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Climate change policies and income inequality[☆,☆☆]

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ABSTRACT

This paper examines the dynamic impact of Climate Change Policies (CCPs) on income inequality, for a sample of 39 developed and developing countries, during the period 1990–2020. The results show that CCPs are associated with a significant and persistent increase in income inequality. The effect is robust across various measures of inequality and sensitivity tests, including an instrumental variable strategy. The effect of CCPs only materializes in the case of market-based CCPs, is stronger in countries characterized by a higher share of low-educated workers and initial level of inequality, while is mitigated in those with comprehensive redistribution policies, and during periods of fiscal expansions and stronger economic growth. These findings have important policy implications, as they emphasize the importance of the timing and design of CCPs, as well as the role of complementary policies.

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 actions (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 distributional costs (Soergel et al., 2021). Indeed, recent studies in the literature suggest that climate change policies (CCPs) may have negative short-term economic consequences—e.g., job losses, higher cost of energy—that can be unevenly distributed among income groups (Markkanen 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).[1] Moreover, not all the types of CCPs may impact inequality in the same way, and country-level characteristics as well as complementary policies (i.e., fiscal or monetary policies) may

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[1] 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 and Zhang, 2022; Bettarelli and Yarveisi, 2023); 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; Chancel, 2022; Hsiang et al., 2017; Dell et al., 2012; Tang et al., 2023); and the impact of climate change on within-country income inequality (Ferrara, 2023; Cevik and Jalles, 2023).

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either mitigate or exacerbate the distributional costs of CCPs (Cameron et al., 2016).

In the last decade, a growing body of literature has analyzed the environmental and economic effects of CCPs. Overall, there is a broad consensus about the effectiveness of CCPs to reduce emissions.[2] Empirically, Yin et al. (2015), Song et al. (2020) and 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 CO_2 emissions, over the period 1990–2019. Cole et al. (2005) provide support 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 reducing 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 et al., 2022), 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 being short-lived. In the longer term, CCPs may contribute to spur innovation (Bettarelli et al., 2023b), thus improving productivity and employment (Porter and Van der Linde, 1995).

Previous studies 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.[3] 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 the estimated Gini coefficient being 0.53% higher than the benchmark scenario (with no CCPs) in 2030. Tang et al. (2023), using a panel dataset of 147 countries between 1961 and 2017 and simulation analysis based on temperature changes and limits, 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 pricing schemes may impose additional financial burdens on the poor, thus increasing poverty and inequality if not compensated by redistribution policies. Dorband et al. (2019) 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 by 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, they find that carbon ETS significantly reduces urban-rural inequality, likely due to the different expenditure patterns of citizens living in the two areas. They also show 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 workers' skills, as communities better endowed may even benefit from climate policies.

Another smaller stream of the literature—more closely related to the current study—has analyzed the effects of CCPs on energy poverty, a concept that has recently gained the attention of scholars and policymakers. Energy poverty broadly refers to aspects such as limited access to energy and unaffordable energy (Welsch and Biermann, 2017), and it has been defined in the literature as a form of inequality (Burlinson et al., 2018; Galvin and Sunikka-Blank, 2018). CCPs, like for instance a flat carbon tax at the global level, may have adverse effects on energy poverty, particularly in developing countries (Leimbach and Giannousakis, 2019). In fact, as well-recognized in the literature, CCPs may impose additional financial burdens on the poor, by increasing prices of energy and food, and undermine their capacity to access energy (Belaïd, 2019; Soergel et al., 2021).

However, as noted by Belaïd (2022), an in-depth analysis of factors potentially mediating the distributional consequences of CCPs, is still lacking.

This paper contributes to the existing literature by analyzing the dynamic—short- and medium-term—effect of CCPs (proxied by the OECD's environmental policy stringency (EPS) index) on several measures of income inequality, for an unbalanced panel of 39 developed and developing economies, during the period 1990–2020 and using the Jordà (2005) local projection approach.[4] The use of a dynamic model is crucial, since the effect of CCPs may take time to materialize. In addition, the breath of country and time coverage allow to explore how the effect of CCPs varies depending on countries' structural characteristics (such as the share of less educated workers), policies (fiscal policy and redistribution), phases of the business cycle (expansions vs. recessions), and specific climate change policy instruments (market vs. non-market vs. technology support policies).

In detail, the objectives of this study are threefold. First, unlike previous studies focusing mainly on single countries or specific areas

[2] 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 CO2 emissions in the short term.

[3] 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, who 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 increase 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.

[4] The focus of the paper is on income inequality (and not on other dimensions, like health and educational inequality), due to more comprehensive data availability. However, existing studies highlight how inequality is a multifaceted concept with the different dimensions being strongly interrelated (Markkanen and Anger-Kraavi, 2019).

(like EU), this paper tries to generalize the effect of CCPs on inequality analyzing a broad sample of 39 developed and developing economies, for more than three decades. Moreover, the adoption of different measures of income inequality—Gini, Palma ratio, and inter-decile ratios (P90/P10, S80/S20, and P50/P10)—that provide different information about the distribution of income (Campagnolo and Davide, 2019), is a critical contribution of this paper.

Second, the study tries to identify causality for such a broad set of countries, using a recent instrumental variable approach suggested in the literature (Nunn and Qian, 2014) to isolate exogenous changes in CCPs. This is done by considering as the instrument the interaction between a global term capturing the policy pressure to implement CCPs due to climate-related shocks (e.g., the yearly number of floods, hurricanes or drought events in the world), and a country-specific factor denoting the exposure of a country to such shocks (such as its length of the coastal area, the minimum distance of a country's centroid to the coast, or the agricultural land (km2) per capita).

