269***	-0.317***	-0.227**	-0.560***	-0.518***
	(0.041)	(0.061)	(0.084)	(0.094)	(0.124)	(0.131)
ΔPatents (log)$_{it-2}$	-0.061	-0.001	0.103	-0.099	-0.106	-0.162
	(0.040)	(0.060)	(0.083)	(0.089)	(0.121)	(0.124)
Observations	865	823	768	717	663	608
KleibergenPaap_rk_Wald_F_statistic	191.9	180	114.7	108.5	85.48	86.96

Note: k=0 is the year of the shock. k=1,2,3,4,5 are the years after the shock. IV first stage estimates based on equation (1.1) in the main text. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Country-specific time trends included but not reported. The Kleibergen–Paap rk Wald F-statistic tests for weak identification.

Table 1.3. F-tests difference

	F-test difference					
	k=0	k=1	k=2	k=3	k=4	k=5
GDP Growth	10.61***	7.41***	0.13	2.49	0.07	0.02
Financial Stress	4.53**	4.95**	1.78	2.13	0.07	0.06
Change in EPS	0.18	0.03	0.002	0.01	0.60	0.65

*** p<0.01, ** p<0.05, * p<0.1. The F-test of the difference between the estimations in the case of low and high regime of the interaction variable with the WUI—(See Figure 1.14).

Appendix 1

Table 1. A1. List of the countries included in the analysis and descriptive statistics - renewable energy patents (in log)

Country	CG	N	mean	sd	min	max
Argentina	HI	17	4.91	0.40	4.30	5.49
Australia	HI	18	7.43	0.41	6.58	8.12
Austria	HI	18	5.69	1.16	2.48	7.00
Belgium	HI	18	3.46	0.72	1.61	4.47
Brazil	LMI	18	6.96	0.80	4.36	7.76
Bulgaria	LMI	18	2.77	0.43	1.95	3.50
Canada	HI	18	7.73	0.52	5.90	8.15
Chile	HI	12	5.30	0.52	4.14	5.81
China	LMI	18	10.47	1.10	8.41	11.86
Colombia	LMI	14	3.73	0.93	1.61	4.70
Costa Rica	LMI	14	2.33	0.80	0.69	3.40
Croatia	HI	18	3.73	1.01	2.40	5.06
Czech Republic	HI	18	4.15	0.41	3.47	4.89
Denmark	HI	18	6.15	0.88	3.61	7.08
Dominican Republic	LMI	8	1.92	0.40	1.39	2.30
Ecuador	LMI	15	2.41	0.89	0.00	3.91
Egypt	LMI	10	3.02	1.06	1.10	4.08
Finland	HI	18	4.29	0.49	3.33	4.95
France	HI	18	7.00	0.75	4.60	7.68
Georgia	LMI	14	1.78	0.52	0.69	2.64
Germany	HI	18	8.77	0.40	7.81	9.21
Greece	HI	18	3.78	0.60	2.64	4.68
Guatemala	LMI	8	1.61	0.77	0.00	2.48
Honduras	LMI	2	0.80	1.14	0.00	1.61
Hong Kong SAR	HI	17	5.26	0.78	3.18	6.45
Hungary	HI	18	4.47	1.04	1.61	5.48
India	LMI	13	3.03	2.25	1.10	7.14
Ireland	HI	14	2.22	0.97	0.69	4.06
Israel	HI	18	5.47	0.65	4.11	6.26
Italy	HI	17	5.50	1.03	2.30	6.58
Japan	HI	18	9.80	0.54	7.81	10.28
Jordan	LMI	12	1.26	0.83	0.00	2.64
Korea	HI	18	9.21	0.60	8.07	9.71
Latvia	HI	17	1.94	0.45	0.69	2.56
Lithuania	HI	18	2.88	1.29	0.00	4.34
Malaysia	LMI	13	4.77	0.72	3.53	5.72
Mexico	LMI	17	6.22	0.86	3.58	6.90
Moldova	LMI	18	2.54	0.87	0.00	3.58
Morocco	LMI	17	4.15	0.82	3.00	5.27
Netherlands	HI	18	4.76	0.66	2.56	5.41
New Zealand	HI	17	4.69	1.39	1.10	5.98
Nicaragua	LMI	4	1.27	1.11	0.00	2.30
Norway	HI	18	4.90	0.49	3.61	5.55
Panama	HI	7	0.61	0.46	0.00	1.10
Peru	LMI	18	3.43	0.87	1.39	4.38
Philippines	LMI	7	5.48	0.34	4.97	5.84
Poland	HI	18	5.98	0.91	3.04	6.77
Portugal	HI	17	5.29	0.71	3.14	5.99
Romania	LMI	18	3.90	0.75	2.20	4.98
Russia	LMI	18	7.01	0.47	5.79	7.52
Saudi Arabia	HI	6	1.69	0.74	0.69	2.56

Singapore	HI	18	5.39	1.02	3.18	6.55
Slovak Republic	HI	18	3.01	0.71	1.39	3.81
Slovenia	HI	17	4.20	0.71	2.48	5.09
South Africa	LMI	18	5.61	0.69	3.76	6.51
Spain	HI	18	6.93	0.76	4.98	7.71
Sweden	HI	18	4.52	0.47	3.37	5.02
Switzerland	HI	18	4.19	0.80	2.56	5.02
Tunisia	LMI	17	2.98	1.37	0.00	4.37
Turkey	LMI	18	4.08	0.61	2.71	4.88
Ukraine	LMI	17	5.05	0.63	3.04	5.74
United Kingdom	HI	18	6.91	0.44	5.84	7.30
United States	HI	18	9.94	0.46	9.00	10.34
Uruguay	HI	18	2.35	0.91	0.00	3.74
Whole sample	-	1008	4.88	2.32	0.00	11.86

Note: CG indicates the country group. HI indicates High income economies; LMI indicates low- and middle-income economies

Table 1. A2. Descriptive statistics – World Uncertainty Index (WUI)

Country	CG	N	mean	sd	min	max
Argentina	HI	17	0.33	0.19	0.15	0.85
Australia	HI	18	0.16	0.10	0.02	0.31
Austria	HI	18	0.18	0.13	0.03	0.40
Belgium	HI	18	0.14	0.09	0.03	0.36
Brazil	LMI	18	0.33	0.26	0.05	1.09
Bulgaria	LMI	18	0.20	0.15	0.05	0.62
Canada	HI	18	0.17	0.10	0.03	0.47
Chile	HI	12	0.20	0.14	0.00	0.44
China	LMI	18	0.11	0.11	0.00	0.35
Colombia	LMI	14	0.22	0.09	0.09	0.38
Costa Rica	LMI	14	0.16	0.11	0.00	0.36
Croatia	HI	18	0.14	0.09	0.03	0.40
Czech Republic	HI	18	0.18	0.08	0.04	0.30
Denmark	HI	18	0.21	0.12	0.05	0.47
Dominican Republ	LMI	8	0.18	0.13	0.09	0.48
Ecuador	LMI	15	0.31	0.19	0.12	0.76
Egypt	LMI	10	0.14	0.21	0.00	0.70
Finland	HI	18	0.14	0.14	0.00	0.46
France	HI	18	0.21	0.09	0.07	0.38
Georgia	LMI	14	0.24	0.23	0.00	0.76
Germany	HI	18	0.23	0.15	0.04	0.62
Greece	HI	18	0.18	0.15	0.00	0.42
Guatemala	LMI	8	0.17	0.08	0.05	0.29
Honduras	LMI	2	0.14	0.07	0.09	0.18
Hong Kong SAR	HI	17	0.10	0.08	0.00	0.25
Hungary	HI	18	0.21	0.14	0.04	0.49
India	LMI	13	0.08	0.06	0.00	0.21
Ireland	HI	14	0.32	0.27	0.07	1.09
Israel	HI	18	0.18	0.08	0.07	0.40
Italy	HI	17	0.25	0.13	0.02	0.46
Japan	HI	18	0.17	0.08	0.05	0.33
Jordan	LMI	12	0.05	0.05	0.00	0.17
Korea	HI	18	0.23	0.14	0.06	0.50
Latvia	HI	17	0.19	0.10	0.03	0.42
Lithuania	HI	18	0.16	0.12	0.00	0.50
Malaysia	LMI	13	0.15	0.14	0.00	0.50
Mexico	LMI	17	0.29	0.16	0.03	0.66
Moldova	LMI	18	0.30	0.24	0.02	0.85
Morocco	LMI	17	0.07	0.05	0.00	0.19
Netherlands	HI	18	0.20	0.12	0.02	0.41
New Zealand	HI	17	0.15	0.11	0.02	0.37
Nicaragua	LMI	4	0.27	0.09	0.15	0.35
Norway	HI	18	0.21	0.15	0.04	0.58
Panama	HI	7	0.10	0.06	0.03	0.20
Peru	LMI	18	0.24	0.14	0.00	0.56
Philippines	LMI	7	0.16	0.07	0.06	0.25
Poland	HI	18	0.25	0.11	0.06	0.47
Portugal	HI	17	0.19	0.10	0.03	0.38
Romania	LMI	18	0.19	0.10	0.07	0.44
Russia	LMI	18	0.26	0.10	0.04	0.48
Saudi Arabia	HI	6	0.13	0.06	0.08	0.23
Singapore	HI	18	0.08	0.06	0.00	0.25
Slovak Republic	HI	18	0.13	0.08	0.02	0.27
Slovenia	HI	17	0.15	0.11	0.00	0.37
South Africa	LMI	18	0.54	0.38	0.06	1.34
Spain	HI	18	0.24	0.11	0.05	0.44

Sweden	HI	18	0.21	0.12	0.03	0.42
Switzerland	HI	18	0.28	0.24	0.06	0.82
Tunisia	LMI	17	0.27	0.25	0.01	0.75
Turkey	LMI	18	0.31	0.15	0.14	0.72
Ukraine	LMI	17	0.27	0.13	0.07	0.62
United Kingdom	HI	18	0.43	0.30	0.15	1.18
United States	HI	18	0.23	0.12	0.06	0.54
Uruguay	HI	18	0.21	0.13	0.03	0.45
Whole sample	-	1008	0.21	0.17	0.00	1.34

Note: CG indicates the country group. HI indicates High income economies; LMI indicates low- and middle-income economies

Table 1. A3. Instrumental Variable – robustness check (WUSI-USA)

First stage	k=0	k=1	k=2	k=3	k=4	k=5
Instrument	0.281***	0.280***	0.273***	0.255***	0.242***	0.330***
	(0.029)	(0.029)	(0.031)	(0.036)	(0.040)	(0.054)
IV results	k=0	k=1	k=2	k=3	k=4	k=5
WUI_{it}	-13.032***	-34.450***	-62.456***	-72.358***	-132.590***	-73.739***
	(4.662)	(7.514)	(10.465)	(15.272)	(25.435)	(18.355)
WUI_{it-1}	-1.181	1.990	19.607***	17.932**	36.506***	12.444
	(2.541)	(4.052)	(5.750)	(7.736)	(12.643)	(8.485)
WUI_{it-2}	-0.585	-1.475	-9.161***	-13.295***	-4.713	-7.318
	(1.616)	(2.607)	(3.337)	(4.082)	(6.167)	(4.779)
∆Patents $(log)_{it-1}$	-0.264***	-0.290***	-0.339***	-0.326***	-0.649***	-0.490***
	(0.039)	(0.062)	(0.083)	(0.106)	(0.155)	(0.136)
∆Patents $(log)_{it-2}$	-0.072*	-0.031	0.052	-0.127	-0.103	-0.142
	(0.038)	(0.061)	(0.082)	(0.102)	(0.154)	(0.124)
Observations	990	946	884	826	765	703
KleibergenPaap_rk_Wald_F_statistic	97.26	90.35	79.20	50.84	36.05	37.58

Note: k=0 is the year of the shock. k=1,2,3,4,5 are the years after the shock. IV first stage estimates based on equation (1.1) in the main text. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Country-specific time trends included but not reported. The Kleibergen–Paap rk Wald F-statistic tests for weak identification.

Table 1. A4. Instrumental Variable – robustness check (WUSI-USA+UK)

First stage	k=0	k=1	k=2	k=3	k=4	k=5
Instrument	0.340***	0.335***	0.341***	0.368***	0.363***	0.518***
	(0.025)	(0.025)	(0.031)	(0.038)	(0.044)	(0.067)

IV results	k=0	k=1	k=2	k=3	k=4	k=5
WUI_{it}	-9.567***	-22.516***	-64.075***	-55.274***	-116.957***	-95.766***
	(3.626)	(5.524)	(9.258)	(10.883)	(17.783)	(16.905)
WUI_{it-1}	-2.926	-2.262	19.970***	9.803	31.192***	20.497**
	(2.215)	(3.372)	(5.350)	(6.060)	(9.559)	(8.196)
WUI_{it-2}	-0.969	-2.689	-9.651***	-11.711***	-4.713	-7.988
	(1.671)	(2.570)	(3.496)	(3.915)	(5.721)	(5.427)
ΔPatents (log)$_{it-1}$	-0.257***	-0.268***	-0.339***	-0.287***	-0.615***	-0.546***
	(0.039)	(0.059)	(0.083)	(0.095)	(0.137)	(0.146)
ΔPatents (log)$_{it-2}$	-0.068*	-0.018	0.054	-0.124	-0.097	-0.148
	(0.038)	(0.058)	(0.082)	(0.092)	(0.139)	(0.137)
Observations	972	928	867	810	750	689
KleibergenPaap_rk_Wald_F_statistic	191.8	182.8	118.2	94.52	67.26	60.27

Note: k=0 is the year of the shock. k=1,2,3,4,5 are the years after the shock. IV first stage estimates based on equation (1.1) in the main text. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Country-specific time trends included but not reported. The Kleibergen–Paap rk Wald F-statistic tests for weak identification

Chapter 2

Environmental Policies and Innovation in Renewable Energy

2.1. 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, e.g., the United Nations (UN) 2030 Agenda for Sustainable Development. 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), and also economic and policy uncertainty. As discussed in the previous chapter, government regulations and policies may also affect the production of innovation (Ashford, 2000; Acemoglu et al., 2012). Although we found that more stringent environmental policies tend to cushion the negative effects of uncertainty on green patenting (thus spurring green innovation), the theoretical effect that such kind of 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 relationship between environmental policies and green innovation can be further conceptualized through the Porter Hypothesis. This hypothesis suggests that well-designed environmental regulations can stimulate innovation that may partially or more than fully offset the costs of complying with these regulations. Porter's Hypothesis posits that stringent but flexible environmental regulations can encourage firms to innovate, leading to the development of new technologies, products, or processes that not only reduce environmental harm but also enhance competitiveness and efficiency.

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 advanced and emerging 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.[7] 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 technology-support policies.[8] 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

[7] See Table 2.A1 in the Appendix for more information about economic sectors.
[8] 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).

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 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 2.2 presents an overview of the literature. Section 2.3 presents the data used in the empirical analysis. Section 2.4 examines the response of green innovation at the macro level. Section 2.5 focuses on the sectoral difference-in-differences analysis. Section 2.6 concludes by summarizing the main results and the policy implications.

2.2 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).

2.3. 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 2.A1-2.A4).

2.3.1. 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.[9] 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.[10] 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.

Figure 2.1 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

[9] 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.
[10] See Table 2.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.

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.

2.3.2. 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 2.2 shows the evolution of the EPS, and of the 25^{th} and 75^{th} 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 2.3, 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 2.3, 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 (these are direct taxes imposed on the emission of pollutants, such as carbon taxes. They provide a financial incentive for polluters to reduce their emissions to avoid or minimize the tax burden); Emission Trading Systems (This creates a market for emission allowances and encourages companies to reduce their emissions), non-market-based instruments such as emission limit (These policies set specific limits on the amount of pollutants that can be emitted from specific sources), and technology-support instruments such as low-carbon R&D expenditures (These are financial incentives provided to support the development of new and improved technologies that reduce pollution or promote energy efficiency).In the empirical analysis, we will show that this distinction is key to better understand the dynamic response of green innovation to CCPs. Figure 2.A1, in the Appendix, shows the breakdown by country of each sub-component of EPS.

2.4. Macro-level analysis

2.4.1. 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:

$$y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^{k} + \beta^{k}\Delta CCP_{i,t} + \sum_{l}\rho_{l}^{k}\,\Delta y_{i,s,t-l} + \sum_{l}\delta_{l}^{k}\,\Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k} \qquad (2.1)$$

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 (2.1) 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.[11]

2.4.2. Baseline Results

Figure 2.4 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 (2.1). 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

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

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 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.[12]

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 2.A3 in the Annex for data sources). Figure 2.5 presents the 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 2.4. As additional robustness checks, we perform the following exercises: first, we change the number of lags in equation (2.1), 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 level as the increase in patents is typically lower

[12] 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 raises 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.

when the initial stock is higher (Eugster, 2021). The results reported in the Annex (Figure 2.A2, panels A2a-.A2h) 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 (2.1) with measures of market-, non-market-based, and technology-support CCPs are reported in Figure (2.6). 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.[13]

2.4.3. 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

[13] 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).

innovation. If green innovation is weak, a country may have more incentives to adopt 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 of 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.[14]

The regression equation takes the following form:

$$y_{i,s,t+k} - y_{i,s,t} = time^{k}_{is,t} + \beta^{k}\widehat{\Delta CCP}_{i,t} + \sum_{l} \rho^{k}_{l}\,\Delta y_{i,s,t-l} + \sum_{l} \delta^{k}_{l}\,\Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$$

$$\Delta CCP_{i,t} = time_{is,t} + \varphi\, Z_{i,t-1} + \sum_{l} \theta_{l}\,\Delta y_{i,s,t-l} + \sum_{l} \lambda_{l}\,\Delta CCP_{i,t-1-l} + \eta_{i,s,t}; \qquad (2.2)$$

[14] 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.

where Z is the instrument.[15]

The IV results are reported in Table 2.1 and Figure 2.7. Table 2.1 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 2.7 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.

2.5. 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 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

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

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:

$$y_{i,s,t+k} - y_{i,s,t} = time^{k}_{is,t} + F(z_{it})\left[\beta^{k}_{L}\Delta CCP_{i,t} + \sum_{l}\rho^{k}_{L,l}\,\Delta y_{i,s,t-l} + \sum_{l}\delta^{k}_{L,l}\,\Delta CCP_{i,t-1-l}\right] +$$
$$\left(1 - F(z_{it})\right)\left[\beta^{k}_{H}\Delta CCP_{i,t} + \sum_{l}\rho^{k}_{H,l}\,\Delta y_{i,s,t-l} + \sum_{l}\delta^{k}_{H,l}\,\Delta CCP_{i,t-1-l}\right] + \phi^{k}_{l}F(z_{it-1}) + \varepsilon_{i,s,t+k} \qquad (2.3)$$

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

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^{k}_{L} 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^{k}_{H} is the coefficient in the case of very high output growth (high competition, uncertainty or financial stress)—that is, when (1 – $F(z_{it})$) ≈ 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 γ=5 to give an intermediate degree of regime switching.[16]

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

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 (2.3) are reported in Figures 2.8-2.11. 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 2.2, we report the F-test for the difference in the responses between the two regimes (e.g., recessions vs expansions), across all horizons.

Figure 2.8 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 2.9 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 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 2.10 presents the results for financial stress as 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 2.11 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. The 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.

2.6. 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 is used to estimate the causal effect of a policy intervention by comparing the before-and-after differences in outcomes between a treatment group (exposed to the policy) and a control group (not exposed to the policy). This methodology is particularly insightful for understanding the nuanced effects of CCPs on industries with varying levels of financial constraints. Financially constrained sectors are generally less able to invest in innovation due to limited access to external capital. Moreover, 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.[17] The regression that we estimate reads as follows:

$$y_{i,s,t+k} - y_{i,s,t} = \alpha_{is}^k + \alpha_{it}^k + \alpha_{st}^k + \beta^k \Delta CCP_{i,t} * EFD_s + \sum_l \rho_l^k \, \Delta y_{i,s,t-l} + \sum_l \delta_l^k \, \Delta CCP_{i,t-1-l} * EFD_s + \varepsilon_{i,s,t+k} \quad (2.4)$$

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 2.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 2.12 (continuous) and Figures 2.A3 in the Appendix (ranking), provide similar results. Consistent with the macro

[17] See Table 2.A1, in the Appendix, for further details.

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. In particular, the 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 25^{th} 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 75^{th} percentile).

2.7. Conclusion and Policy Implications

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. For example, the implementation of financial measures such as grants, low-interest loans, and tax incentives to support R&D and the commercialization of green technologies, especially in sectors that are financially constrained or in the early stages of green technology adoption, can help magnifying the positive effect of more stringent CCPs on green innovation.