Third, the paper uncovers 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., recessions vs. booms), the extent of redistribution policy and countries' structural characteristics (such as the initial level of inequality and the share of low-skilled workers). Indeed, the literature suggests that the climate and economic impact of CCPs 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, 2018; Bettarelli and Yarveisi, 2023), they are also those associated with larger employment fall in the short-term (Bettarelli et al., 2023a) and higher political costs (Furceri et al., 2023). However, existing studies have not investigated so far the likely heterogeneous effect of specific CCPs on inequality. In this paper this is done 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. Moreover, the response of income inequality to CCPs is allowed to be nonlinear, depending on country-specific factors and economic conditions, using the smooth transition local projection approach (Auerbach and Gorodnichenko, 2013).

The main beneficiaries of this study are policymakers, as our results can inform them on how to mitigate the potential distributional costs associated with CCPs (Furceri et al., 2023). In so doing, results may increase the support for strict CCPs—and ease their implementation—-that is a crucial step to contrast climate change and facilitate a green transition. Moreover, the study also provides useful intuitions for scholars investigating the impact of CCPs, by discussing in depth identification issues.

The rest of the paper is structured as follows. Section 2 introduces the data and the empirical strategy. Section 3 presents the results. Section 4 concludes and draws some policy recommendations.

2. Data and methodology

2.1. Data

The paper exploits an unbalanced panel dataset consisting of 39 advanced and developed economies for the period 1990–2020. [5] All data are taken from the OECD's databases to guarantee a consistent country/time coverage.[6]

To quantify the extent to which countries implement climate change policy, the Environmental Policy Stringency (EPS) index is used. The index is available on yearly basis and represents a proxy of the implemented climate policy in each country of the sample. It ranges from zero to six, with higher values corresponding to more stringency (Botta and Koźluk, 2014). As shown in Fig. 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 associated with the implementation of the Kyoto protocol and European Emission Trading Scheme (ETS).

The OECD also provides a score for the sub-components of the EPS, distinguishing between market-based (e.g., taxes and certificates), non-market based (e.g., performance standards) and technology support policies (e.g., R&D support policies).[7] This granularity allows us to empirically investigate whether the impact of CCPs on inequality depends on the type of policy implemented. In fact, it is expected that different types of policy actions may have heterogeneous effects on inequality, thus making an aggregate analysis not entirely informative.

In terms of income inequality data, several indicators from OECD's Income Distribution Database (IDD) are used, 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.[8] In detail, five indicators of income inequality are adopted. 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 is 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 all received by the 40% with the lowest income.[9] The use of alternative measures of income inequality provides 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

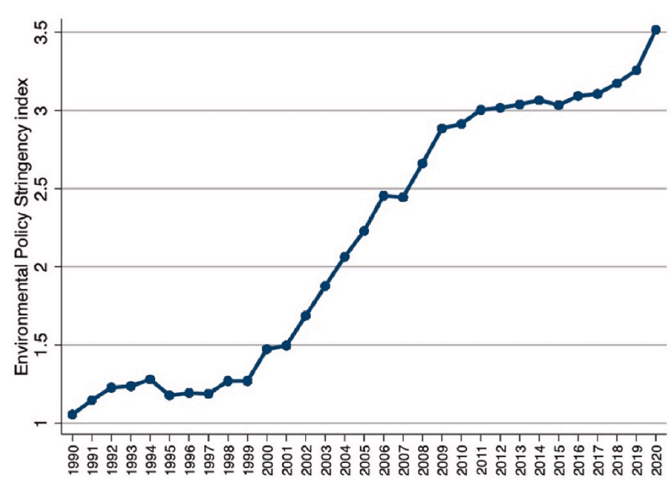

Fig. 1. Evolution of the Environmental Policy Stringency (EPS) index, from 1990 to 2020. Source: OECD.

[5] See Table 1 for the list of countries included in the empirical analyses.

[6] The dataset generated and analyzed during this study is available from the corresponding author on request.

[7] To download OECD's EPS data (both aggregate score and sub-components): https://stats.oecd.org/Index.aspx?DataSetCode=EPS.

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

[9] Income inequality data can be downloaded from: https://stats.oecd.org/index.aspx?queryid=66670#. More information on IDD's methods and concepts: https://www.oecd.org/social/income-distribution-database.htm.

distribution (Campagnolo and Davide, 2019). Table 2 reports descriptive statistics of the key variables used in the analysis.[10]

2.2. Methodology

2.2.1. Baseline model

This analysis relies on the local projection approach (Jordà, 2005) to directly estimate impulse response functions (IRFs) of income inequality to an increase in the degree of CCPs stringency. Specifically, the following dynamic equation is estimated, for each horizon (year) k, with $k=0, \ldots, 5$ (years):

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k CCP_{i,t} + \delta^k X_{i,t-l} + \varepsilon_{i,t+k} \tag{1}$$

Subscripts i and t indicate country and time, respectively. The term $y_{i,t+k} - y_{i,t-1}$ denotes the cumulative change (in percentage points) in 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, in the baseline, includes two lags (with $l=1,2$) of the dependent variable, and of CCP. $\varepsilon_{i,t+k}$ is the error term. Equation (1) is estimated using OLS with Driscoll-Kraay standard errors. The policy shock is considered at time zero, and its impact on inequality is directly estimated at t=0—the contemporaneous effect—and on the years ahead, through separate regressions.