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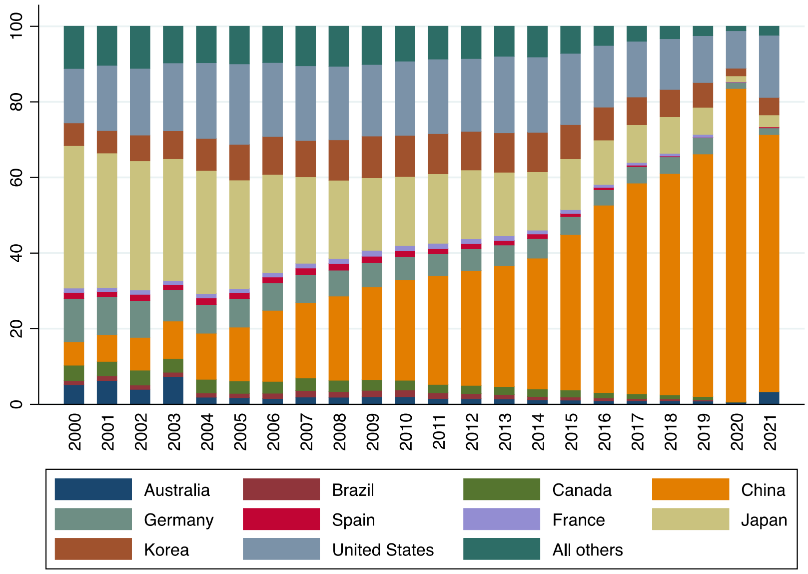
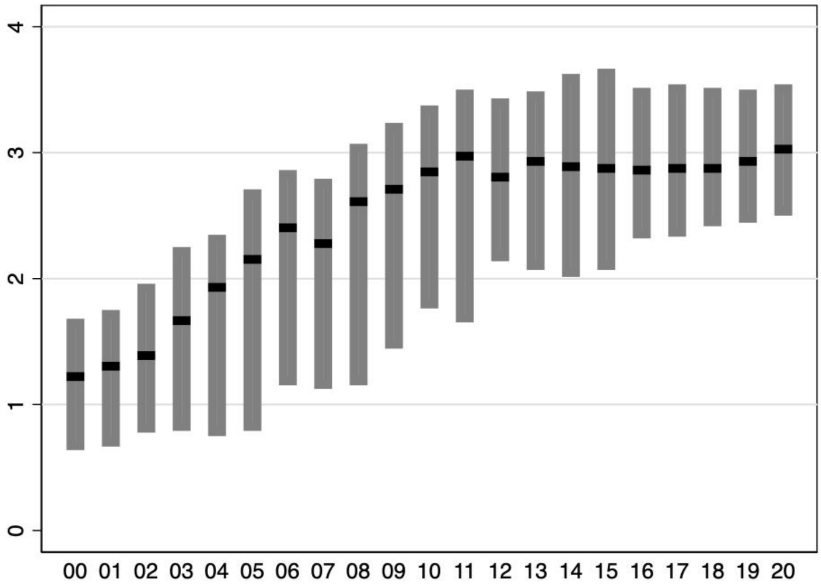
Figures

Figure 2.1. Evolution of patents by country



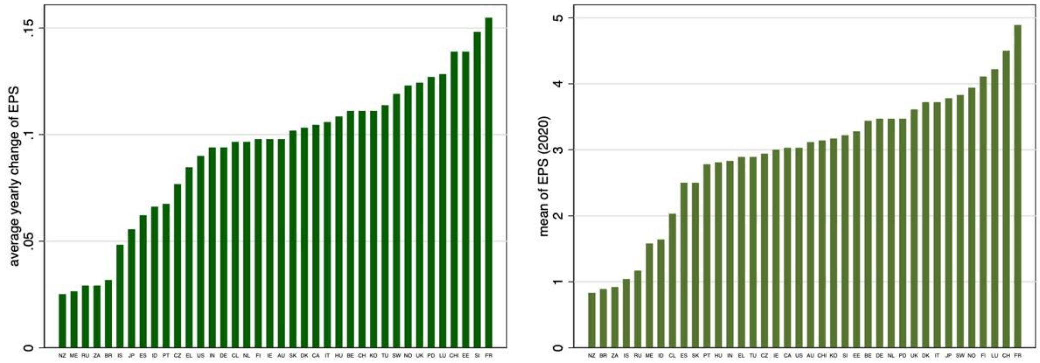
Notes: The chart shows the share of new renewable energy patents by country, for top 10 countries with higher average share over the period 2000-2021. All the other 30 countries in our sample are grouped together.

Figure 2.2: Evolution of the EPS index over time (median, 25th percentile, 75th percentile)



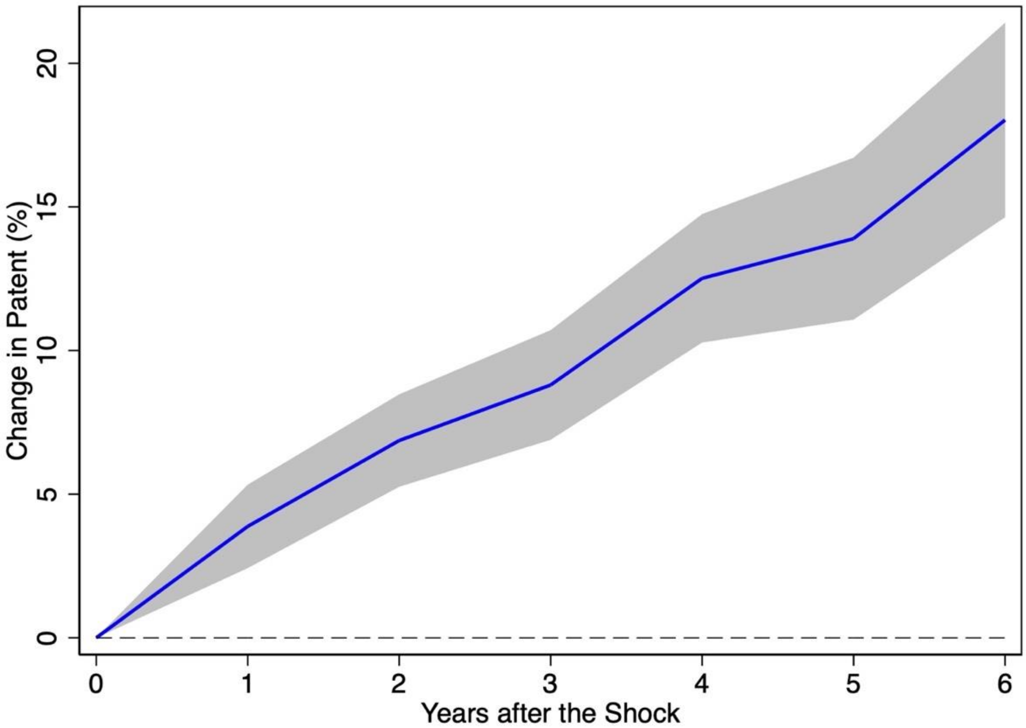
Notes: authors elaboration on OECD data. x-axis indicates years (from 2000 to 2020); y-axis indicates the EPS score, where the box refers to the 25th and 75th percentiles of the EPS distribution and the black line the median across countries.

Figure 2.3: 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.

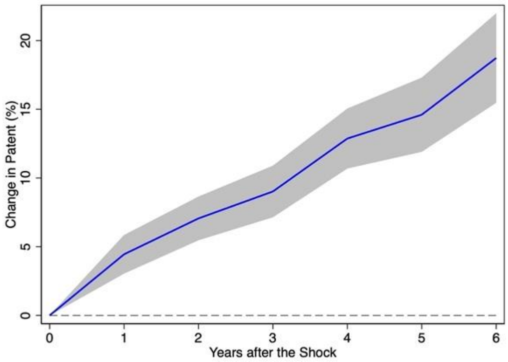
Figure 2.4: Impact of CCPs on green innovation



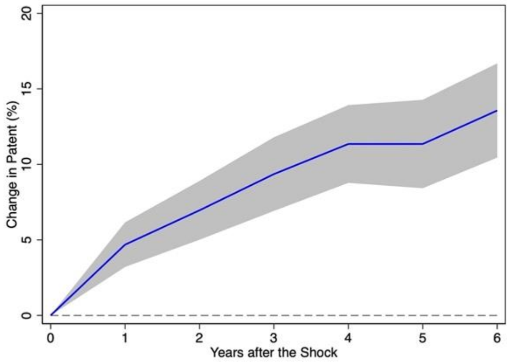
Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.1): $y_{i,s,t+k} - y_{i,s,t} = time^{k}_{is,t} + \beta^{k} \Delta CCP_{i,t} + \sum_{l} \rho^{k}_{l} \Delta y_{i,s,t-1} + \sum_{l} \delta^{k}_{l} \Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; 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 2.5: Impact of CCPs on green innovation—robustness checks with additional controls

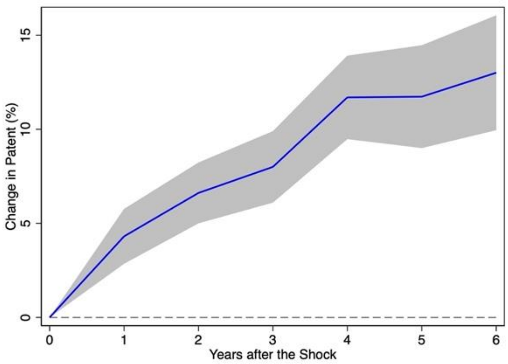
(a) baseline with GDP growth



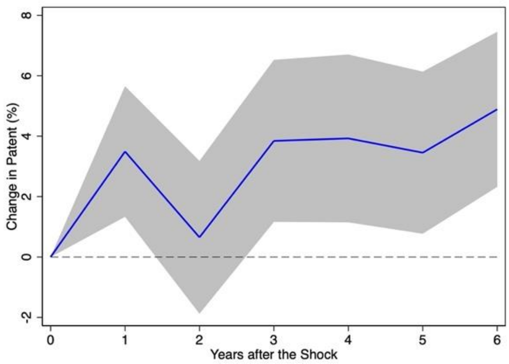
(b) baseline with financial stress



(c) baseline with oil price

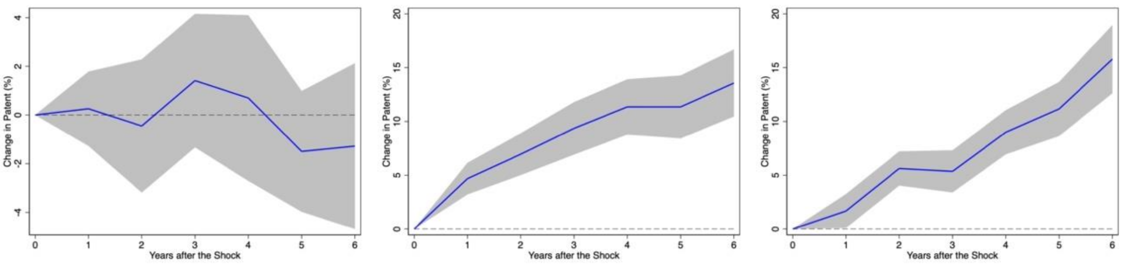


(d) baseline with GDP growth, financial stress, oil price



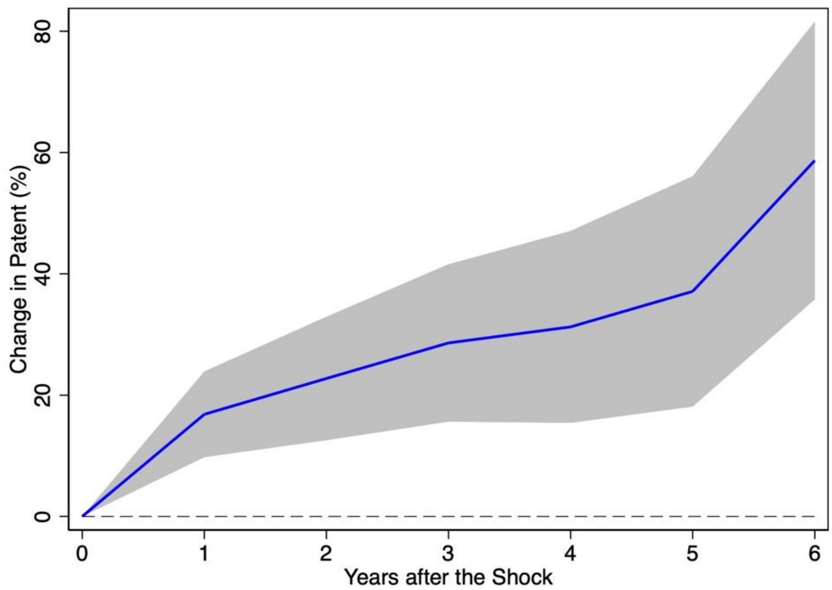
Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.1): $y_{i,s,t+k} - y_{i,s,t} = time^k_{is,t} + \beta^k \Delta CCP_{i,t} + \sum_l \rho^k_l \, \Delta y_{i,s,t-1} + \sum_l \delta^k_l \, \Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; 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. 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 2.6: Impact of market based (left), non-marked based (center) and technology-support (right) CCPs on green innovation



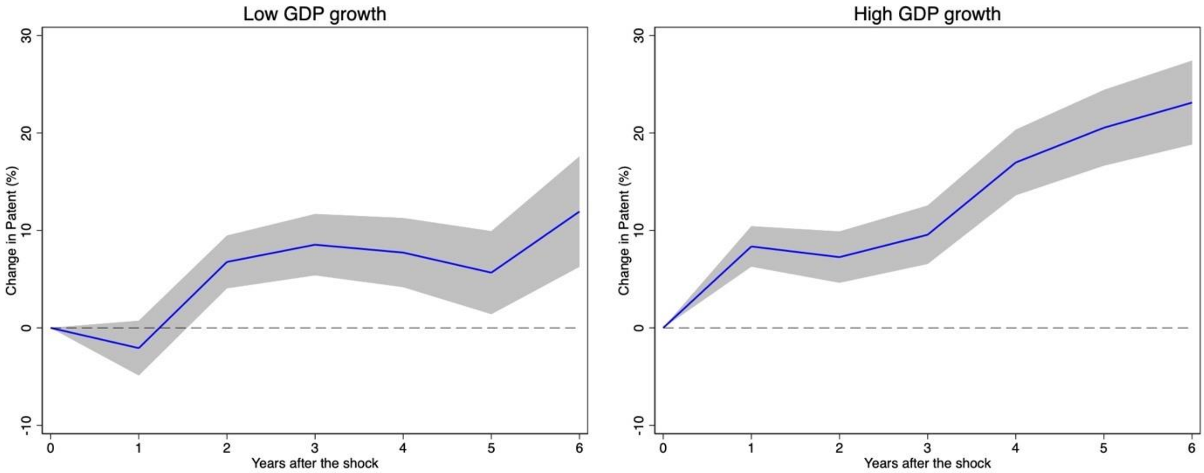
Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^{k} + \beta^{k}\Delta CCP_{i,t} + \sum_{l}\rho_{l}^{k}\Delta y_{i,s,t-1} + \sum_{l}\delta_{l}^{k}\Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; 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. 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 2.7: impact of CCPs on green innovation—IV approach



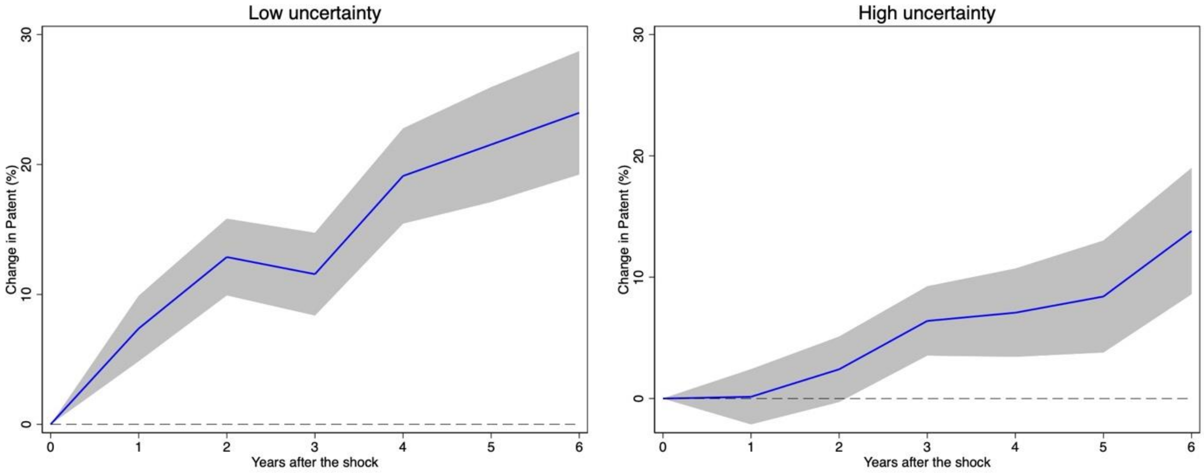
Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.2): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^{k} + \beta^{k}\widehat{\Delta CCP}_{i,t} + \sum_{l}\rho_{l}^{k}\Delta y_{i,s,t-1} + \sum_{l}\delta_{l}^{k}\Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; 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 $\widehat{\Delta CCP}_{i,t}$ 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 2.8: impact of CCPs on green innovation in case of economic recession or growth



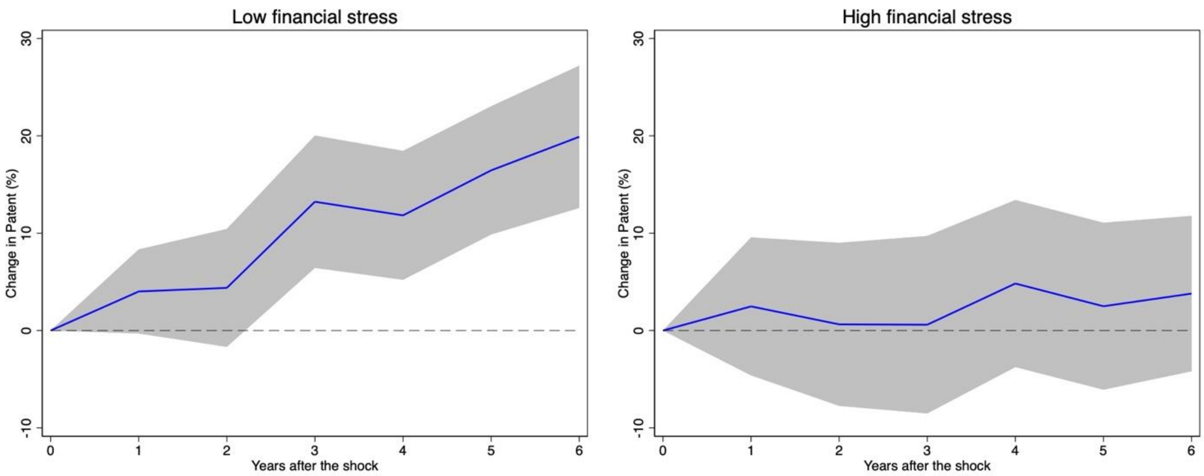
Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.3): $y_{i,s,t+k} - y_{i,s,t} = time^{k}_{is,t} + F(z_{it})\left[\beta^{k}_{L}\Delta CCP_{i,t} + \sum_{l}\rho^{k}_{L,l}\,\Delta y_{i,s,t-1} + \sum_{l}\delta^{k}_{L,l}\,\Delta CCP_{i,t-1-l}\right] + \left(1 - F(z_{it})\right)\left[\beta^{k}_{H}\Delta CCP_{i,t} + \sum_{l}\rho^{k}_{H,l}\,\Delta y_{i,s,t-1} + \sum_{l}\delta^{k}_{H,l}\,\Delta CCP_{i,t-1-l}\right] + \phi^{k}_{l}F(z_{it}) + \varepsilon_{i,s,t+k}$; 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., 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 2.9: impact of CCPs on green innovation when uncertainty is low or high



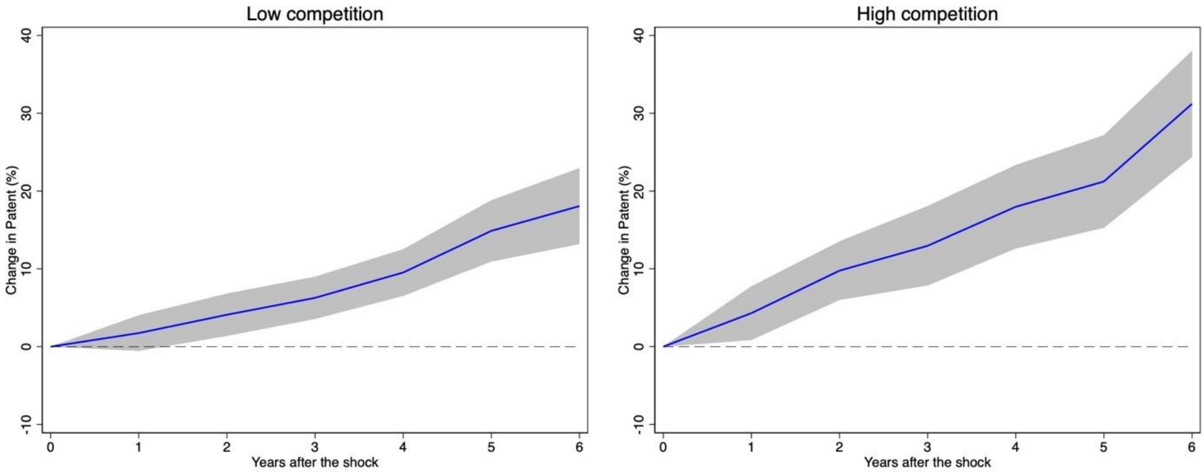
Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.3): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^{k} + F(z_{it})[\beta_L^k \Delta CCP_{i,t} + \sum_l \rho_{L,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{L,l}^k \Delta CCP_{i,t-1-l}] + (1 - F(z_{it}))[\beta_H^k \Delta CCP_{i,t} + \sum_l \rho_{H,l}^k \Delta y_{i,s,t-1} + \sum_l \delta_{H,l}^k \Delta CCP_{i,t-1-l}] + \phi_l^k F(z_{it}) + \varepsilon_{i,s,t+k}$; 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 2.10: impact of CCPs on green innovation when financial constraints are low or high



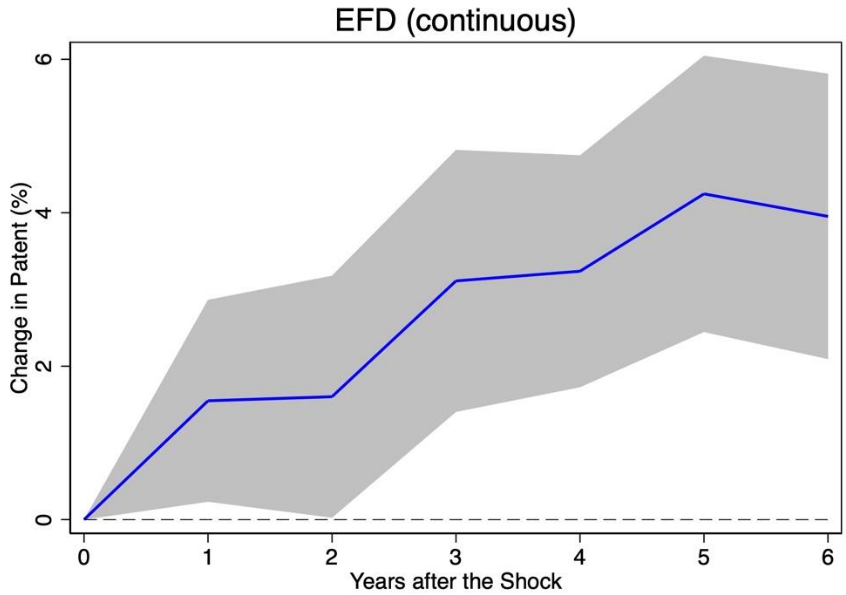
Notes: The charts show the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.3): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^{k} + F(z_{it})\left[\beta_L^k \Delta CCP_{i,t} + \sum_l \rho_{L,l}^k \Delta y_{i,s,t-l} + \sum_l \delta_{L,l}^k \Delta CCP_{i,t-1-l}\right] + \left(1 - F(z_{it})\right)\left[\beta_H^k \Delta CCP_{i,t} + \sum_l \rho_{H,l}^k \Delta y_{i,s,t-l} + \sum_l \delta_{H,l}^k \Delta CCP_{i,t-1-l}\right] + \phi_l^k F(z_{it}) + \varepsilon_{i,s,t+k}$; 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 2.11: 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 (2.3): $y_{i,s,t+k} - y_{i,s,t} = time^k_{is,t} + F(z_{it})\left[\beta^k_L \Delta CCP_{i,t} + \sum_l \rho^k_{L,l}\, \Delta y_{i,s,t-1} + \sum_l \delta^k_{L,l}\, \Delta CCP_{i,t-1-l}\right] + \left(1 - F(z_{it})\right)\left[\beta^k_H \Delta CCP_{i,t} + \sum_l \rho^k_{H,l}\, \Delta y_{i,s,t-1} + \sum_l \delta^k_{H,l}\, \Delta CCP_{i,t-1-l}\right] + \phi^k_l F(z_{it}) + \varepsilon_{i,s,t+k}$; 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 2.12: 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 (2.4): $y_{i,s,t+k} - y_{i,s,t} = \alpha_{is}^{k} + \alpha_{it}^{k} + \alpha_{st}^{k} + \beta^{k}\Delta CCP_{i,t} * \mathrm{EFD_s} + \sum_l \rho_l^k \,\Delta y_{i,s,t-1} + \sum_l \delta_l^k \,\Delta CCP_{i,t-1-1} * \mathrm{EFD_s} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country *i*, sector *s*, between *t*+*k* and *t*, with *k*=1, …,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 (2.4) also includes three batteries of fixed effects: country-year, country-sector, and sector-year. The EFD is included in equation (2.4) 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).

Tables

Table 2.1. 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*** (.00000)	.00008*** (.00000)	.00008*** (.00000)	.00008*** (.00000)	.00008*** (.00000)	.00008*** (.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: $\Delta CCP_{i,t} = time_{is,t} + \varphi Z_{i,t-1} + \sum_l \theta_l \; \Delta y_{i,s,t-l} + \sum_l \lambda_l \; \Delta CCP_{i,t-1-l} + \eta_{i,s,t}$. 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 2.2. 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 (2.3): $y_{i,s,t+k} - y_{i,s,t} = time^k_{is,t} + F(z_{it})\left[\beta^k_L \Delta CCP_{i,t} + \sum_l \rho^k_{L,l} \Delta y_{i,s,t-l} + \sum_l \delta^k_{L,l} \Delta CCP_{i,t-1-l}\right] + \left(1 - F(z_{it})\right)\left[\beta^k_H \Delta CCP_{i,t} + \sum_l \rho^k_{H,l} \Delta y_{i,s,t-l} + \sum_l \delta^k_{H,l} \Delta CCP_{i,t-1-l}\right] + \phi^k_l F(z_{it}) + \varepsilon_{i,s,t+k}$. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 2

Figure 2.A1: Distribution of sub-components of EPS, by country.

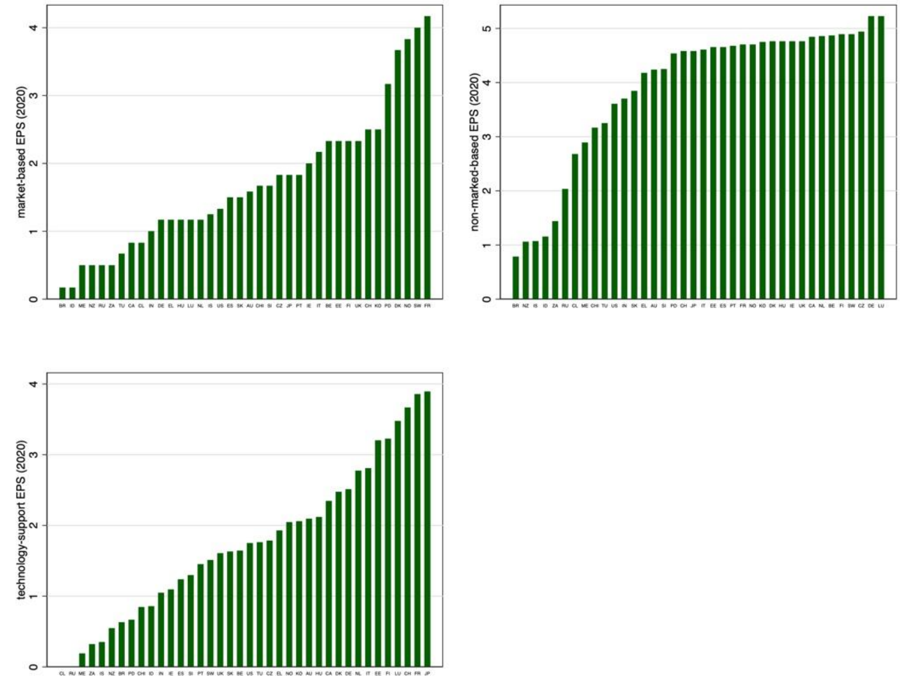
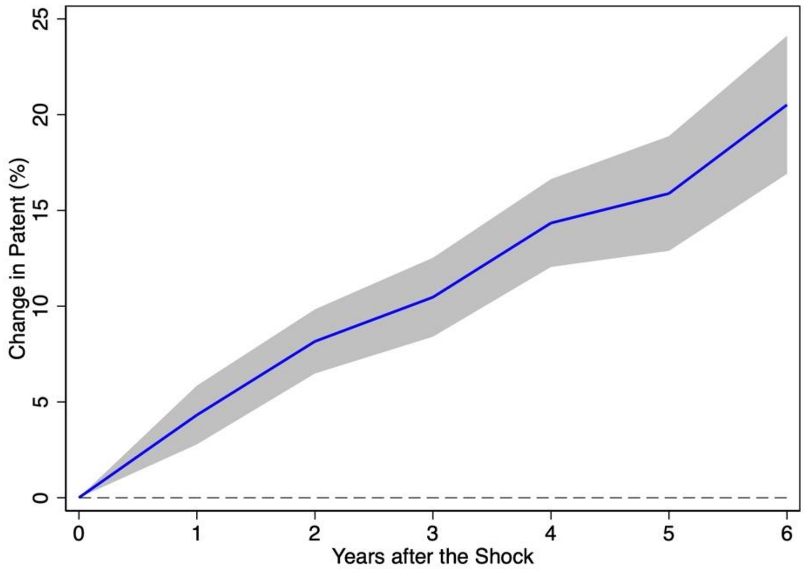
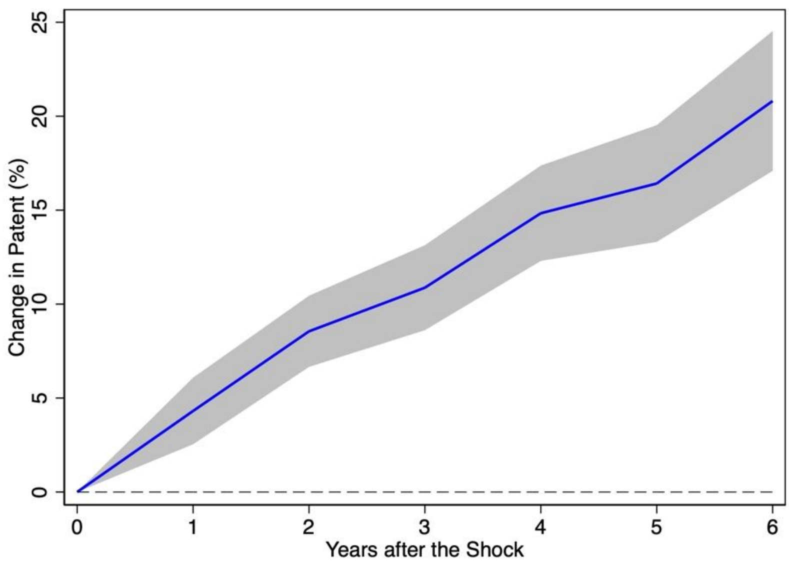


Figure 2.A2: Impact of CCPs on green innovation—robustness checks.
A2a—baseline with different lag structure, i.e., using 3 lags

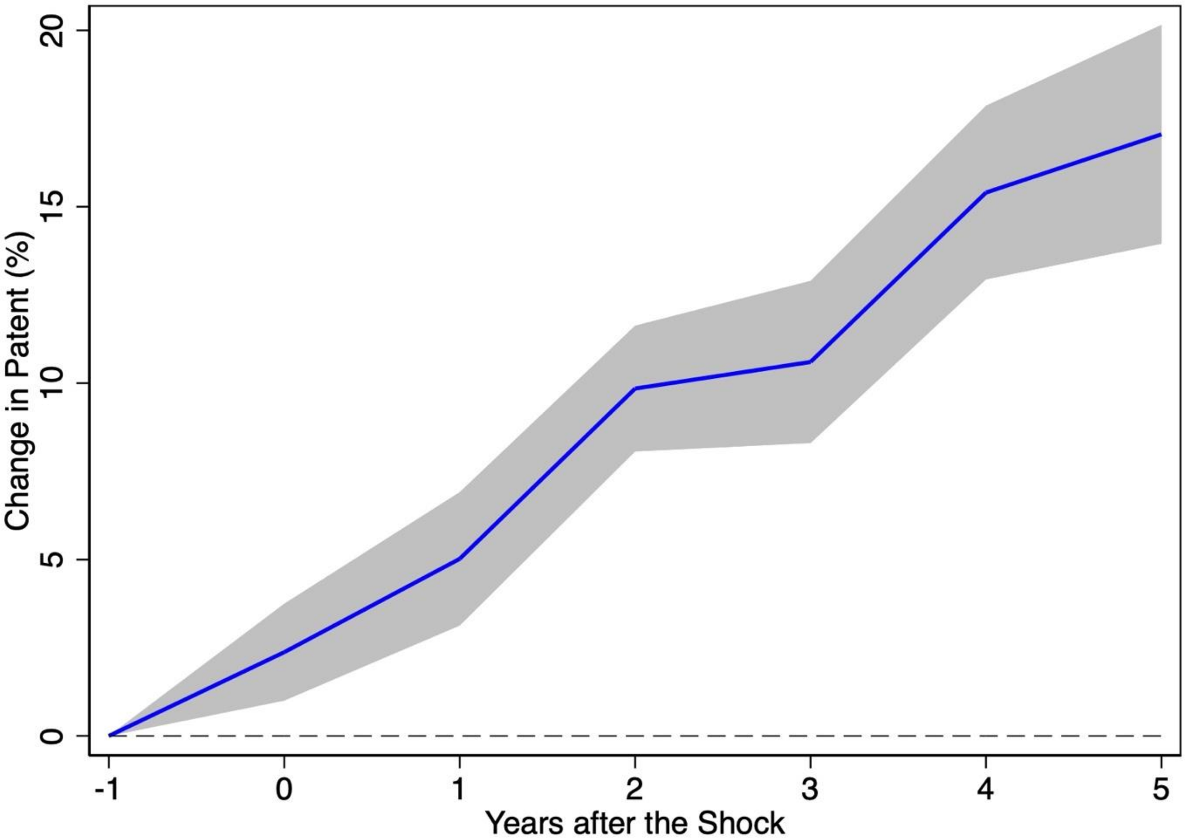


A2b—baseline with different lag structure, i.e., using 4 lags



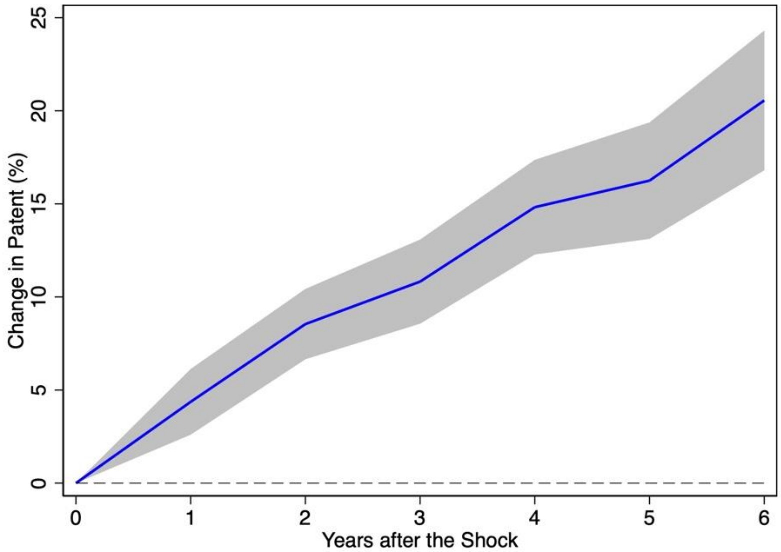
Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.1): $y_{i,s,t+k} - y_{i,s,t} = time^k_{is,t} + \beta^k \Delta CCP_{i,t} + \sum_l \rho^k_l \Delta y_{i,s,t-1} + \sum_l \delta^k_l \Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; 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 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



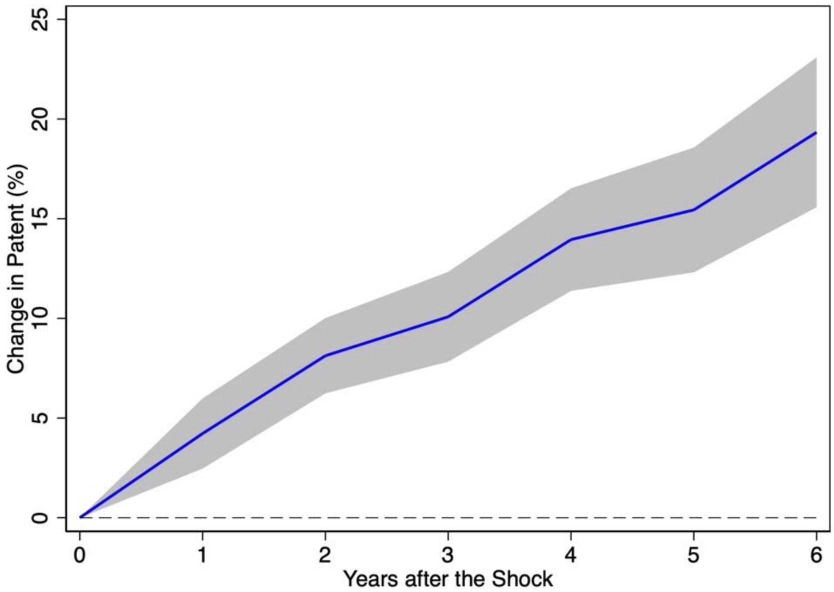
Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.1): $y_{i,s,t+k} - y_{i,s,t} = time^k_{is,t} + \beta^k \Delta CCP_{i,t} + \sum_l \rho^k_l \Delta y_{i,s,t-1} + \sum_l \delta^k_l \Delta CCP_{i,t-1} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country *i*, sector *s*, between $t+k$ and t, with k=1, …,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



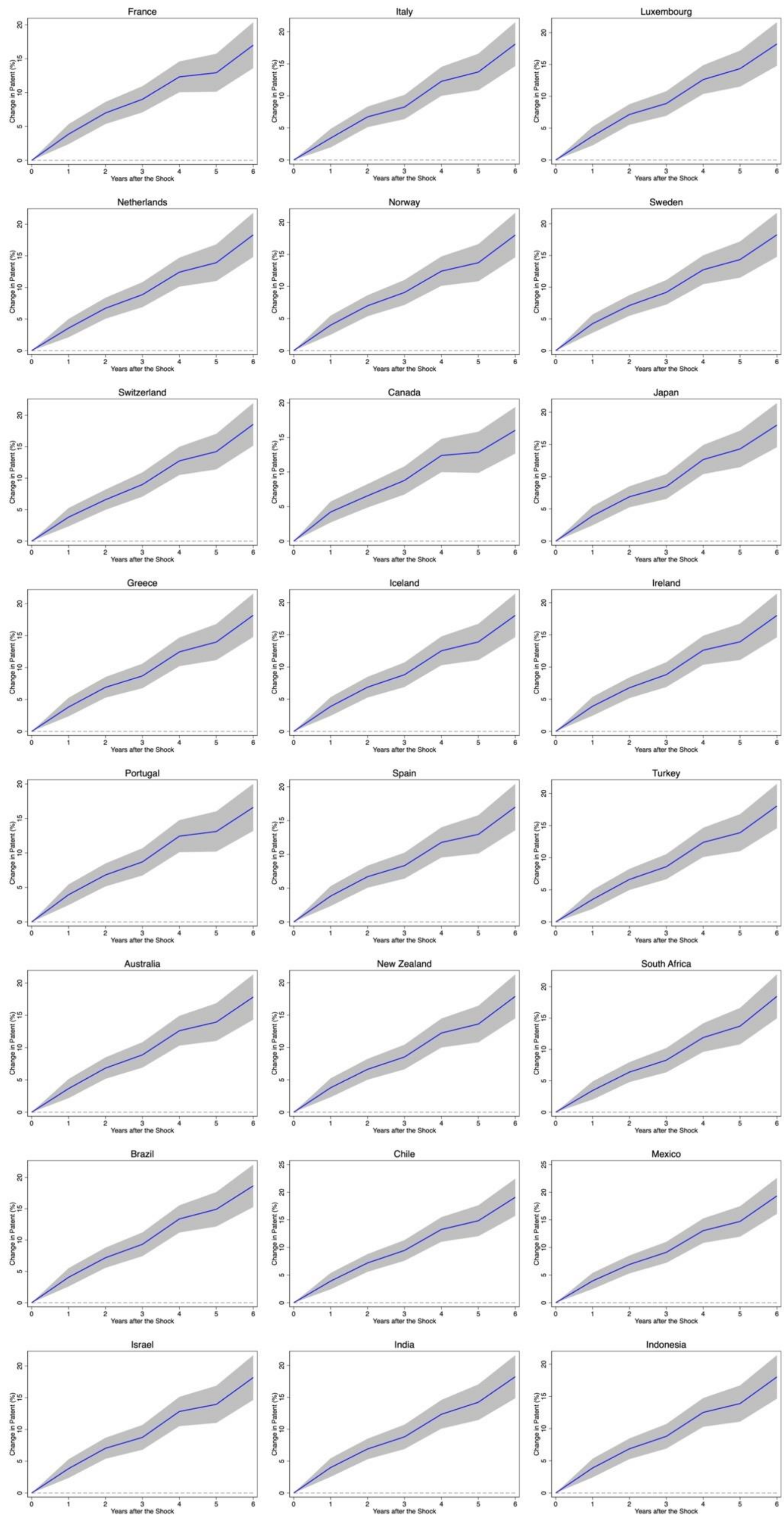
Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^{k} + \beta^{k}\Delta CCP_{i,t} + \sum_{l}\rho_{l}^{k}\,\Delta y_{i,s,t-1} + \sum_{l}\delta_{l}^{k}\,\Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; 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 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.