Several robustness checks are provided to support the validity of our findings. In detail, the analysis considers: (i) the exclusion of potential outliers, i.e., top and bottom 1% of the distribution of the dependent variable; (ii) different set of fixed effects; (iii) standard errors clustered at the country level; (iv) alternative lags' structure; and (v) the exclusion of the contemporaneous effect of CCPs on inequality. In addition, to mitigate issues of omitted variables, several additional controls potentially related to inequality have been added to vector X in equation (1)—such as, unemployment, inflation, GDP growth, specific crises (Great Recession, Covid-19), the degree of uncertainty at country-level and fiscal policy shocks.

Finally, to test the effect of different types of policy, the model is estimated alternatively replacing the aggregate variable of CCPs —based on the aggregate EPS—with its subcomponents: market-based policies, non-market-based policies, technology support policies.

2.2.2. Instrumental variable

It is well known that such kind of analysis may suffer from endogeneity issues. For example, when inequality is high, governments 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, an instrumental variable strategy is adopted. Following the approach proposed by Nunn and Qian (2014) and Furceri et al. (2023), the probability of a country to adopt a strict CCP is let to depend on the product between (i) the policy pressure at the global level induced by climate-related shocks and (ii) the country-level morphological conditions that may make the exposure to such shocks more likely, and thus the adoption of CCPs. The global time-varying term—-which is exogenous to country-specific factors, including inequality—is constant across countries. This term is intended to capture policy pressure that climate change events induce at supra-national level (independently from the actual distribution of the event by country). The second component of the instrument exploits the fact that the policy pressure exerted by climate-related events may vary depending on country-specific characteristics (e.g., morphological characteristics, the geographical position). 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.[11]

Following the above intuition, the instrument is constructed 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, the following equations are estimated:

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

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k \widehat{CCP}_{i,t} + +\delta^k X_{i,t-l} + \varepsilon_{i,t+k}; \tag{2}$$

where, in the first stage, $CCP_{i,t}$ is regressed on the same set of controls as in equation (1), and contemporaneous and lagged $Z_{i,t}$, in order to increase the predictive power of the instrument, as there may exist a time-gap between policy-pressure and the actual implementation of CCPs. Note that the country (time) fixed effects in the first stage effectively

Table 1
List of countries included in the dataset.

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 2
Descriptive statistics of the main variables used in the empirical analyses.

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
Environmental Policy Stringency (EPS) index	424	2.596	1.04	0	4.72	OECD
Market-based Environmental Policy Stringency (EPS) index	424	1.332	0.902	0	4.17	OECD
Non-market-based Environmental Policy Stringency (EPS) index	424	4.403	1.597	0	6	OECD
Technology support Environmental Policy Stringency (EPS) index	424	2.085	1.354	0	6	OECD
GINI	424	0.31	0.057	0.211	0.626	OECD
P50/P10	423	2.11	0.434	1.6	7.8	OECD
P90/P10	424	4.208	1.944	2.1	23	OECD
PALMA	424	1.227	0.574	0.69	7.14	OECD
S80/S20	424	5.371	2.833	3	33.1	OECD

Notes: GINI 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 is 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 all received by the 40% with the lowest income.

[10] Note that each inequality indicator has been multiplied by 100 to allow the interpretation of results in percentage points.

[11] The validity of the instrumentation strategy is discussed in Section 3, when presenting IV results.

control for country-specific characteristics (global shocks) that may be directly associated with inequality, thereby alleviating concerns related to the exclusion restriction of the instrument.

The second stage is equivalent to equation (1), with the predicted value of CCP. Using first-stage statistics, it can be clearly seen that the identification strategy satisfies standard test for strong instrument and (for the analysis with more than one instrument) the exclusion restriction based on the Hansen-Sargan over-identification tests (Alfaro et al., 2022).

As a robustness check, alternative instruments, built using the same theoretical rationale of the previous one, are considered. In detail, two alternative indicators are used: (i) the number of hurricanes at global level in year *t*, interacted with the minimum distance of a country's centroid to the coast; (ii) the number of drought events at global level in year *t*, multiplied by country's agricultural land (km2) per capita.

2.2.3. Nonlinear effects

The flexibility of the local projection approach to nonlinear frameworks allows a straightforward investigation of whether 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), the baseline specification is augmented as follows:

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + F(z_{it})\left[\beta_L^k \Delta CCP_{i,t} + \theta_L^k X_{i,t-l}\right] + (1 - F(z_{it}))\left[\beta_H^k \Delta CCP_{i,t} + \theta_H^k X_{i,t-l}\right] + \varepsilon_{i,t+k}; \quad (3)$$

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

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.[12] Both within and cross-country variation in the normalization for all the mediating variables are exploited, i.e., using $z_{it} = \frac{s_{it} - \bar{s}}{sd(s_{it})}$, with the only exception of GDP growth for which only within-country variation is exploited by constructing $z_{it} = \frac{s_{it} - \bar{s}_i}{sd(s_{it})}$, as GDP growth 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 Terasvirta (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. Results

3.1. Baseline results

Fig. 2, and Table A1 in the Appendix, report the evolution of income inequality following a 1 standard deviation increase in the average yearly change of the EPS index in our sample, corresponding to an increase in the index of about 0.2. In fact, to ease the interpretation of results and to provide a realistic picture of the impact of CCPs on inequality, results show the estimated β^k coefficients from equation (1), for each horizon k=*0, …,5* (years), multiplied by 1 standard deviation of the change in EPS between *t* and *t-1*. 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 confirm that CCPs are associated with distributional costs, as income inequality persistently increases after the policy shock, with the effect materializing in the medium term. The fact that the effect is increasing over time corroborates the dynamic modelling choice proposed in this paper. Moreover, the effect is consistent across income inequality measures, as each of them increases after the implementation of a stricter climate policy. In terms of magnitude, the effect is not negligible. Specifically, a 1 standard deviation increase in the yearly change of the EPS index increases inequality by approximately 1/4 standard deviation of the yearly change in the sample, with results that are quantitatively similar across inequality measures. Taking these effects at the face value and translating it to major reforms (corresponding to changes in EPS at the 99th percentile of the distribution in the sample under analysis—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 inequality over the medium term of about 1 standard deviation. Given that inequality measures are typically slow-moving indices, these effects are sizeable.

Several robustness checks have been provided. First, additional control variables, that may potentially be correlated with CCP and have an impact on inequality are included: unemployment, inflation and GDP growth at country level. They are included one-by-one and together, with a 1-year lag.[13] In addition, it is recognized that other (macroeconomic) shocks, occurred during the period under analysis, may affect inequality at the country-level, and/or affect the likelihood of implementation of strict CCPs, thus potentially biasing the baseline results. To address this issue, several shocks are included one-by-one as additional controls in baseline specifications: (i) fiscal policy shocks as in Cacciatore et al. (2021)[14]; (ii) dummy variables capturing Great Recession; (iii) an index of uncertainty at country-year level, i.e., the World Uncertainty Index by Ahir et al. (2022).[15] Next, the outbreak of Covid-19 pandemic may bias the results and thus the analysis is replicated excluding the Covid-19 period (year<2019). In terms of empirical strategy, the robustness of the baseline results are assessed to alternative specifications, such as: excluding the contemporaneous effect of CCP on inequality; considering an alternative lag structure in equation (1) that includes 4 lags, instead of 2; excluding potential outliers, i.e., 1st and 99th percentiles of the distribution of the dependent variable; including country-specific time trends; clustering the standard errors at the country level. The results, reported in Figures A1-A13 in the Appendix, are qualitatively identical to those presented in Fig. 2, thus reassuring about the validity of the main findings.

3.2. Instrumental variable approach

To address potential endogeneity issues, an instrumental variable strategy is adopted, where the index of climate change policy is instrumented with (contemporaneous and lagged) values of a composite variable that considers weather-related shocks at the global level—the

[12] These variables are better discussed in Section 3, when commenting the results.

[13] 1-year lag is considered as these variables capture the channel through which CCP can affect inequality.

[14] The authors compute government spending shocks as forecast errors for government spending, as in Auerbach and Gorodnichenko (2013).

[15] (Unexpected) expansionary fiscal policy may contribute to decreasing inequality; negative growth and recessions may both affect inequality and the capacity of governments to implement strict CCPs, as the latter may cause short-term economic costs. Conversely, uncertainty is a factor potentially improving the capacity of governments to implement major and/or costly reforms, like CCPs (Alesina and Cukierman, 1990). Note that the correlation between these shocks and CCP index is very low: CCPs-fiscal shocks = 0.03; CCPs-great recession = 0.11; CCPs-uncertainty = 0.32.

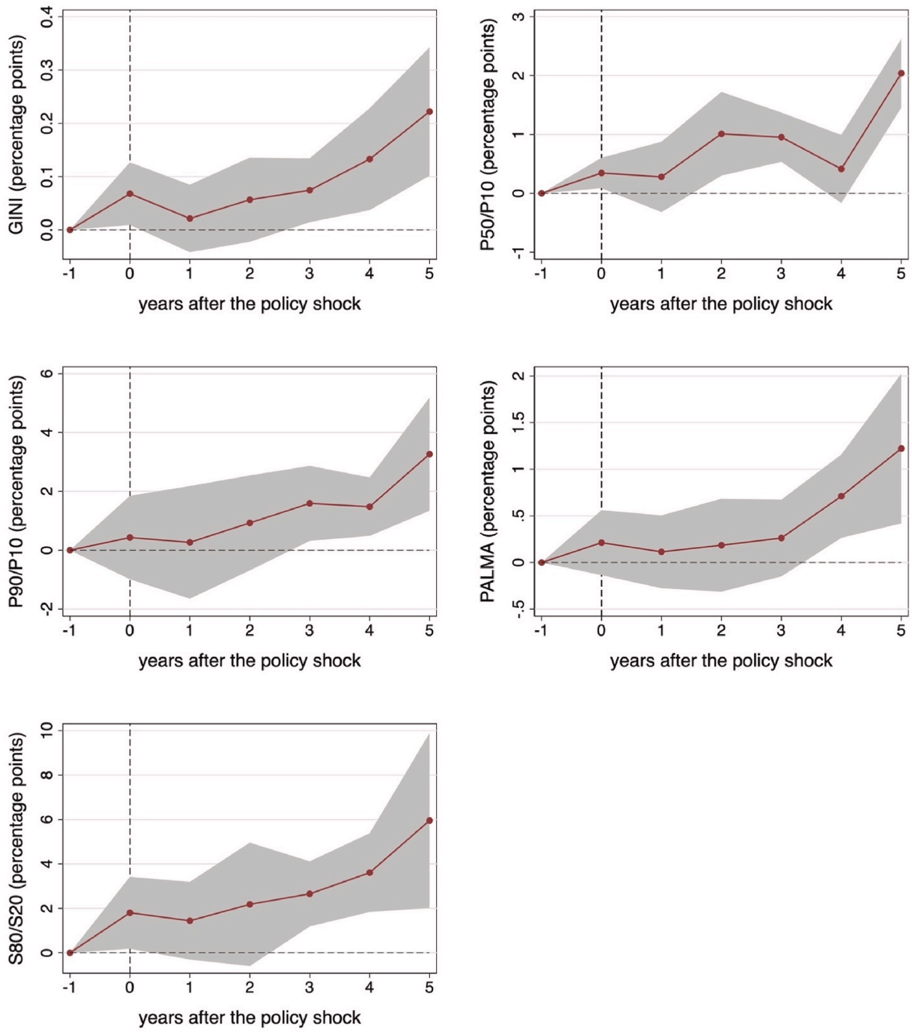

Fig. 2. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock.