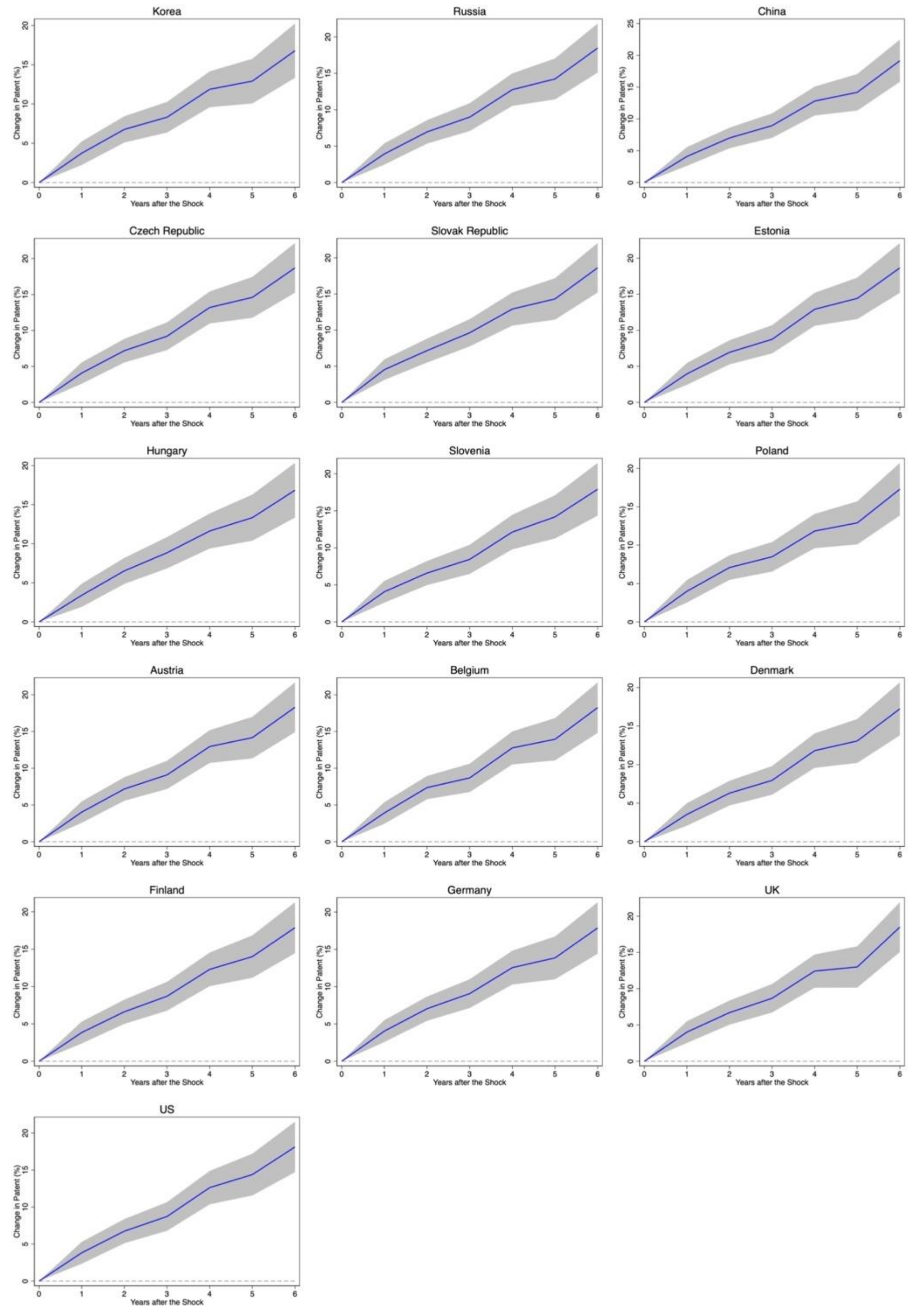
A2e— baseline excluding top and bottom 5% percent of the distribution of the dependent variable



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 (2.1): $y_{i,s,t+k} - y_{i,s,t} = time^k_{is,t} + \beta^k \Delta CCP_{i,t} + \sum_l \rho^k_l \Delta y_{i,s,t-1} + \sum_l \delta^k_l \Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; 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.

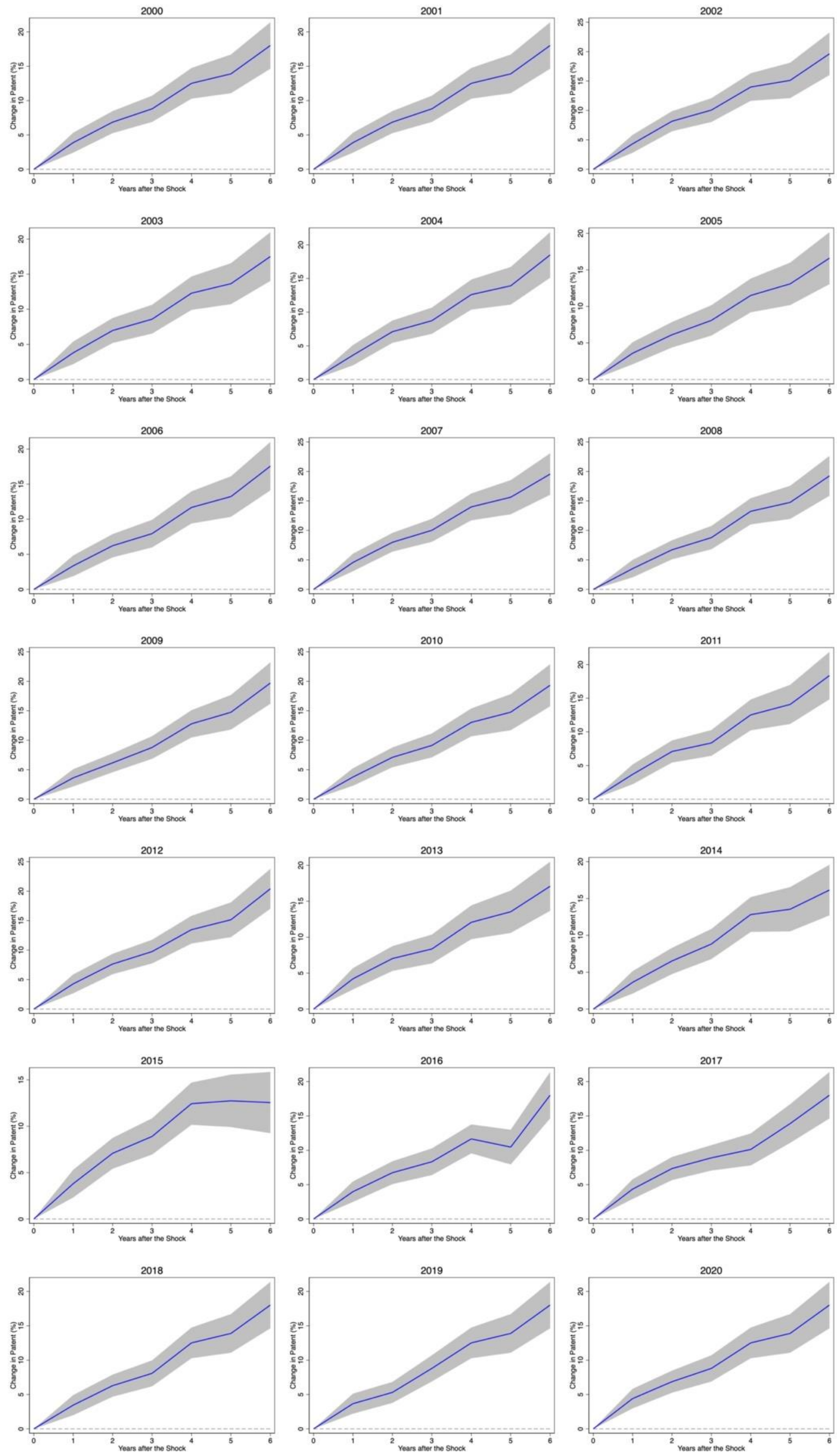
Figure A2f—baseline excluding a country at time (reported in chart's caption)





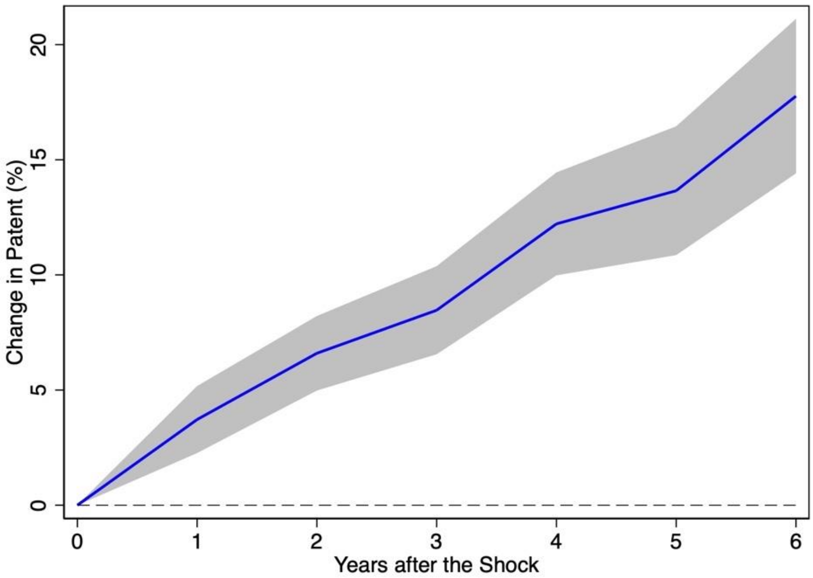
Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^{k} + \beta^{k} \Delta CCP_{i,t} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1-1} + \varepsilon_{i,s,t+k}$; 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. 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)



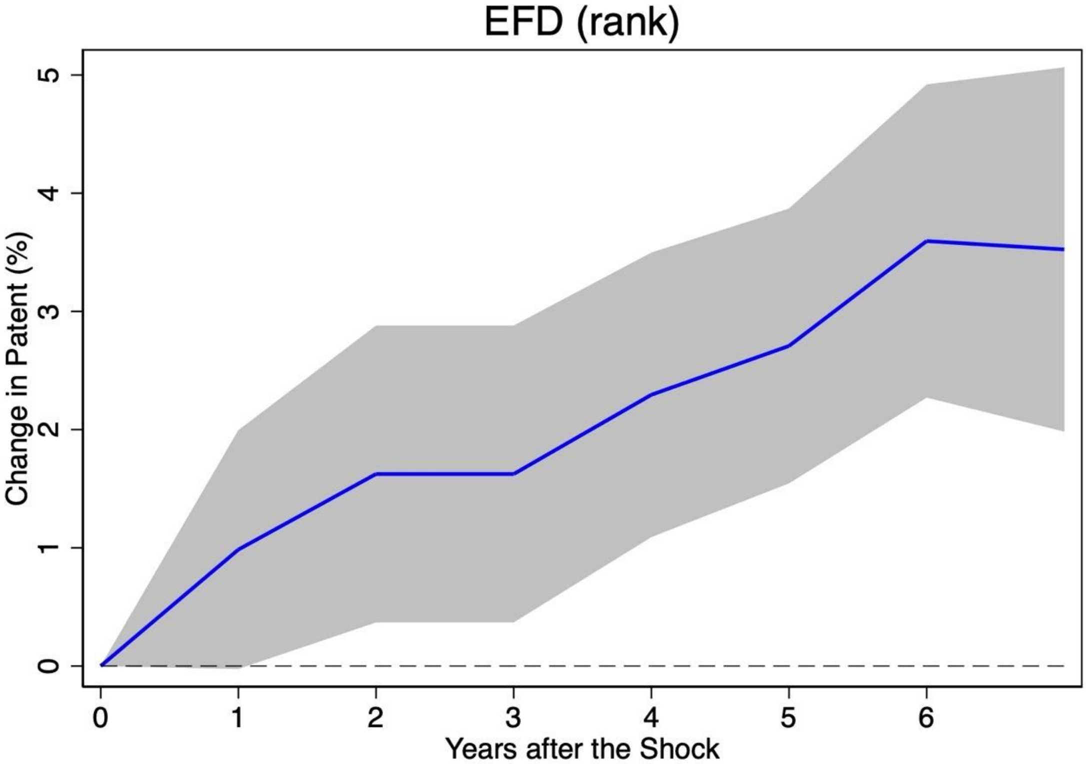
Notes: The chart shows the impulse response functions and the associated 90 percent confidence bands; t=-1 is the year of the shock. Coefficients have been estimated using equation (2.1): $y_{i,s,t+k} - y_{i,s,t} = time_{is,t}^{k} + \beta^{k}\Delta CCP_{i,t} + \sum_{l}\rho_{l}^{k}\,\Delta y_{i,s,t-1} + \sum_{l}\delta_{l}^{k}\,\Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; 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 (2.1): $y_{i,s,t+k} - y_{i,s,t} = time^{k}_{is,t} + \beta^{k} \Delta CCP_{i,t} + \sum_{l} \rho^{k}_{l} \Delta y_{i,s,t-l} + \sum_{l} \delta^{k}_{l} \Delta CCP_{i,t-1-l} + \varepsilon_{i,s,t+k}$; 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 2.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 (2.4): $y_{i,s,t+k} - y_{i,s,t} = \alpha_{is}^k + \alpha_{it}^k + \alpha_{st}^k + \beta^k \Delta CCP_{i,t} * \mathrm{EFD_s} + \sum_l \rho_l^k \Delta y_{i,s,t-1} + \sum_l \delta_l^k \Delta CCP_{i,t-1} * \mathrm{EFD_s} + \varepsilon_{i,s,t+k}$; where the dependent variable indicates the percent variation in patenting activity in country *i*, sector *s*, between *t+k* and *t*, with *k*=1, …,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 (2.4) also includes three batteries of fixed effects: country-year, country-sector, and sector-year. The EFD is included in equation (2.4) 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 2.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 2.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 2.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 2.A4: Ranking of sectors in terms of External Financial Dependence (EFD)

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

Source:author’s elaboration based on compustat data

Chapter 3

Climate Change Policies and Income Inequality

3.1. Introduction

In 2015, the United Nations (UN) adopted the Agenda 2030 for Sustainable Development, commonly known as Agenda 2030. All the 193 countries of the UN General Assembly committed to unprecedent policy efforts to achieve 17 Sustainable Development Goals (SDGs), that range from fight poverty and zero hunger (SDG1 and SDG2, respectively), to quality education (SDG4), innovation (SDG9) and climate action (SDG13). While the achievement of each individual SDG is key to guarantee a sustainable future, there may exist trade-offs between goals. An example of potential trade-off is related to climate actions (SDG13) and the achievement of reduced inequality (SDG10), as the implementation of strict climate actions may lead to significant distributional costs. Indeed, recent studies in the literature suggest that climate change policies (CCPs) may have negative short-term economic consequences—e.g., job losses, higher costs of energy—that are unevenly distributed among income groups (Markannen and Anger-Kraavi, 2019; Kanzig, 2023), therefore resulting in higher income and consumption inequality (e.g., Kanzig, 2023; Yu et al., 2021; Zhao et al., 2022; Soergel et al., 2021).[18]

In this paper, we contribute to this literature by analyzing the dynamic—short- and medium-term—effect of CCPs on several measures of income inequality for an unbalanced

[18] Other streams of the literature have analyzed the economic and environmental effects of CCPs (Abrell et al., 2011; Kozluk and Timiliotis, 2016; Marin and Vona, 2021; Wang et al., 2022); the impact of climate change—increasing temperature, frequency of extreme events—on global (between-country) inequality—as climate change greatly affects developing regions, typically more exposed to extreme climate events (Burke et al., 2015; Hsiang et al., 2012; Dell et al., 2017; Tang et al., 2023); and the impact of climate change on within-country income inequality (Ferrara, 2023; Cevik and Jalles, 2023).

panel of 39 developed and developing economies, during the period 1990-2020.[19] The use of a dynamic model is crucial, as the effect of CCPs1 may take time to materialize. In addition, the breath of the country and time coverage allows us to explore how the effect of CCPs varies depending on countries' structural characteristics (such as the share of less educated workers), the role of policy (fiscal policy and redistribution), and the phase of the business cycle.

In terms of data, we use the OECD's environmental policy stringency (EPS) index that measures the stringency of climate policy regulation. We consider several measures of income inequality—Gini, Palma ratio, P90/P10, S80/S20, and P50/P10—as they provide different information about the distribution of income (Campagnolo and Davide, 2019)—for consistency, these indicators have been also retrieved from the OECD.

The results—obtained using the local projection method (Jordà, 2005)—show that a unitary increase in the EPS leads to a significant and persistent increase of income inequality of about 1 standard deviation. This effect is sizeable, given that inequality measures are typically slow-moving indices. The results are consistent across all the measures of inequality considered, and they are robust to a battery of sensitivity tests, including a difference-in-differences instrumental variable approach, which considers as instrument the interaction between a global term capturing the policy pressure to implemented CCPs (e.g., the yearly number of floods in the world) and a country-specific factor denoting the exposure of a country to climate change events (such as its length of the coastal area). The effects of CCPs on income distribution are also consistent with the evidence that CCPs tend to reduce employment, specially with workers with lower education.

Next, we acknowledge that different climate policy instruments may have heterogeneous effects on inequality. The literature has already shown that the impact of CCPs

[19] We focus on income inequality because of more comprehensive data availability and given that it directly influences other measures of inequality, such as the health status, access to education and housing (Markkanen and Anger-Kraavi, 2019).

may vary depending on the specific policy implemented. For example, while market-based policies are the most effective in reducing emissions (e.g., Yin et al., 2015; Shapiro and Walker, 2022), they are also those associated with larger employment (Bettarelli et al., 2023a) and political costs (Furceri et al., 2023). However, studies so far do not have investigated the same source of heterogeneity in the effect of CCPs on inequality. We do so by exploiting the sub-indicators of the EPS index; in fact, OECD also provides a disaggregated score for different policy instruments, thus allowing separate estimations. We show that the negative impact of CCPs on inequality materializes in the case of market-based policies—such as taxes on emissions—while is not statistically different from zero for non-market-based or technology support policies.

We also allow the response of income inequality to CCPs to be nonlinear, depending on country-specific factors and economic conditions, using the smooth transition local projection approach (Auerbach and Gorodnichenko, 2013). The results indicate that the impact of CCPs on income inequality is larger in countries with a high share of low-skilled workers and those characterized by higher initial level of inequality. In contrast, the effects are smaller in countries with comprehensive redistribution policies, and during periods of fiscal expansions and stronger economic growth.

Overall, the results have important policy implications for the design of CCPs—in terms of policy instrument—and for the role of compensatory (fiscal) policies that may alleviate the regressive effects of CCPs.