number of floods at time *t* in this case—multiplied by morphological conditions of country *i*—the length of the coastline. The results from the first-stage equation suggest that the instrumentation strategy works well, as the instruments exhibits the expected sign (+) and are "strong"—with the Kleibergen–Paap rk Wald F statistic being larger than the associated Stock-Yogo critical value for strong instruments; moreover, the Hansen-Sargan over-identification test always fails to reject the null hypothesis, with p-values ranging from 0.198 to 0.879 (see Tables A2-A6, in the Appendix).

As for the exclusion restriction, the global term is exogenous by construction, as any time-unvarying country-characteristic potentially correlated with inequality is absorbed by the country fixed effects. Despite that, further checks related to potential endogeneity issues of the instruments are performed—that is, the possibility that the instrument is correlated with the error term of the baseline equation, in two ways. First, the direct association between the instruments and inequality measures is tested, by including the former as regressors in the baseline specifications, as in equation (1). Second, the correlation between the instruments and the residuals of the baseline regressions is tested; significant coefficients would indicate that the instruments are part of the error term and do not satisfy the exclusion restriction. Reassuringly, none of these exercises signal potential issues of endogeneity of the selected instrument (see Tables A7 and A8, in the Appendix).[16]

Fig. 3 and Tables A2-A6 in the Appendix report the effects of a 1 standard deviation increase in the yearly change of CCPs on income inequality (in percentage points), using the IV approach. The findings remain qualitatively similar to those obtained with the baseline estimation strategy, with the estimated coefficients being approximately two times larger than in the baseline, in the medium term. This indicates that, not accounting for potential endogeneity, may lead to underestimate the effect of CCPs on income inequality.

Even if the above evidence it is reassuring about the validity of the instrumental variable approach adopted—in terms of strength of instrument and exclusion restriction—it is possible that considering other

[16] However, it is recognized that these tests are data-driven and depend on the sample used. Theoretically, issues with the exclusion restriction of the instrument may be present in other setting, using different specification or sample of countries.

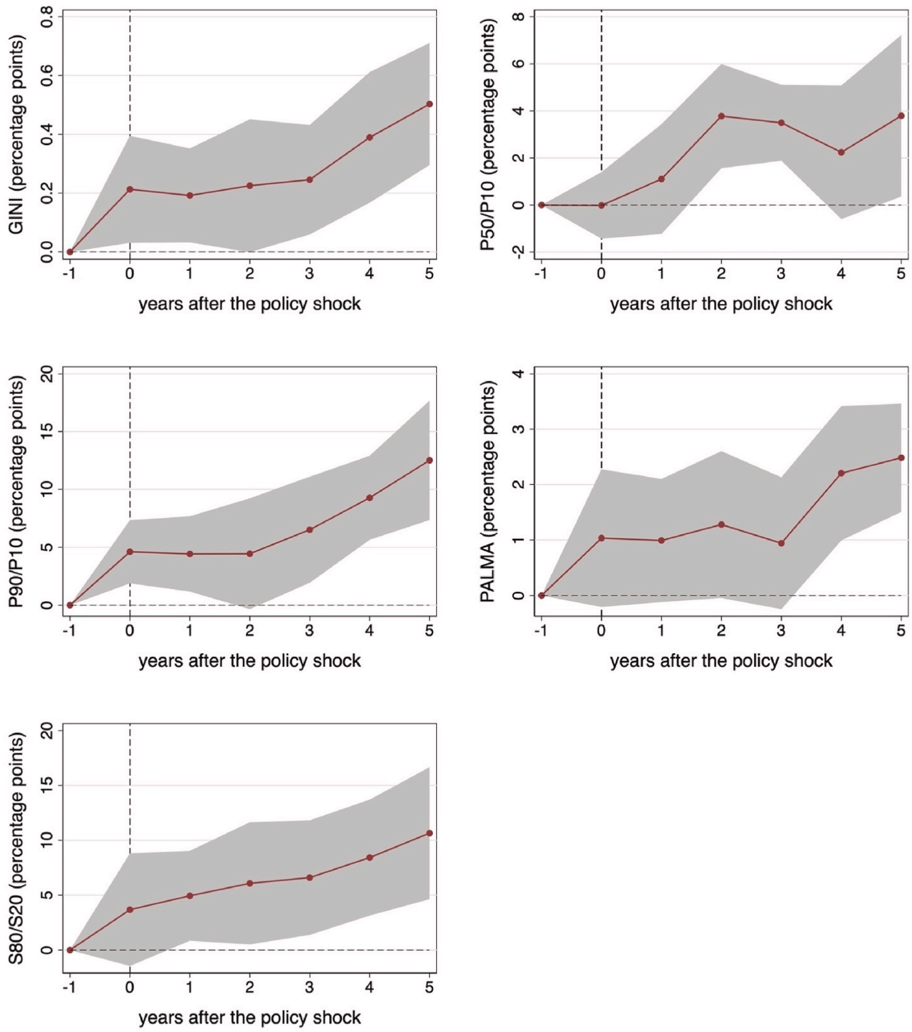

Fig. 3. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); $t = 0$ is the year of the shock. Estimates are based on an Instrumental Variable (IV) approach, where the instrument is the product between the length of coastline in country *i* and the number of floods at the global level.

climate-related events may have led to different results. Thus, the robustness of results to alternative instruments is tested. In detail, two alternative instruments are considered: (i) the number of major hurricanes at global level in year *t*, multiplied by the minimum distance of a country's centroid to the coast; (ii) the number of drought events at global level in year *t*, multiplied by country's agricultural land (km2) per capita. Figures A14 and A15, in the Appendix, show that results are qualitatively similar to those reported in Fig. 3.[17]

3.3. Transmission channels

To shed light on some of the transmission channels through which climate policy actions may affect inequality, equation (1) is estimated, but alternatively using the unemployment rate, and the share of employment of workers with low education, as dependent variables.[18]

Fig. 4 shows that stricter CCPs contribute to increasing the unemployment rate, with coefficients that are large in magnitude, highly statistically significant and persistent. Specifically, a 1standard deviation increase in the yearly change of CCPs raises unemployment rate by about 0.3 percentage points, in the medium term, a result similar to that found by Kanzig (2023). In addition, job disruptions are likely to affect more those workers—such as those with lower skills—that are unable to easily reallocate to green jobs. In fact, Fig. 5 shows that the effect of CCPs on the share of employment of worker with low-education/low-skills is negative in the medium term. These two

[17] Results of standard tests for strength of instruments and exclusion restriction are qualitatively similar to those obtained with the first instrument. Note that using global disasters not related to climate change, e.g., the number of earthquakes at global level multiplied by the share of urban population in country *i*, lead to not significant correlation with CCPs, thus further corroborating the validity of the approach proposed.

[18] In detail, the dependent variables are: (i) unemployment rate, in country *i*, at time *t*, (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.

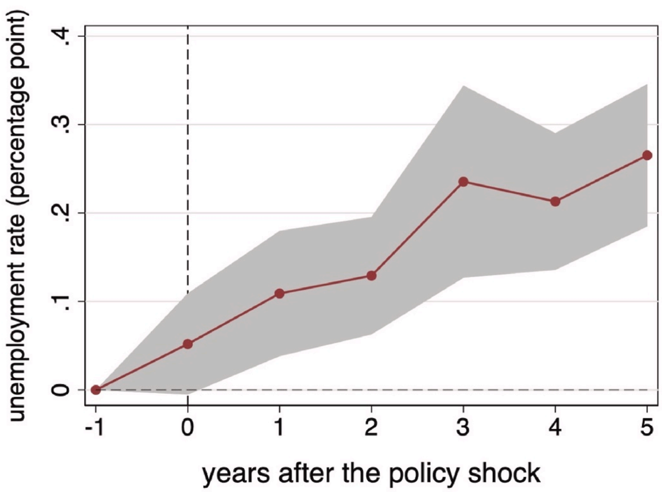

Fig. 4. The chart shows the impulse response functions of the unemployment rate to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock.

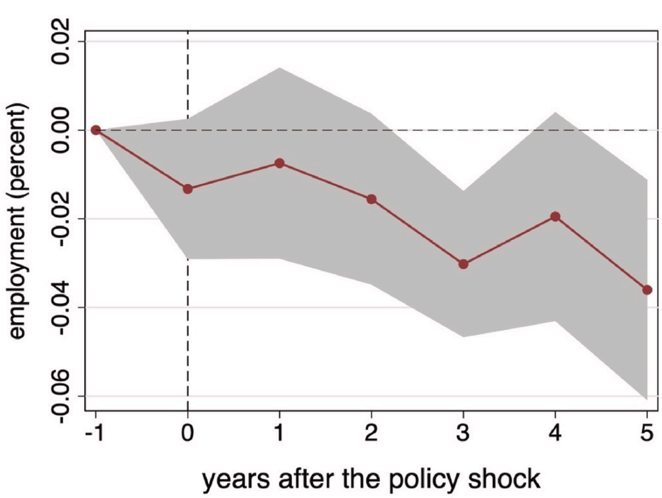

Fig. 5. The chart shows the impulse response functions of the (logarithm of) employment to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock.

results confirm the idea that CCPs have adverse employment effects, especially for low-skilled workers.[19]

3.4. Heterogeneity due to the type of policy

As outlined above and confirmed by the 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, the subcomponents of the EPS index are used. In detail, the analysis differentiates 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 they are included one-by-one in equation (1). Fig. 6 reports the results of this exercise applied to different indicators of income inequality. They suggest that the baseline results are mainly driven by market-based policy actions. In fact, the implementation of market-based policy is associated with an increase in income inequality that is 50% larger than in the baseline. Particularly, larger increases are observed for the P90/P10 indicator (+70%), thus suggesting that market-based policies may be detrimental for households at the bottom of the distribution. In contrast, non-market-based, and technology support policies have no, or feeble, effects on income inequality.

3.5. Heterogeneity due to country characteristics and economic conditions

Next, different country-level characteristics/conditions mediating the way CCPs affect income inequality, either amplifying or moderating the effect, are considered. In so doing, the analysis discloses potentially efficient compensating policy actions that policymakers may implement to alleviate distributional costs associated with CCPs. Empirically, smooth transition functions based on the moderating variables are constructed and interacted with the EPS index, as well as controls, as described in equation (3).

First, the analysis considers the role of country's structural characteristics related to the share of workers with low education (lower than upper secondary education), and initial levels of income inequality—i.e., the GINI index of market income—with data retrieved from the OECD. Figs. 7–8 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.