The rest of the paper is structured as follows. Section 3.2 reviews the existing literature; Section 3.3 introduces the data and the empirical strategy; Section 3.4 presents the results; Section 3.5 concludes and draws some policy recommendations.

3.2. Literature Review

In the last decade, a growing body of literature has analyzed the efficacy and costs of CCPs, in terms of environmental and economic effects. Overall, there is a broad consensus in the literature about the efficacy of CCPs to reduce emissions.[20] Empirically, Yin et al., (2015); Song et al., (2020) and more recently Wang and Zhang, (2022) find that environmental regulation mitigates carbon emissions in China. Shapiro and Walker, (2018) find a similar negative relationship between increasing regulations and emissions in the US. Yirong (2022), using a sample of high-polluted countries (i.e., China, USA, India, Russia, and Japan), shows that CCPs reduces CO2 emissions, over the period 1990–2019. Cole et al., (2005) provide supports that environmental regulations successfully mitigate pollution emissions of industries in the UK. De Angelis et al., (2019) focus on 32 European and non-European countries, over the years 1992–2012, and show that the impact of CCPs on emissions is particularly strong in Europe and in the post-2005 period, when the European Trading System (ETS) and the Kyoto Protocol entered into force.

As for the economic effects, scholars have predominantly emphasized potential short-term detrimental effects of CCPs. CCPs may increase input costs for firms with negative consequences on productivity (Albrizio et al., 2017) employment (Dechezleprêtre and Nachtigall, 2020) domestic investment (Dlugosch and Kozluk, 2017) foreign direct investment (Garsous et al., 2020) and international trade (Koźluk and Timiliotis, 2016). However, these negative economic effects are likely to be concentrated in energy-intensive sectors (Marin and Vona, 2021) and short-lasting. Indeed, CCPs may contribute to spur innovation (Bettarelli et

[20] Exceptions are Sinn (2008) and Smulders et al., (2012), who sustain the "green paradox" theory, according to which households and firms increase fossil energy consumption, and energy owners increase their extraction activities if they predict more stringent environmental regulations, thereby increasing CO_2 emissions in the short term.

al., 2023b), thus improving productivity and employment in the longer term (Porter and Van der Linde, 1995).

Previous studies in the literature also suggest that CCPs are likely to have negative distributional consequences, mainly through two main channels: by reducing employment, especially for less-skilled workers, and by increasing energy costs.[21] Kanzig, (2023) uses a dynamic setting and a high-frequency identification strategy that looks at how carbon prices change around regulatory events in the EU carbon market. He shows that the enactment of CCPs—carbon pricing schemes—in Europe reduces emissions, but at economic costs, as production and employment declines, with the effects on employment being particularly severe. In addition, he finds that the economic costs of carbon policy are unequally distributed across the population, with low-income households suffering the most. Zhao et al., (2022) show that carbon pricing policies significantly increase income inequality in China, with Gini coefficient that is estimated to be 0.53% higher than the benchmark scenario (with no CCP) in 2030. Tang et al., (2023), using a panel dataset of 147 countries between 1961-2017, show that inequality may decline in the short term but increase in the long run, as a result of strict policy actions to limit global warming. A similar effect is found by Hussein et al., (2013); Nyiwul, (2021) and Soergel et al., (2021), who note that climate policies implemented through carbon price may impose additional financial burdens on the poor globally, thus increasing poverty and inequality if not compensated by redistribution policies. Dorband et al., (2019)

[21] In particular, policies imposing costs on production and consumption of dirty energy—e.g., carbon pricing—affect relative prices of clean and dirty energy (Pisani-Ferry J, 2021). In a situation in which the production of clean energy is still insufficient to meet rising demand, the overall cost of energy is expected to increase (Stern and Stiglitz, 2021. This may lead to higher consumption inequality, as low-income households devote a larger share of their total budget to energy relative to higher-income segments of the population (Menyhért, 2022; Battistini et al., 2022). Empirically, Cullen et al., (2005) find that increasing home energy costs affect consumption habits of low-income US households, which may decide to cut back on spending for other essential goods and services (e.g., medical care). Long and Zhang, (2022) show that Chinese urban residents' consumption significantly increases in response to a decline in oil price. In a recent article, Bettarelli et al., (2023c), studying a large sample of 129 advanced and developing economies during the period 1970-2013, show that a 100% increase in energy prices increases consumption inequality by about 0.2 Gini point. They also show that the effect is larger in developing economies, where access to finance is limited, and during weak monetary policy framework and economic growth.

assess the incidence of moderate carbon price increases for different income groups in low- and medium-income countries, and find that poorest households would be charged a greater proportion of their income than national average. Dinan and Rogers, (2002) found that for a 15% reduction in CO_2 emissions by an ETS, each US household in the lowest income quintile would be worse off on average by around 500 dollars per year, while each household in the top income quintile would reap a net gain of about 1000 dollars. In contrast, Yu et al., (2021) focus on the effect of carbon emissions trading schemes on urban-rural income inequality, based on data of 273 cities in China during the period 2010-2018, and find that carbon ETS significantly reduces urban-rural inequality, possibly because costs of CCP are more binding for urban citizens due to differences in expenditure patterns. He also shows that the impact of carbon ETS on inequality changes depending on the level of development of China's cities and of CO_2 emissions, with the effect that is larger in case of highly polluting and rich cities. Vona, (2023) highlights that costs of CCPs also depend on the set of skills available to workers, as communities with the right set of green skills may benefit from climate policies.

We contribute to this growing literature in several ways. First, we focus on a large set of developed and developing economies and use a dynamic model that is particularly suitable to examine persistent and non-nonlinear effects. Second, we try to identify causality using a recent instrumental variable approach suggested in the literature to isolate exogenous changes in CCPs. Third, we try to uncover several potential sources of heterogeneity and examine how the effect of CCPs vary with the type of policy implemented (e.g., market- vs. non-market-based CCPs), the economic conditions (e.g., recession vs. boom), the extent of redistribution policy and countries' structural characteristics (such as the initial level of inequality and the share of low-skilled workers).

3.3. Data and methodology

3.3.1 Data

We assemble an unbalanced panel dataset consisting of 39 OECD and non-OECD countries, for the period 1990-2020.[22] All data used in this article have been retrieved from OECD to guarantee a consistent country/time coverage.

The OECD Environmental Policy Stringency Index (EPS) is a country-specific and internationally comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. The EPS index allows for a year-by-year comparison of policy stringency across countries, ranging from zero to six, with higher values corresponding to the adoption of more stringent policies (Botta and Koźluk, 2014). As shown in Figure 3.1—which portrays the average evolution of EPS over time—the index has steadily increased during the period under analysis, particularly from 2000 following waves of tighter regulations associates with the implementation of the Kyoto protocol and European Emission Trading Scheme (ETS).

In addition, the OECD database offers climate stringency indices that are disaggregated and categorized according to (i) market-based instruments, including taxes on emissions (which are carbon taxes or other direct levies on pollutant emissions. Fiscal incentives for polluters to reduce emissions in order to avoid or minimize the tax burden); Emission trading systems (which encourages companies to reduce emissions by creating a market for emission allowances); (ii) non-market-based instruments such as emission limits (which establish specific limits on the quantity of pollutants that can be emitted from particular sources); (iii) and technology-support instruments such as investments in low-carbon research and development (Financial incentives, known as such, are established to facilitate the

[22] See Table 3.1 for the list of countries included in the analysis.

progress of innovative and enhanced technologies aimed at energy conservation and pollution reduction).

Further, Market-based policies create economic signals that encourage firms and individuals to internalize the costs of environmental degradation and adopt cleaner, more efficient practices. Non-market-based policies use legal and administrative mechanisms to enforce environmental requirements, ensure compliance, and protect public health and the environment. Technological policies provide financial, technical, and institutional support to accelerate the development, deployment, and commercialization of sustainable solutions. Overall, these policy approaches complement each other and can be tailored to specific contexts and objectives. By combining market-based incentives, regulatory measures, and technology support initiatives, policymakers can create a comprehensive policy framework that promotes environmental sustainability, economic prosperity, and social well-being.

This granularity allows us to empirically investigate whether the impact of CCPs on inequality depends on the type of policy implemented.

In terms of income inequality data, we use several indicators from OECD, where income is defined as household disposable income, and consists of earnings, self-employment and capital income and public cash transfers, after income taxes and social security contributions.[23] In detail, we use five indicators of income inequality. The Gini coefficient compares the cumulative proportions of population and income, and it ranges between 0 (perfect equality) and 1 (perfect inequality); S80/S20 represents the ratio of the average income of the 20% richest to the 20% poorest; P90/P10 is the ratio of upper bound values of the 10% of people with highest income, to that of the 10% of people with lowest income; P50/P10 the median income to the upper bound value of the first decile; the Palma ratio is the share of all income received by the 10% people with highest income, divided by the share of

[23] Household income is attributed to each member, with an adjustment that considers differences in needs for households of different sizes.

all received by the 40% with the lowest income. The use of alternative measures of income inequality allows us to provide a more comprehensive characterization of how CCPs affect income distribution, given the different information provided by each indicator. For instance, the Gini index provides a broad picture of the entire income distribution, and it is more sensitive to changes in the middle of the distribution, while P90/P10 focuses on the extremes of the distribution (Campagnolo and Davide, 2019).

Table 3.2 reports descriptive statistics of the key variables used in the analysis.

3.3.2. Methodology

Baseline model

We use the local projection approach (Jordà, 2005) to directly estimate impulse response functions (IRFs) of income inequality to an increase of the degree of CCP stringency. Specifically, we estimate the following dynamic equation, for each horizon *k*, with *k=0,…,5* (years):

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k CCP_{i,t} + \delta^k X_{i,t-l} + \varepsilon_{i,t+k}. \qquad (3.1)$$

Subscripts *i* and *t* indicate country and time, respectively. The term $y_{i,t+k} - y_{i,t-1}$ denotes the variation of income inequality in country *i* between *t+k* and *t-1*. α_i^k and γ_t^k are country and time fixed effects, respectively, included to account for differences in countries' time-invariant characteristics and global shocks, e.g. the Great Recession, that simultaneously impact on income inequality in a similar way across countries. $CCP_{i,t}$ is the EPS index. $X_{i,t-l}$ is a vector of controls that includes two lags (with *l=1,2*) of the dependent variable, and of *CCP*. $\varepsilon_{i,t+k}$ is the error term. Equation (3.1) is estimated using OLS with Driscoll-Kraay standard errors.

We test the robustness of baseline results to: (i) the inclusion of additional controls such as unemployment rate, inflation and GDP growth, (ii) excluding potential outliers, i.e., top and bottom 1% of the distribution of the dependent variable, (iii) different set of fixed effects, (iv) standard errors clustered at country level, and (v) alternative lags' structure. In addition, to test the effect of different types of policy, we substitute the variable CCP—based on the aggregate EPS—with its subcomponents: market-based policy, non-market-based policy, technology support policy.

Instrumental variable

We recognize that our analysis may suffer from issues of endogeneity. For example, when inequality is high the government may lack the political capital to implement strict CCPs, due to the expected distributional costs. This may lead to reverse causality. Moreover, as typical with variables assigning a score to policy, there may exist measurement or evaluation errors (Clinton, 2017). To address these potential concerns, we adopt an instrumental variable strategy. Following the approach proposed by Furceri et al., (2023), we let the probability of a country to adopt a strict CCP to depend on (i) the policy pressure at the global level induced by weather-related shocks and (ii) country-level morphological conditions that may make the adoption of CCPs more likely. In fact, previous evidence shows that preferences toward CCPs changes after major natural disasters (Bird et al., 2014; Latré et al., 2017). Moreover, it is reasonable to assume that global indicators are independent to specific policy actions implemented in a single country.

Following the above intuition, we construct our instrument as the interaction between the number of global flood events in a given year and the length of the coastline of a country, i.e., $Z_{i,t} = FLOODS_t \ \times \ COASTLINE_i$.

Empirically, we estimate the following equation:

$$CCP_{i,t} = \alpha_i^k + \gamma_t^k + \varphi \, Z_{i,t-1} + +\delta^k X_{i,t-l} + \eta_{i,t}$$

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k \widehat{CCP}_{i,t} + +\delta^k X_{i,t-l} + \varepsilon_{i,t+k}; \qquad (3.2)$$

where, in the first stage, we regress $CCP_{i,t}$ on the same set of controls as in equation (3.1), and one lag of the instrument $Z_{i,t-1}$, as defined above. The second stage is equivalent to equation (3.1), with the predicted value of CCP.

The expectation is that years with a higher number of global flood events would see an increased push for the adoption of stricter CCPs, as countries respond to the heightened awareness and pressure to act against climate change. Moreover, countries with longer coastlines are more exposed to the impacts of climate change, such as sea-level rise and extreme weather events, making them more likely to adopt stringent CCPs as a preventive or mitigative measure.

Nonlinear effects

We exploit the flexibility of the local projection approach to nonlinear frameworks to investigate if the effect of CCPs on inequality depends on country-specific characteristics and economic conditions. In particular, following the approach proposed by Auerbach and Gorodnichenko, (2013). We augment the baseline specification as follows:

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + F(z_{it})\left[\beta_L^k \Delta CCP_{i,t} + \theta_L^k X_{i,t-l}\right] + \left(1 - F(z_{it})\right)\left[\beta_H^k \Delta CCP_{i,t} + \theta_H^k X_{i,t-l}\right] + \varepsilon_{i,t+k}; \quad (3.3)$$

with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{1+exp^{-\gamma z_{it}}}$, $\gamma = 2.5$

where z is alternatively an indicator of the business cycle (GDP growth), magnitude of redistribution policy, fiscal policy shocks, and the share of workers with low education, normalized to have zero mean and unit variance.[24] We exploit both within and cross-country variation in the normalization for all mediating variables, i.e., we use $z_{it} = \frac{s_{it}-\bar{s}}{sd(s_{it})}$, with the only exception of GDP growth for which we exploit only within-country variation and we construct $z_{it} = \frac{s_{it}-\bar{s}_i}{sd(s_{it})}$, as it varies widely across countries. $F(z_{it})$ is the smooth transition function, which varies between 0 and 1, and indicates the probability of being in a specific country-(time-)regime. Taking the example of the business cycle, when $F(z_{it})$ is close to zero, it indicates a situation of recession, while $F(z_{it})$ close to one refers to booms.

This approach—qualitatively identical to the smooth transition model developed by Granger and Teravistra, (1993)—permits a direct test of whether the effect of CCPs varies across different regimes, such as recessions vs. expansions. Moreover, it allows the magnitude of the effect of CCPs to vary non-linearly and smoothy as a function of the different country-level characteristics.

3.4. Results

3.4.1. Baseline Results

Figure 3.2 reports the evolution of income inequality following a unitary increase of the EPS index, that is the estimated β^k coefficients from equation (3.1), for each horizon *k=0,…,5* (years). Time (year) is indicated on the x-axis; the solid line displays the average estimated response; shaded areas denote 90 percent confidence bands. The results show that CCPs lead to distributional costs, as income inequality persistently increases after the policy shock, with the effect that particularly materializes in the medium term. The fact that the effect is increasing with time corroborates our dynamic modelling choice. Moreover, the effect is consistent across income inequality measures, as each of them increases after the

[24] We will describe these variables in Section 3.4, when commenting results.

implementation of a strict climate policy. In terms of magnitude, the effect is not negligible, considering that inequality is typically slow-moving. Specifically, a 1-point increase in the EPS index increases inequality of approximately 1 standard deviation of the yearly change in the sample, with results that are quantitatively identical across inequality measures. To give a sense of the magnitude of the effect, the average (across indicator/country/year) increases in inequality in response to a 1-point increase of EPS is about the 5%, while the average yearly change of EPS in our sample is much smaller than 1-point, i.e. 0.08. Thus, our data suggest that, on average, the yearly change of EPS increases inequality by about 0.4 percent, per year. If we consider the entire period under analysis (1990-2020), our results suggest that climate policy may have contributed to increasing inequality by up to 10%.

In what follows, we test the robustness of baseline results to several checks. First, we include additional control variables, that may potentially have an impact on inequality and bias our estimates: unemployment, inflation and GDP growth at country level. We include them one-by-one and together, with a 1-year lag.[25] Second, we change the lag structure in equation (3.1) to 4 lags, instead of 2. Third, we control for the presence of outliers by excluding 1 and 99 percentiles of the distribution of the dependent variable. Fourth, we include country-specific time trends. Fifth, we cluster standard errors at the country level. The results in Figures 3.A1-3.A5 in the Appendix are qualitatively identical to those presented in Figure 3.2, reassuring us about the validity of our analysis.

3.4.2. Instrumental variable approach

To address potential endogeneity issues, we also adopt an instrumental variable strategy, where we instrument our index of climate change policy with a composite variable that considers weather related shocks at global level—the number of floods at time *t* in our case—

[25] We consider 1-year lag as these variables capture the channel through which CCP can affect inequality.

multiplied by morphological conditions of country *i*—the length of the coastline. The results from the first-stage equation suggests that instrument exhibits the expected sign (+) and is "strong", with the Kleibergen–Paap rk Wald F statistic being larger than the associated Stock-Yogo critical value for strong instruments.

Figure 3.3 shows results from the headline equation (equation 3.2) and the effect of CCPs on income inequality remains qualitatively similar to baseline results, but the estimated coefficients are now approximately two times larger than in the baseline scenario, in the medium term. This indicates that, not controlling for endogeneity, may lead to underestimating the effect of CCPs on income inequality.

3.4.3. Transmission Channels

To shed light on the transmission channels through which climate policy actions affect inequality, we use the same empirical framework as in equation (3.1) and regress unemployment rate, and the share of employment of workers with low education, on CCP.[26]

Figures 3.4 shows that stricter CCPs contribute to increase the unemployment rate, with coefficients that are large in magnitude, highly statistically significant and persistent. Specifically, a 1-point increase in the degree of stringency of CCPs raises unemployment rate by about 1.3 percentage points, in the medium term. Considering the average yearly change of EPS index in our sample, CCPs may increase unemployment rate by about 0.12 percentage points in the medium term, a result similar to that in Kanzig, (2023). In addition, job disruptions are likely to affect more those workers—such as those with lower skills—that are unable to reallocate to green jobs. In fact, from Figure 3.5 we observe that the effect of CCPs on the share of employment of worker with low-education/low-skills is negative in the medium

[26] In detail, we use equation (3.1) and we alternatively consider as dependent variables (i) unemployment rate, in country *i,* at time *i,* (ii) the share of employment of people aged 25-64 with lower than upper secondary education over total employment of people aged 25-64 in country *i* at time *t.* Data are retrieved from OECD.

term. These two results confirm the idea that CCPs have adverse employment effects, especially for low-skilled workers.

3.4.4. Heterogeneity due to the type of policy

As outlined above and confirmed by previous literature, not all the policy instruments available to policymakers have the same effect (Furceri et al., 2023). Some may be better fitted to deal with specific goals such as reducing emissions or promoting green innovation, other may be less costly in terms of political support. The same may be true for inequality.

To test this potential heterogeneous effect across policy, we use the sub-components of EPS index. In detail, we differentiate between market-based policies (i.e., taxes and certificates), non-market-based policies (i.e., emission standards), and technology-support policies (i.e., support to low-carbon R&D expenditure and technology adoption support policies) (see Botta and Koźluk, 2014, for a detailed description of types of policy), and include them one-by-one in equation (3.1). Figure 3.6 reports the results of this exercise applied to different indicators of income inequality. They suggest that the baseline results are driven by market-based policy actions. In fact, the implementation of such type of policy leads to increases in income inequality that are, on average across indicators, 50% larger than in the baseline scenario. Particularly larger increases are observed for the P90/P10 indicator (+70%), thus suggesting that market-based policies are especially detrimental for households at the bottom of the distribution. In contrast, non-marked-based and technology support policies have no or feeble effects on income inequality.

3.5. Heterogeneity due to country characteristics and economic conditions

Next, we consider that different country-level characteristics/conditions may mediate the way CCPs affect income inequality, either amplifying or moderating the effect. In so doing, we can disclose potentially efficient compensating policy actions that policymakers may implement to alleviate distributional costs associated with CCPs. Empirically, we construct smooth transition functions based on moderating variables, and interact them with the EPS index, as well as controls, as described in equation (3.3).

We first investigate the role of the business cycle. The results in Figure 3.7 show that while CCPs tend to increase inequality when implemented in recessions (with the medium-term effect about 1.2-1.5 times larger in the baseline), they are associated with a decline in inequality when are implemented during economic expansions.

Next, we consider the role of country's structural characteristics related to the share of workers with low education (lower than upper secondary education), and the GINI index of market income, with data retrieved from the OECD. Figures 3.8-3.9 show that the effect of CCPs on inequality is 2-3 times larger in countries where the share of workers with low education is high; and 2-2.5 times larger in countries characterized by higher initial inequality.