Next, the role of the business cycle is investigated. The results in Fig. 9 show that while CCPs are associated with an increase in inequality when implemented in recessions (with the medium-term effect about 1.2–1.5 times larger than in the baseline), they are linked to a decline in inequality when they are implemented during economic expansions.

Fig. 10 focuses on the role of fiscal policy at the time of the adoption of stricter climate change policy. In line follow Furceri and Zdzienicka (2020), unexpected fiscal policy shocks are identified using the forecast errors in government spending at annual frequencies (see Furceri and Zdzienicka, 2020; for additional details about the methodology). This approach allows 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. Regardless to the measure of income inequality considered, the results show that expansionary fiscal policies significantly reduce the negative impact of CCPs on inequality.

Finally, another potentially relevant mediating aspect is the extent to which governments implement redistribution policy. Here, the difference between Gini based on market income before taxes and transfers and Gini based on disposable income post taxes and transfers is used, with data taken from OECD. The results in Fig. 11 show that in countries with strong redistribution policies, the effect of CCPs on inequality is not significantly different from zero.

[19] These findings are in line with the previous literature analyzing the employment effects of CCPs. For instance, lower employment levels after CCPs are found in Adamson et al. (2021), and Dechezleprêtre and Nachtigall (2020). Yip (2018) finds ambiguous effects, strongly dependent on workers' skills, with the less educated being the most affected, as it is shown. However, data available do not allow to prove the effective causality of these findings by, e.g., comparing employment effects across industries, or across workers within the same industry.

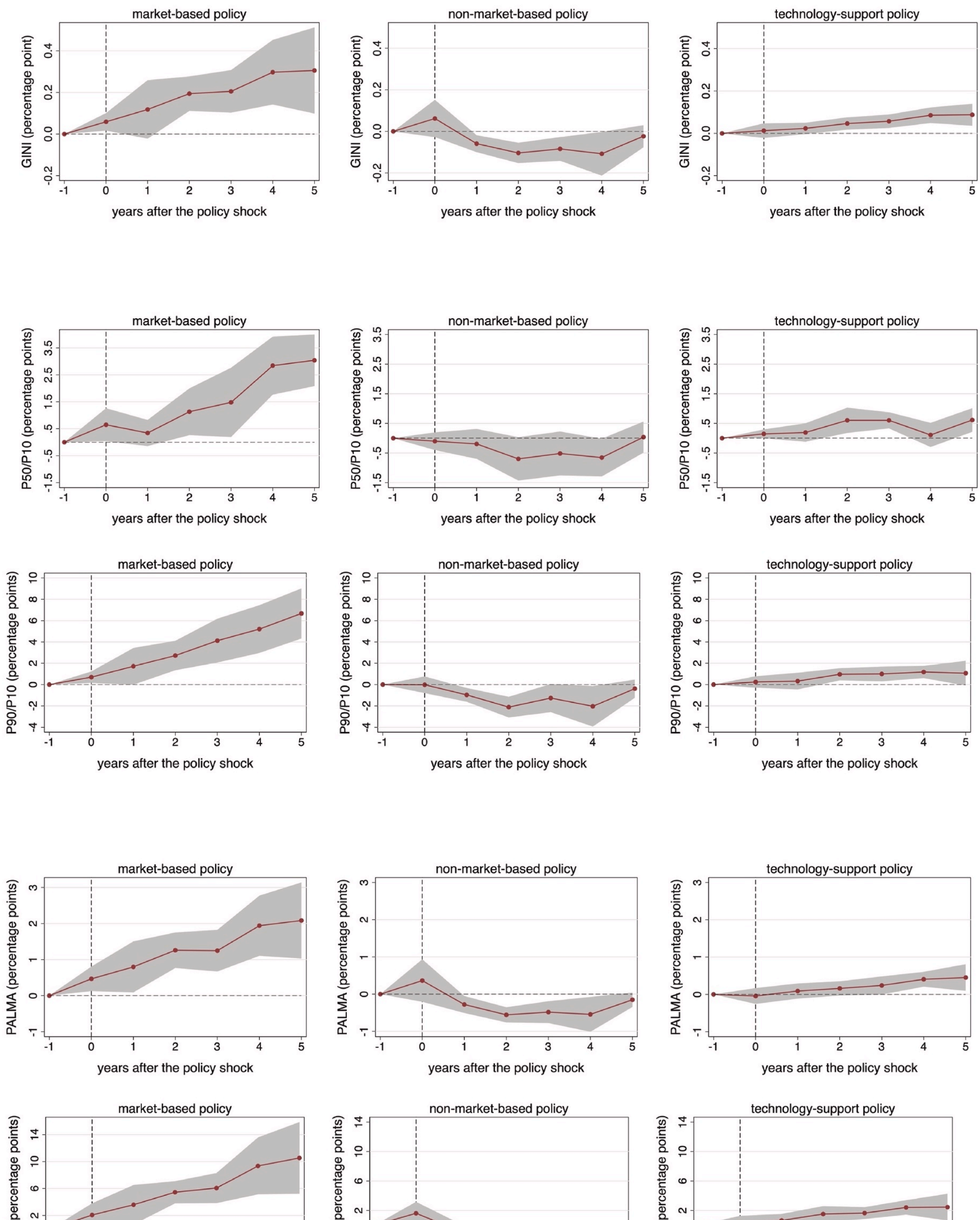

Fig. 6. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the sub-components of the Environmental Policy Stringency (EPS) index in our sample, i.e.: market-based policy, non-market-based policy, technology-support policies. GINI 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock.