In Figures 3.10, we focus on the role fiscal policy at the time of the adoption of stricter climate change policy. We follow Furceri and Zdzienicka, (2020) to identify unexpected fiscal policy shocks using the forecast errors in government spending at annual frequencies (see Furceri and Zdzienicka,(2020) for additional details about the method). This approach allows us to capture unanticipated changes in government spending, that are exogenous to other relevant macroeconomic variables—such as lagged output growth, output gap and government revenues—and other macroeconomic shocks. The results, independently from the measures of income inequality, show that expansionary fiscal policies significantly reduce the negative impact of CCPs on inequality.

Finally, we consider the extent to which governments implement redistribution policy. Here, we use the difference between GINI based on market income before taxes and transfers and GINI based on disposable income post taxes and transfers, with data from OECD. The results in Figure 3.11 show that in countries with strong redistribution policies, the effect of CCPs on inequality is not statistically significantly different from zero.

3.6 Conclusion and Policy Implications

The literature has shown that CCPs may cause some negative economic effects—e.g., job losses, high energy prices—that are potentially concentrated among the weakest household and workers.

In this paper, we contribute to this literature by using a dynamic empirical approach that estimates the short- and medium-term response of income inequality to an increase in the degree of stringency of climate change policy, for an unbalanced panel of 39 OECD and non-OECD economies for the period 1990-2020. We consider several measures of income inequality—i.e., GINI, P90/P10, P50/P10, Palma ratio, S80/S20—and the OECD Environmental Policy Stringency Index to quantify the stringency of climate change policy at the country level.

The results show that CCPs significantly and persistently contribute to increasing income inequality, independently from the measure of inequality used. According to our estimates, back-to-the envelope calculations suggest that the increase in the stringency of CCPs occurred between 1990 and 2020 may have led to an increase in income inequality by approximately the 10%. We prove that baseline results are robust to several sensitivity tests, as well as to an instrumental variable approach.

The type of environmental policy implemented also affects the magnitude of the impact of CCPs on income inequality. In this regard, we show that side-effects of CCPs on inequality only materialize in the case of market-based policies—e.g., carbon pricing—while non-market-based or technology support policies do not lead to any relevant effect on income inequality. Moreover, the increases in inequality after CCPs are 1.5-3 times larger during recessions, and in countries where the share of workers with low education is high and those characterized by high initial inequality. In contrast, the effect of CCPs on inequality nullifies if a country adopts comprehensive redistribution policy and expansionary fiscal policy.

Taken together, these results can shed light on how to design CPPs to mitigate their distributional effects. First, they show that is crucial to consider the timing of adoption of CCPs. Second, they highlight the importance to invest in training programs and education to increase skills and facilitate the reallocation of workers to green sectors. Third, they show that redistribution as well as expansionary fiscal policy are key to prevent the increase in inequality after the implementation of CCPs. Fourth, involve stakeholders from various sectors, including vulnerable communities, in the policy design process to ensure that the policies are equitable and do not disproportionately burden low-income groups.

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Figures

Figure 3.1: Evolution of EPS.

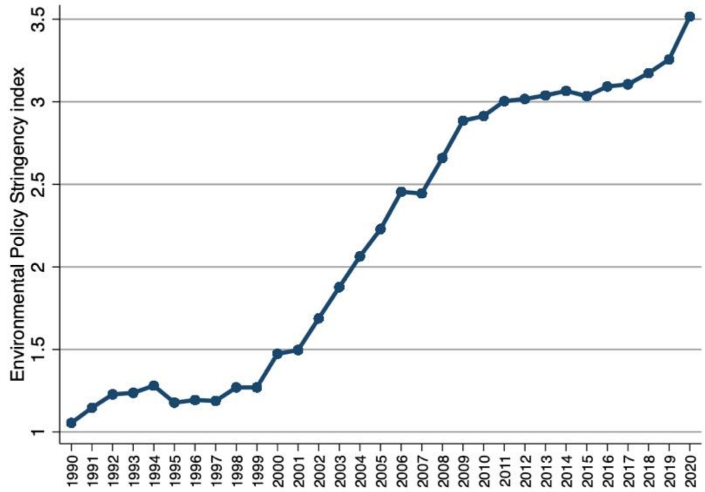
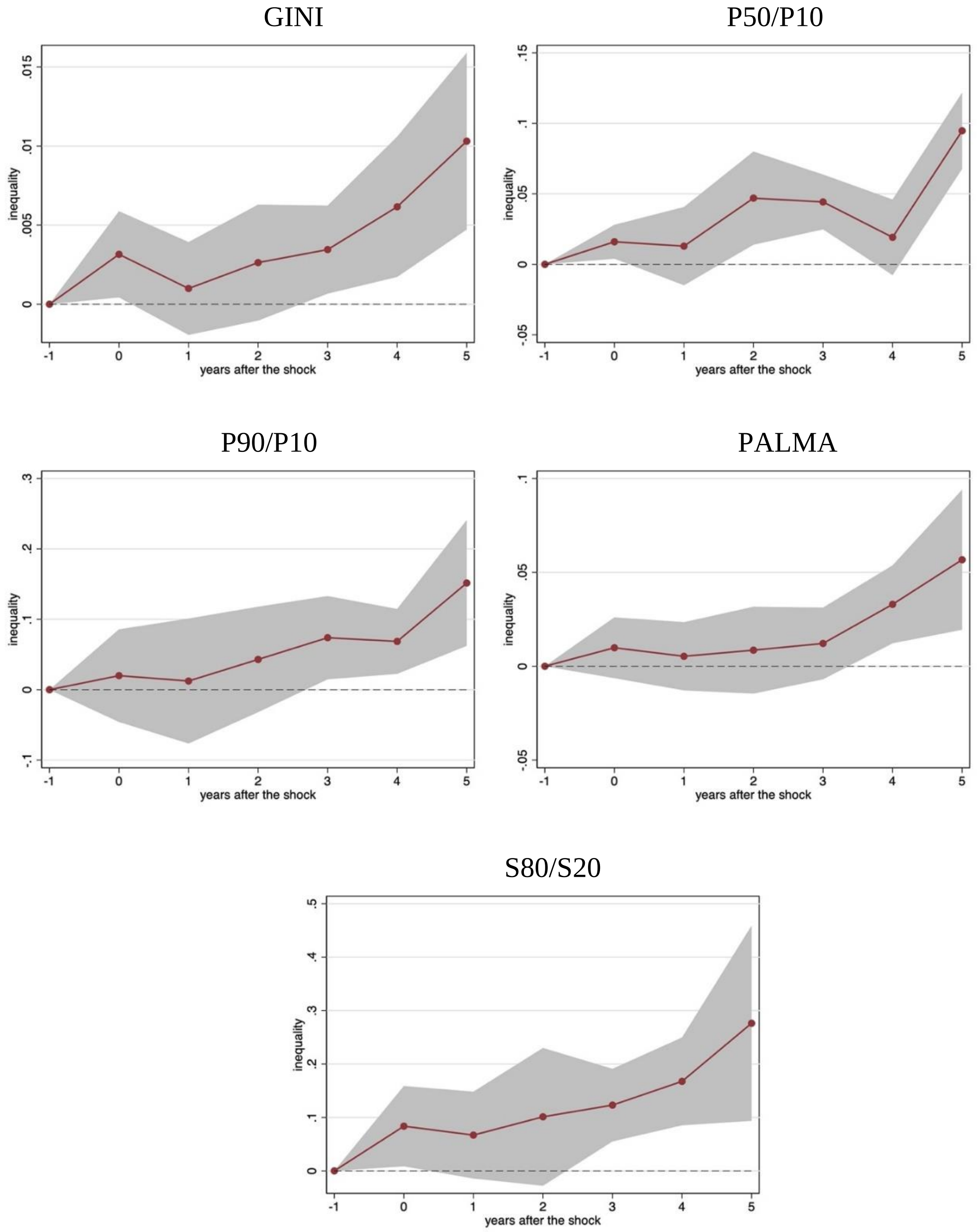
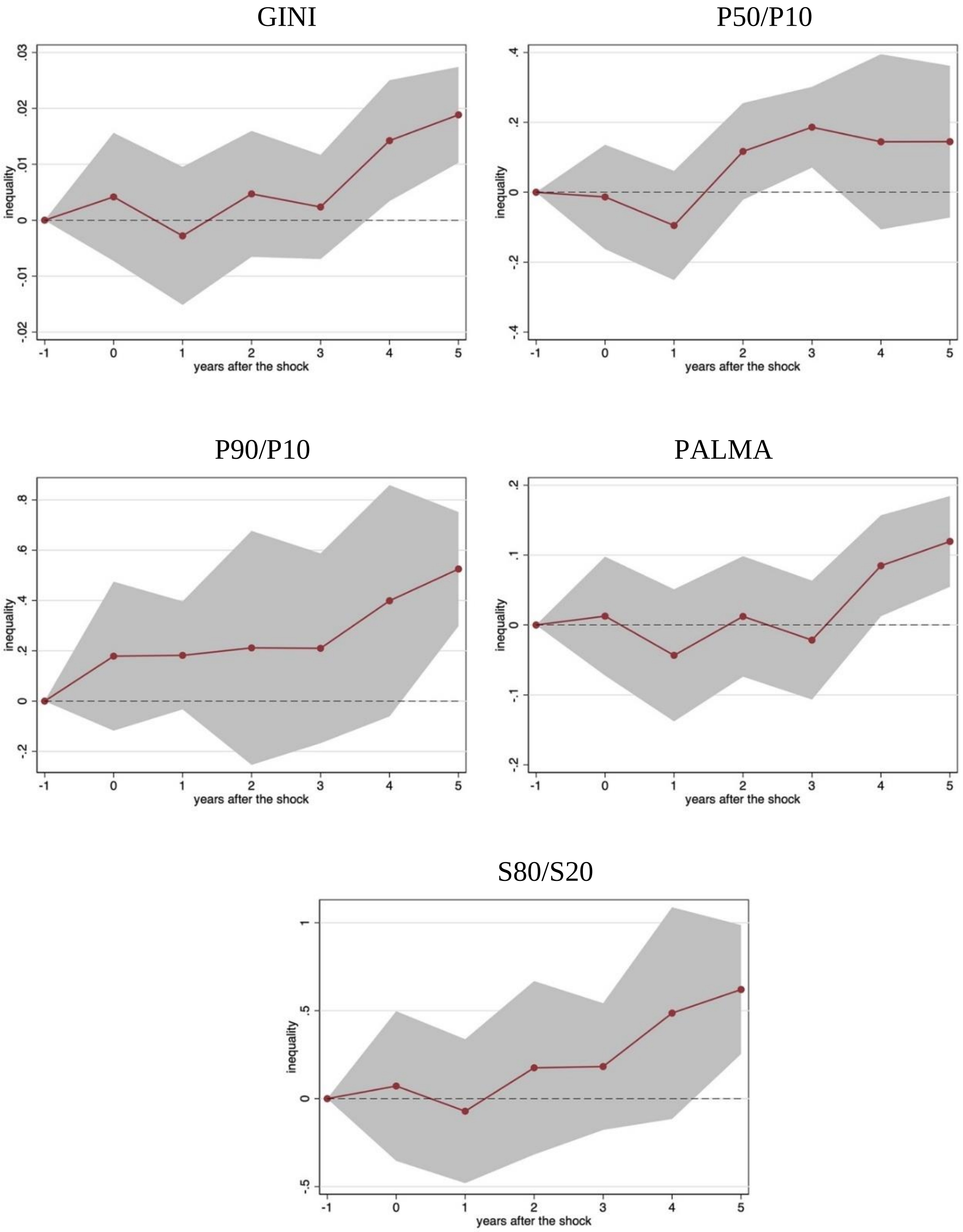


Figure 3.2: Baseline results for different income inequality measures.



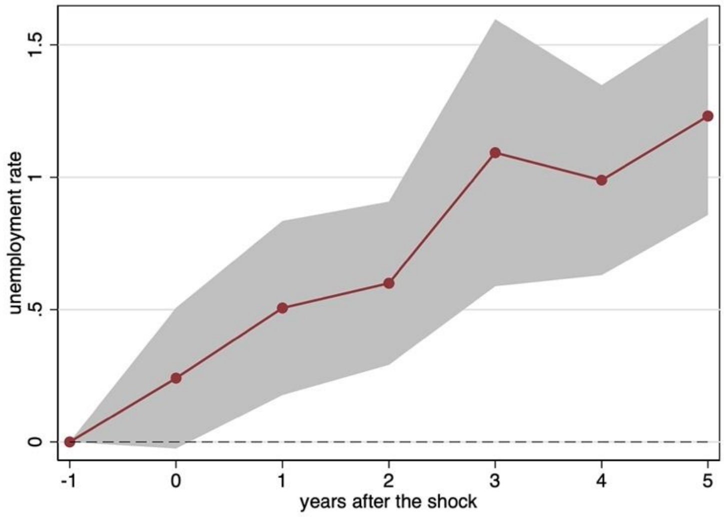
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-pont of EPS. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Figure 3.3: Instrumental variable approach.



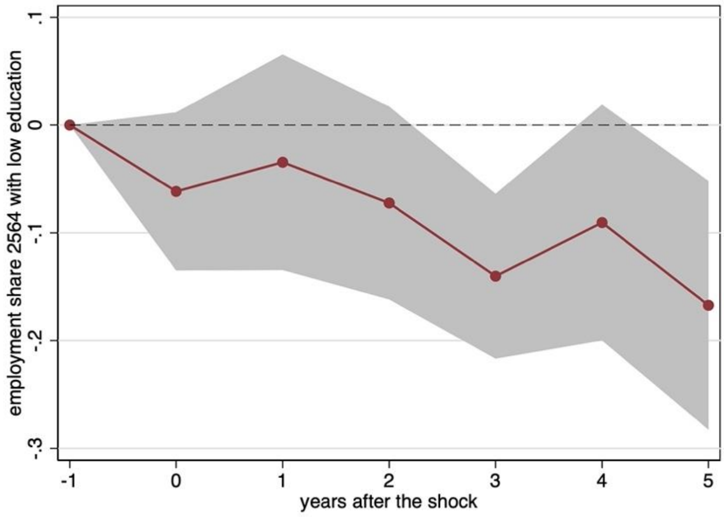
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-pont of EPS. Estimates are computed using an instrumental variable approach. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Figure 3.4: The effect of CCPs on unemployment.



Note: The charts show the impulse response function of unemployment rate to an increase of 1-point of EPS. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Figure 3.5: The effect of CCPs on workers with low education.

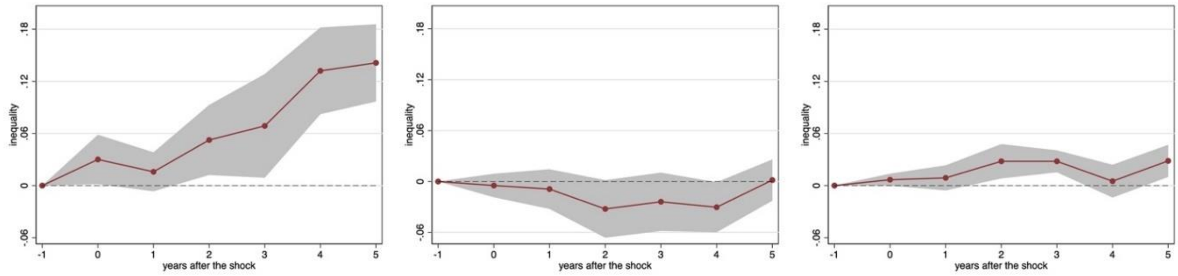


Note: The charts show the impulse response function of share of workers with low education to an increase of 1-point of EPS. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Figure 3.6: Effect of different types of policy on income inequality measures.

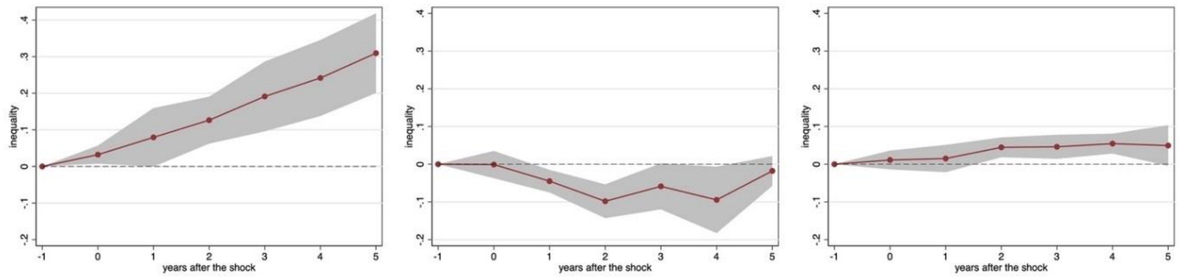
GINI

market | non-market | technology support



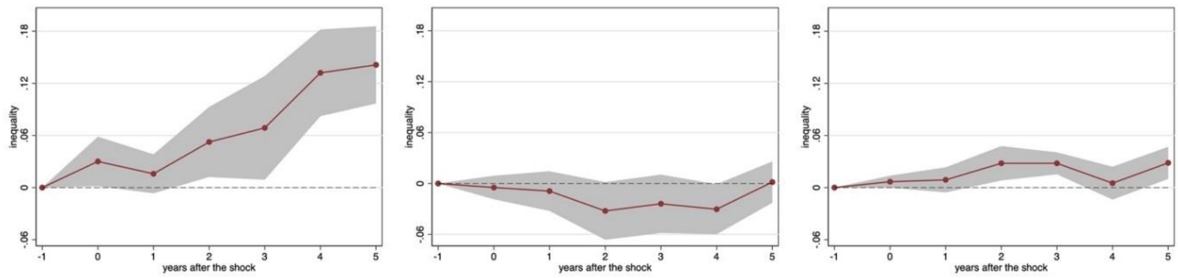
P90/P10

market | non-market | technology support



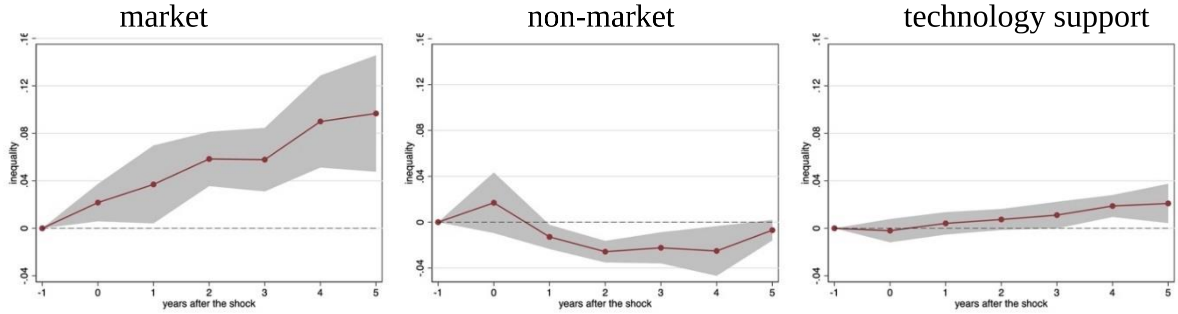
50/10

market | non-market | technology support



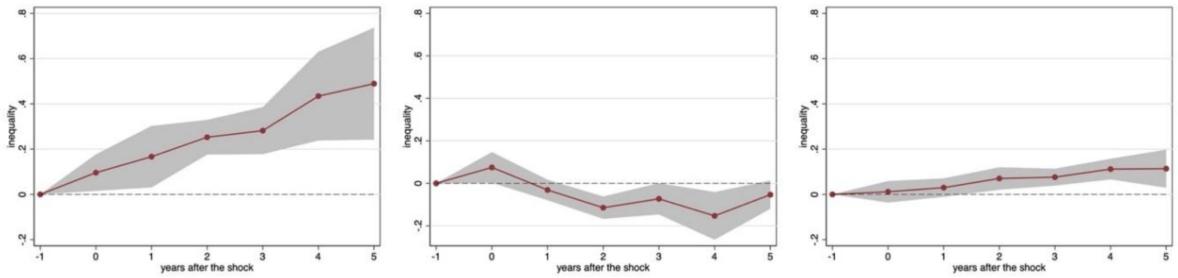
PALMA

market | non-market | technology support



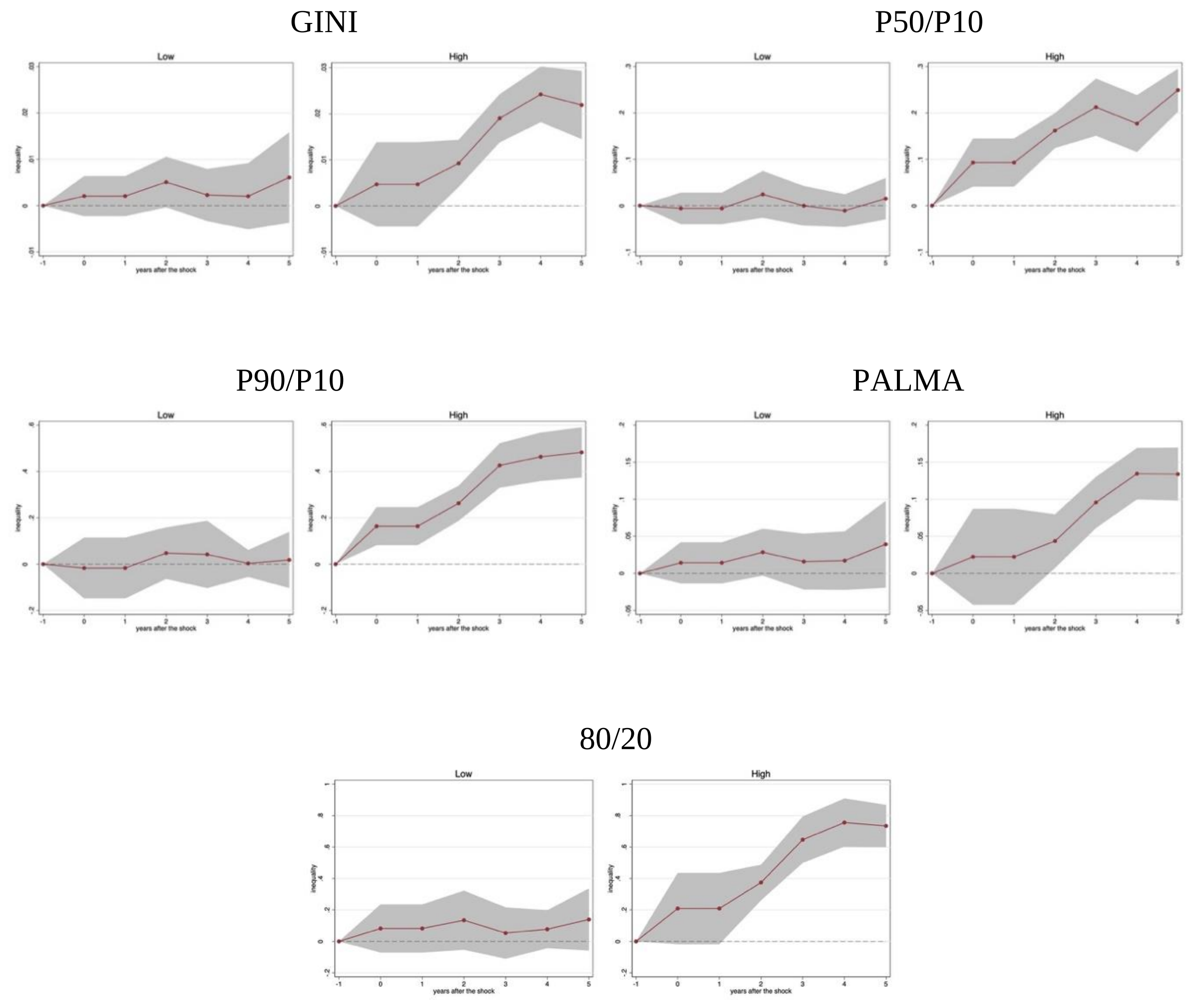
80/20

market | non-market | technology support



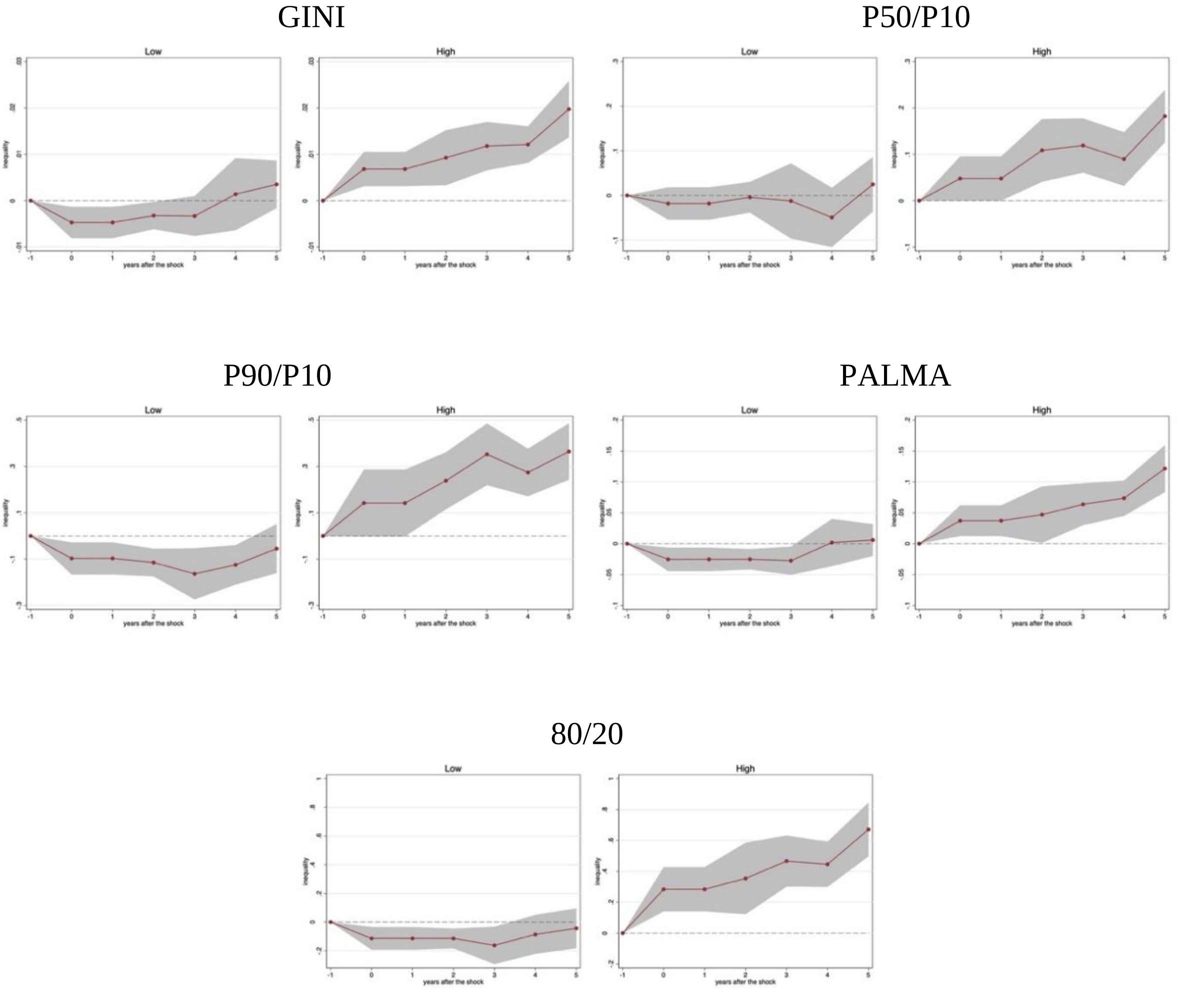
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-point of different policy instruments. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Figure 3.7: Nonlinear effects based on the share of workers with low education.



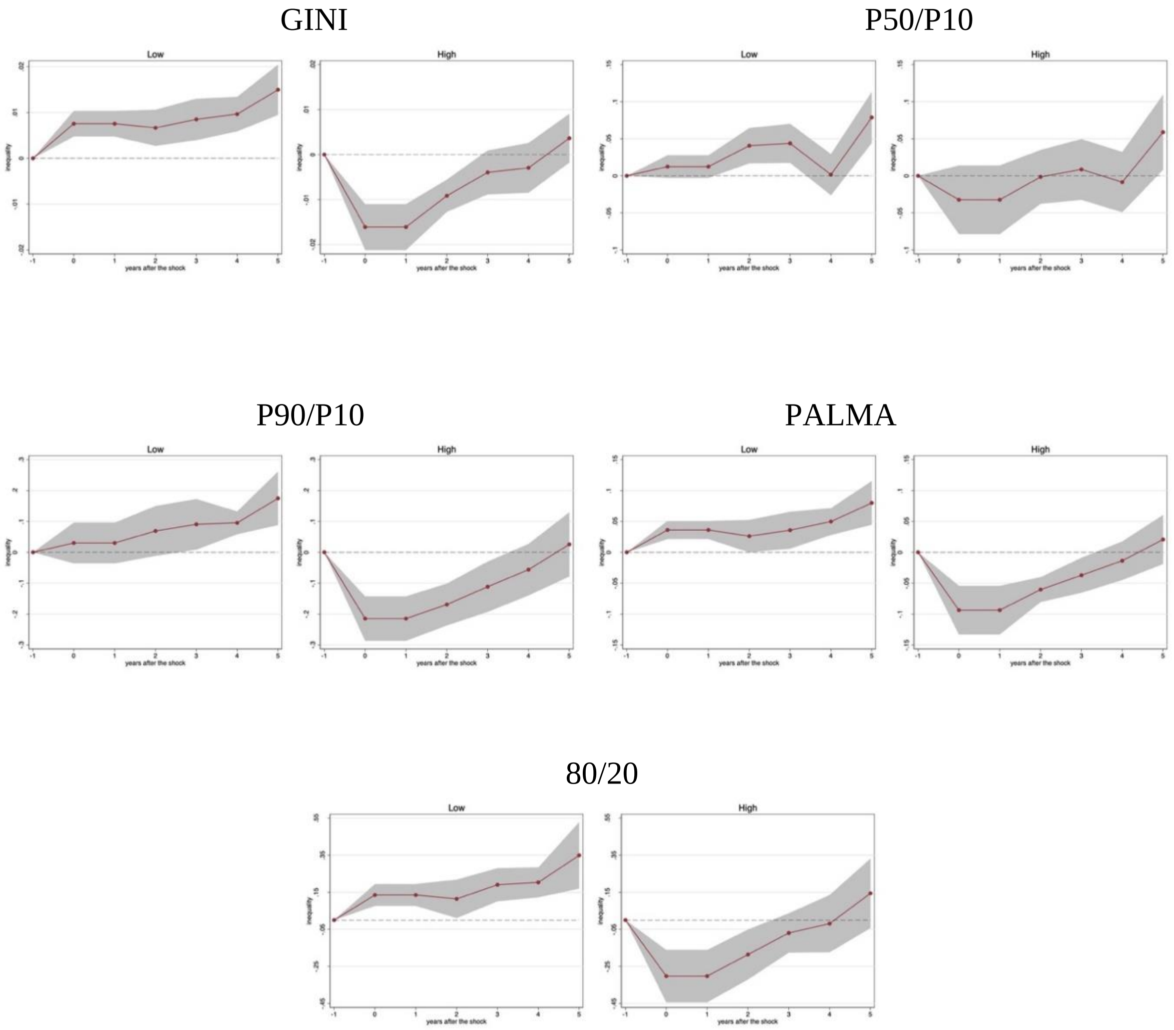
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-pont of EPS. Estimates are computed using smooth transition local projection approach, as described in eq. (3.3), with the share of workers with low education as mediating factor. Left charts report low scenarios (i.e., low share of workers with low education); right charts report high scenarios (i.e., high share of workers with low education). The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Figure 3.8: Nonlinear effects based on initial level of inequality.



Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-pont of EPS. Estimates are computed using smooth transition local projection approach, as described in eq. (3.3), with the share of workers with low education as mediating factor. Left charts report low scenarios (i.e., low initial levels of inequality); right charts report high scenarios (i.e., high initial levels of inequality). The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

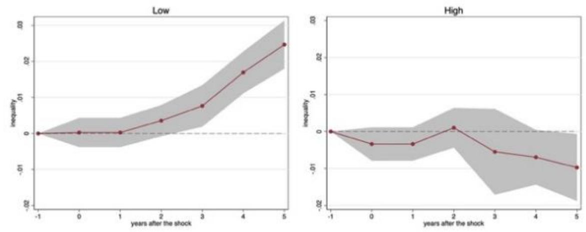
Figure 3.9: Nonlinear effects based on per capita GDP growth.



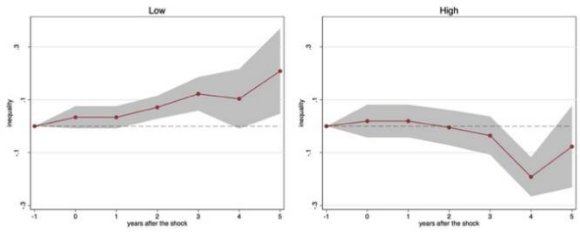
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-pont of EPS. Estimates are computed using smooth transition local projection approach, as described in eq. (3.3), with the share of workers with low education as mediating factor. Left charts report low scenarios (i.e., low per capita GDP growth); right charts report high scenarios (i.e., high per capita GDP growth). The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Figure 3.10: Nonlinear effects based on expansionary fiscal policy shock.

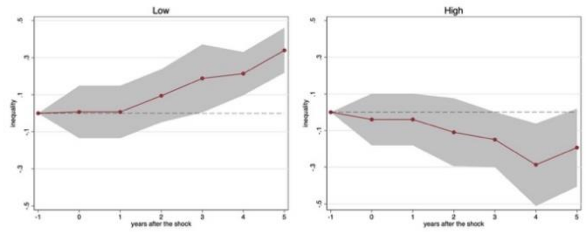
GINI



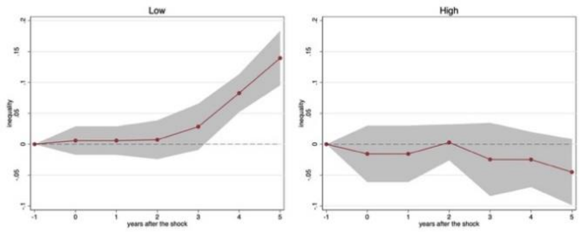
P50/P10



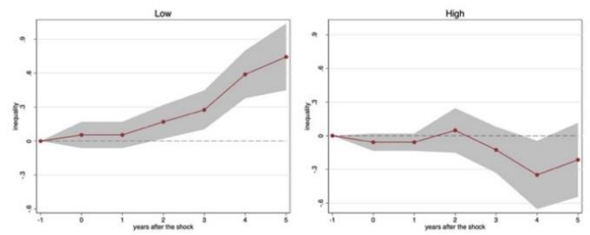
P90/P10



PALMA



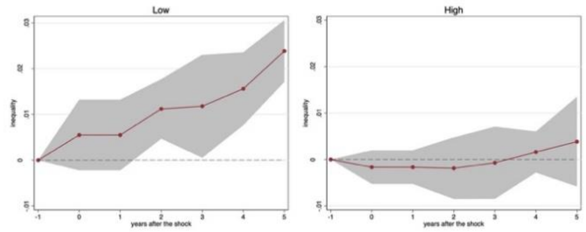
80/20



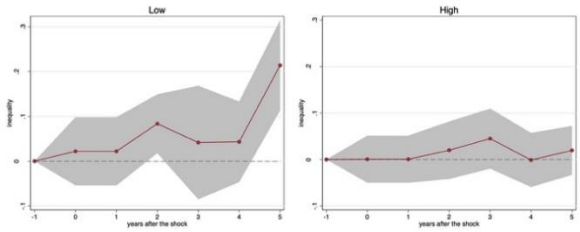
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-pont of EPS. Estimates are computed using smooth transition local projection approach, as described in eq. (3.3), with the share of workers with low education as mediating factor. Left charts report low scenarios (i.e., low expansionary fiscal policy shock); right charts report high scenarios (i.e., high expansionary fiscal policy shock). The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Figure 3.11: Nonlinear effects based on redistribution policy.

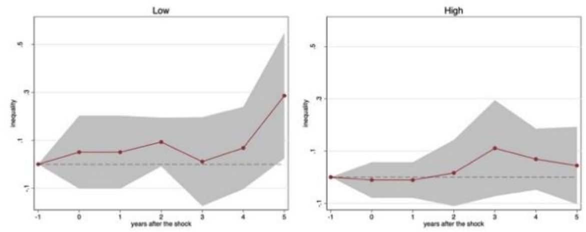
GINI



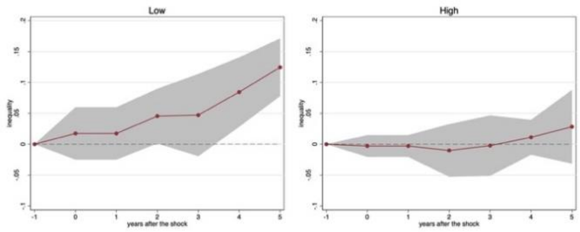
P50/P10



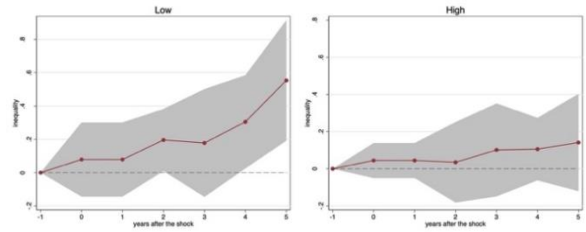
P90/P10



PALMA



80/20



Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-pont of EPS. Estimates are computed using smooth transition local projection approach, as described in eq. (3.3), with the share of workers with low education as mediating factor. Left charts report low scenarios (i.e., low redistribution policy); right charts report high scenarios (i.e., high redistribution policy). The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

Tables

Table 3.1: List of countries.

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

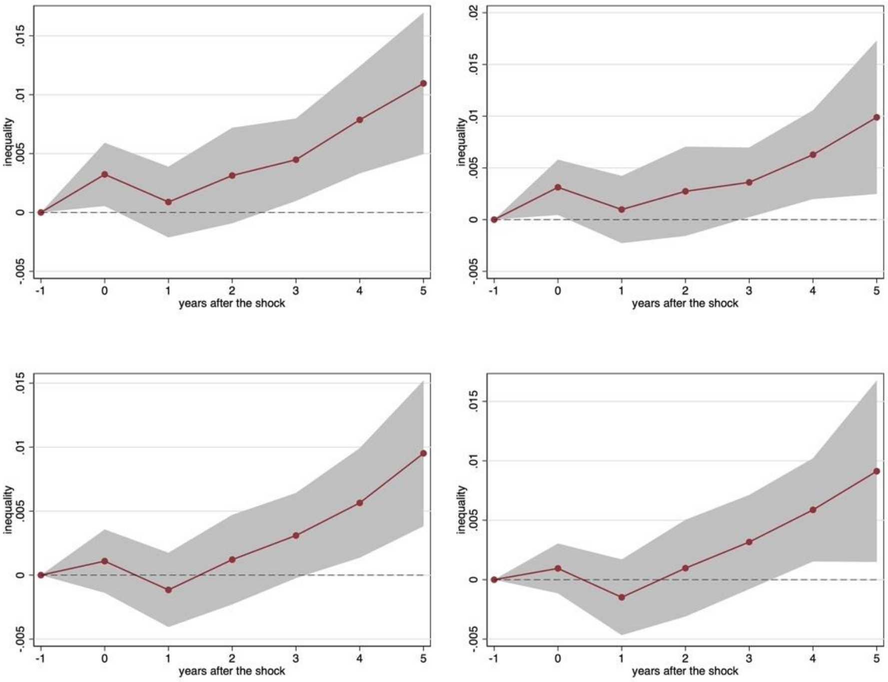
Table 3.2: Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
EPS	424	2.596	1.04	0	4.72
market-based	424	1.332	.902	0	4.17
non-marked-based	424	4.403	1.597	0	6
technology support	424	2.085	1.354	0	6
GINI	424	.31	.057	.211	.626
P50/P10	423	2.11	.434	1.6	7.8
P90/P10	424	4.208	1.944	2.1	23
PALMA	424	1.227	.574	.69	7.14
S80/S20	424	5.371	2.833	3	33.1

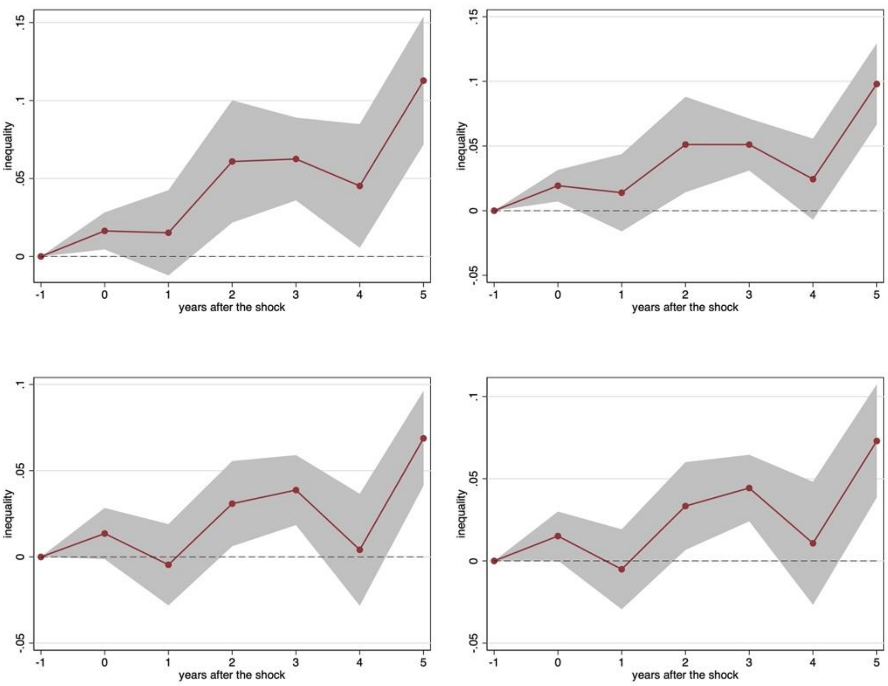
Appendix 3

3.A1: Robustness checks – additional controls (from left to right: unemployment, inflation, GDP growth, all controls).

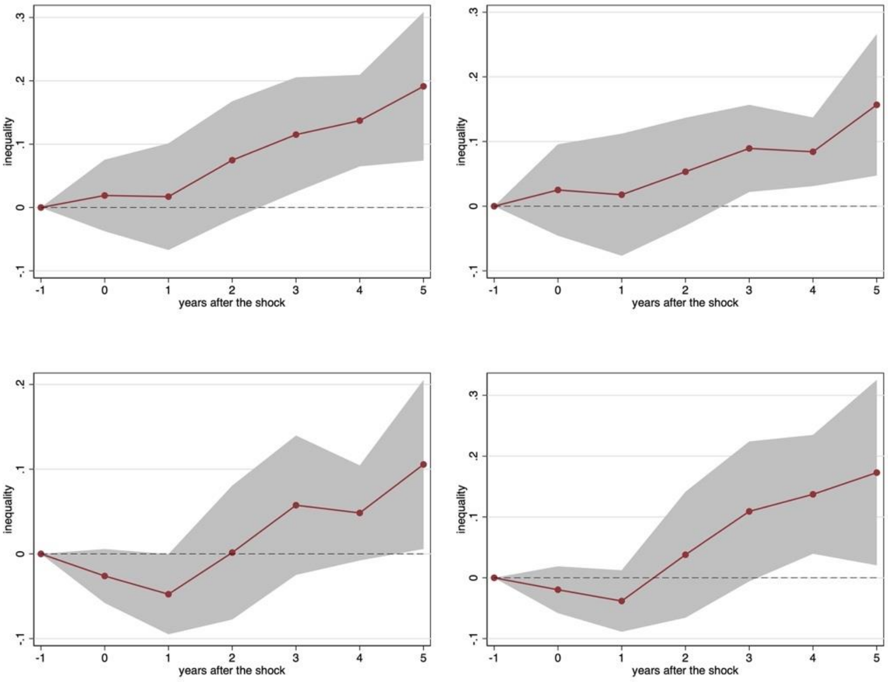
GINI



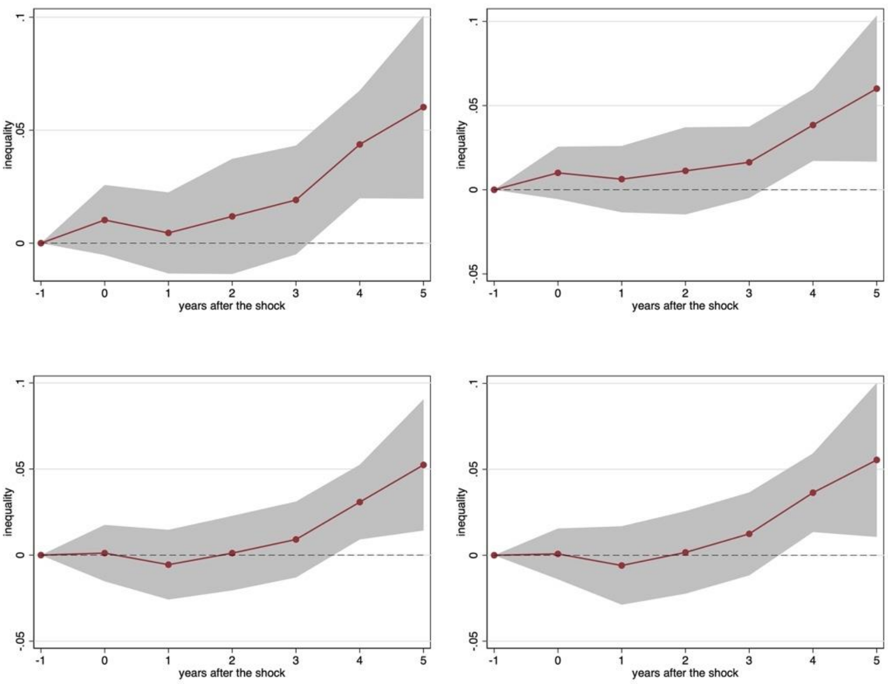
P50/P10



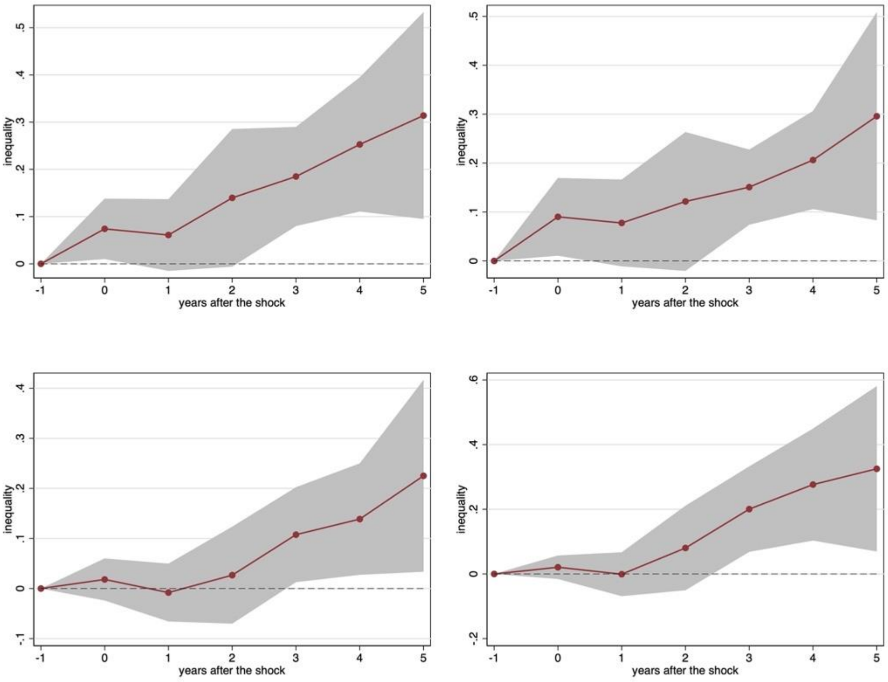
P90/P10



PALMA

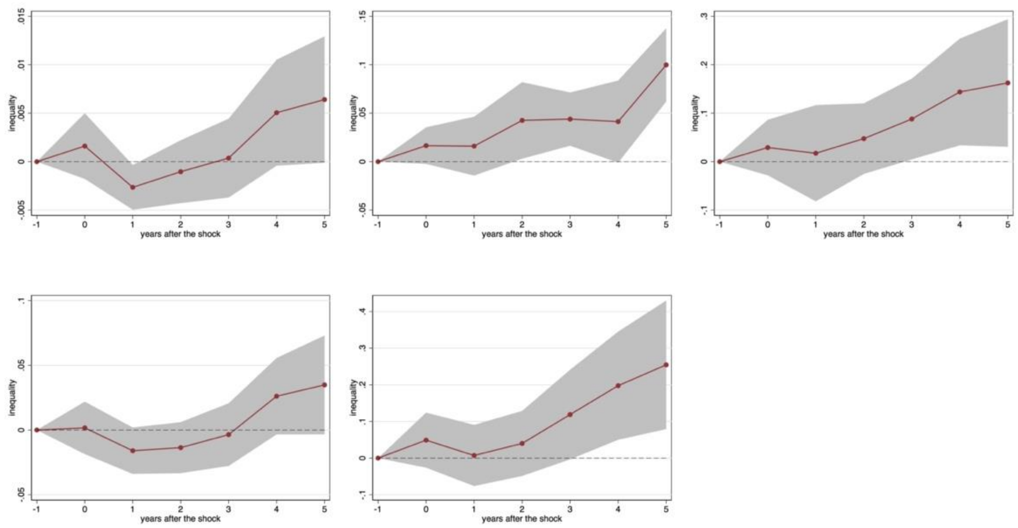


S80/S20



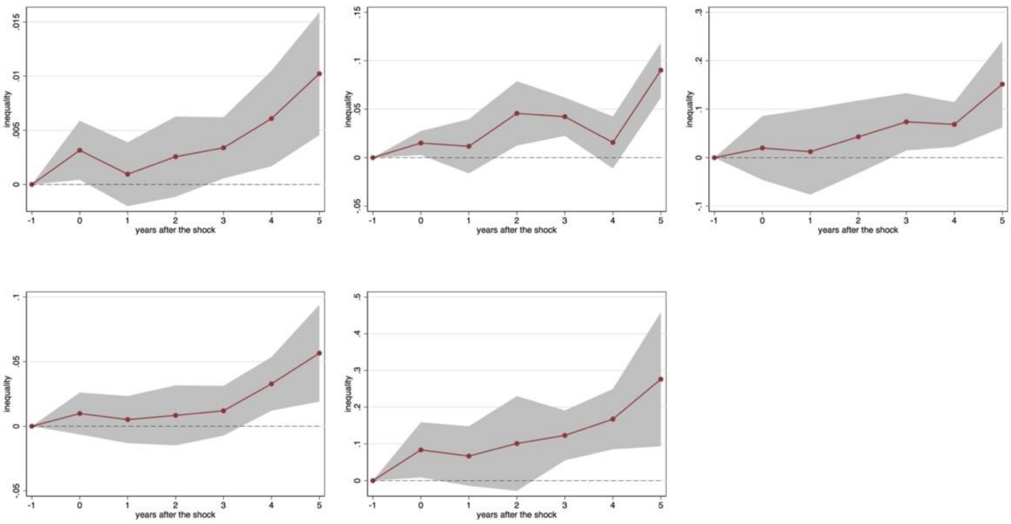
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption of each chart, to an increase of 1-pont of EPS. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

3.A2: Robustness checks – country-specific time trend (from left to right: GINI, P50/P10, P90/10, PALMA, S80/S20).



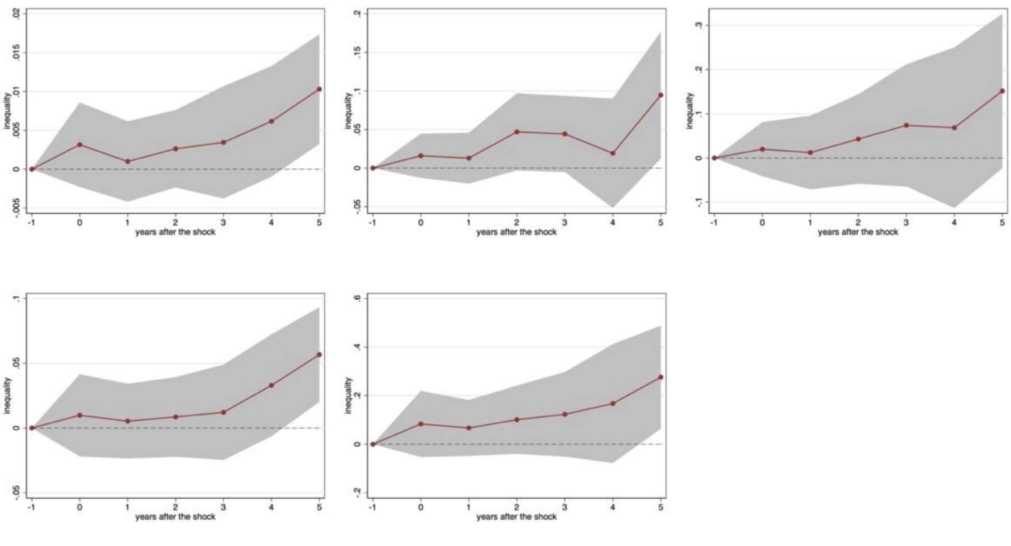
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption, to an increase of 1-pont of EPS. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

3.A3: Robustness checks – excluding outliers (from left to right: GINI, P50/P10, P90/10, PALMA, S80/S20).



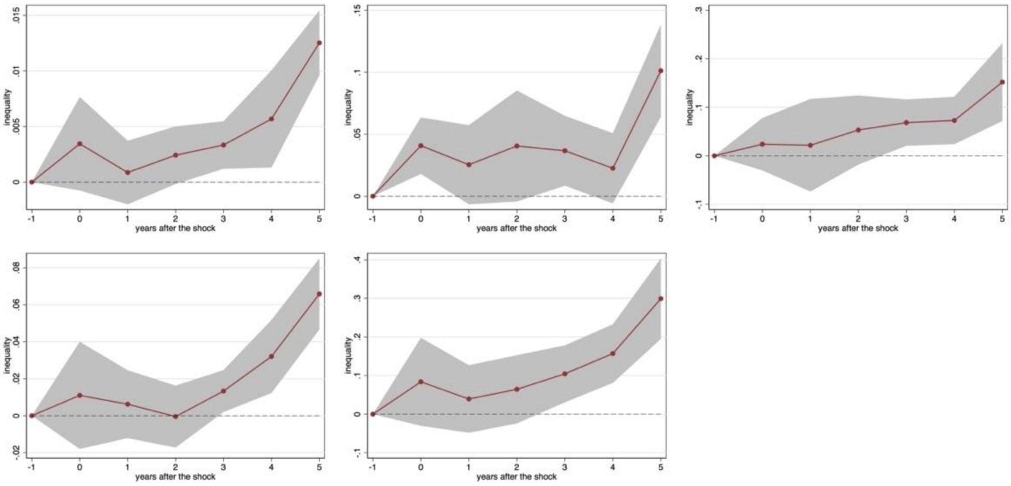
Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption, to an increase of 1-pont of EPS. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

3.A4: Robustness checks – SE clustered at country-level (from left to right: GINI, P50/P10, P90/10, PALMA, S80/S20).



Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption, to an increase of 1-pont of EPS. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

3.A5: Robustness checks – different lags structure (from left to right: GINI, P50/P10, P90/10, PALMA, S80/S20).



Note: The charts show the impulse response function of income inequality, based on different indicators as in the caption, to an increase of 1-pont of EPS. The shaded area represents the 90 percent confidence interval; t=-1 is the year of the shock.

General Conclusion:

The intricate interplay between environmental imperatives, green innovation, policy frameworks, and socio-economic outcomes underlines the multifaceted challenges of transitioning to a sustainable future. Uncertainty—whether political, economic, or regulatory—poses significant threats to green innovation. While stringent environmental policies have proven effective in driving green technological advancements, they also come with unintended socio-economic consequences, particularly in the realm of income inequality. The renewable energy sector, emblematic of the broader green innovation landscape, is particularly sensitive to these dynamics. On one hand, it benefits from clear policy directives and incentives that promote sustainable practices. On the other hand, it remains vulnerable to the vagaries of shifting political and economic landscapes. The challenge, therefore, lies in crafting policies that not only stimulate green innovation but also ensure that the potential costs associated with climate policy are equitably distributed.

The dissertation findings presented offer a comprehensive understanding of the multifaceted impact of uncertainty and climate change policies (CCPs) on green innovation and income inequality. Particularly, the first chapter emphasizes the detrimental impact of uncertainty on green innovation measured by renewable energy patents. A significant finding is the magnitude of this impact, with a standard deviation increase in global uncertainty potentially leading to a 40% reduction in patents five years after the policy shock. The recent upsurge in uncertainty generated by the COVID-19 pandemic exemplifies this, potentially causing a medium-term decline in renewable energy patents by 70%. This adverse effect is consistent across various sectors, with pronounced impacts on the power and building sectors, as well as on wind and solar energy technologies. Furthermore, during periods of financial stress and weak demand, the negative effects of uncertainty on patents are exacerbated. However, a silver lining emerges in the form of policy support for a greener economy, which can mitigate the negative repercussions of uncertainty on green innovation.

In the second chapter, we extend the analysis and investigate the effect of Climate Change Policies (CCPs) on green innovation. The empirical analysis delineates the positive influence of CCPs on green patents, especially when carried out by using non-market-based policies like emission limits and R&D subsidies. However, the study also acknowledges potential endogeneity issues, suggesting that countries might be more inclined to implement CCPs during periods of weak green innovation. To address this, we employ an instrumental variable strategy, leveraging cross-sectional variations in a country's exposure to climate risks. The study further delves into the state-dependent response of green innovation to CCPs, highlighting that innovation tends to be lower in countries with limited market competition and during periods of economic uncertainty, financial stress, and weak demand. A sectoral analysis further strengthens the causal relationship between CCPs and innovation, emphasizing the importance of considering sector-specific constraints.

In the third and final chapter, we examine the impact of Climate Change Policies (CCPs) on income inequality. The results show that CCPs lead to a significant and persistent increase in income inequality. The magnitude of this effect is substantial, with a unitary increase in the Environmental Policy Stringency (EPS) leading to a surge in income inequality by about one standard deviation of the change observed in our sample. The study further analyzes the heterogeneous effects of different climate policy instruments on inequality. Market-based policies, while effective in reducing emissions, are associated with increased employment challenges, especially for lower-educated workers. In contrast, non-market-based or technology support policies do not exhibit a statistically significant impact on inequality. The study also identifies that the repercussions of CCPs on income inequality are more pronounced in countries with a higher proportion of low-skilled workers and those with pre-existing high levels of inequality. However, countries with robust redistribution policies and expansionary fiscal policy as well as countries experiencing periods of economic growth are better positioned to offset such negative effects of CCPs on income inequality.

The comprehensive research findings on the relationship between uncertainty, climate change policies (CCPs), green innovation, and income inequality discussed in this thesis, offer several policy implications. First, they unveil the profound impact of uncertainty on green innovation. Economic and policy uncertainty, especially during global events like the COVID-19 pandemic, can significantly hamper the growth and development of renewable energy patents. Policymakers must prioritize proactive management of such uncertainties. This can be achieved through clear communication, consistent policy directions, and robust contingency planning. By ensuring a stable environment, governments can foster and accelerate green innovation across various sectors. Moreover, during periods of weak demand and financial stress, firms are more vulnerable to the negative effects of uncertainty. Policymakers should be aware of these state-dependent effects and design interventions that can bolster firms during such challenging times.

Second, the relationship between climate change policies (CCPs) and green innovation is multifaceted. While certain CCPs can stimulate green innovation, the type and design of these policies matter. Non-market-based policies, such as emission limits and R&D subsidies, have shown a positive and significant impact on green innovation. On the other hand, market-based policies might not always yield the desired results. Policymakers should adopt a tailored approach, considering the specific needs and challenges of different sectors. Regular assessments, feedback loops, and cross-sectoral collaborations can help refine and optimize policies over time, ensuring they effectively promote green innovation.

Third, while CCPs are essential for a sustainable future, their socio-economic implications cannot be overlooked. The research indicates that certain CCPs, especially market-based ones, can exacerbate income inequality. As countries transition to a green economy, it is crucial to ensure that this shift doesn't disproportionately burden certain segments of the population. Policymakers should design CCPs with an equity lens, considering their potential impact on income distribution. Compensatory measures, such as social safety nets, retraining programs for affected workers, and targeted subsidies, can help mitigate the regressive effects of CCPs. Furthermore, countries with robust redistribution mechanisms are better positioned to manage the inequality effects of CCPs. Strengthening such mechanisms, alongside the implementation of CCPs, can ensure a fair and inclusive transition to a green economy.

Summarizing, while the transition towards a greener economy through CCPs is commendable and necessary, it is imperative to consider the broader socio-economic implications. This research underscores the need for a balanced approach, where the pursuit of green innovation does not inadvertently exacerbate income disparities. Policymakers are thus tasked with the challenge of designing CCPs that not only promote green innovation, but also to ensure equitable economic growth.