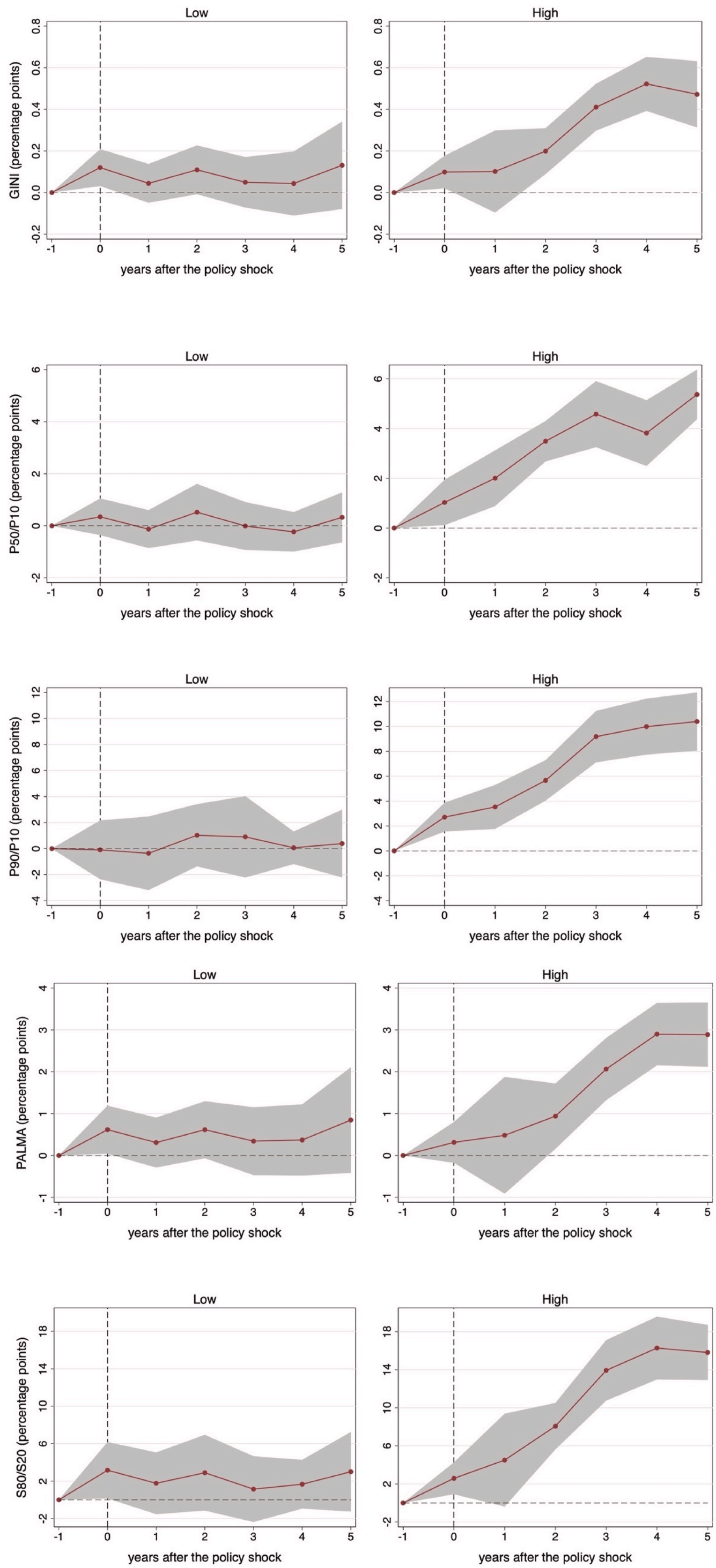

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Fig. 7. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on the smooth transition local projection approach, as described in equation (3), with the share of workers with low education as mediating factor. Left chart reports the low-scenario (i.e., low share of workers with low education); right chart reports the high-scenario (i.e., high share of workers with low education).

4. Conclusion and policy implications

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

The objective of this study it to contribute to this literature by analyzing 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 advanced and developing economies, for the period 1990–2020. Several measures of income inequality are considered—i.e., Gini, Palma ratio, and inter-decile ratios (P90/P10, S80/S20, and P50/P10)—and the OECD Environmental Policy Stringency Index is adopted to quantify the stringency of climate change policy at the country level.

The results show that the implementation of CCPs is followed by significant and persistent increases in income inequality, independently from the measure of inequality used. According to the estimates obtained, back-to-the envelope calculations suggest that major reforms 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, may have been associated with a medium-term increase in inequality of about 1 standard deviation of the average increase of inequality indices in our sample. The paper also shows 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, the paper shows that the adverse 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 for policymakers 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. Finally, they suggest that policymakers may consider a mix of CCPs, including both market- and non-market-based policies, to efficiently contrast climate change, while mitigating the economic and distributional costs of CCPs (Bettarelli and Yarveisi, 2023).

The analysis presented in this paper has some limitations that leave several questions open for future research. First, it would be interesting to extend the degree of granularity of the current analysis, to examine the distributional costs of CCPs across industries, and across jobs/occupations within the same industry. Future analyses may also consider the implications for other dimensions of inequality, such as in healthcare and education. This would allow a more accurate examination of the welfare effects of CCPs. Moreover, additional data collection efforts would allow to extend the analysis to a larger number of developing countries, where other aspects may play a key role in mediating the effect of CCPs on inequality. This would require the construction of a wider database, with internationally comparable measures.

CRediT authorship contribution statement

Luca Bettarelli: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Davide Furceri:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Pietro Pizzuto:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Nadia Shakoor:** Writing – review & editing, Writing – original draft, Resources, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Figures

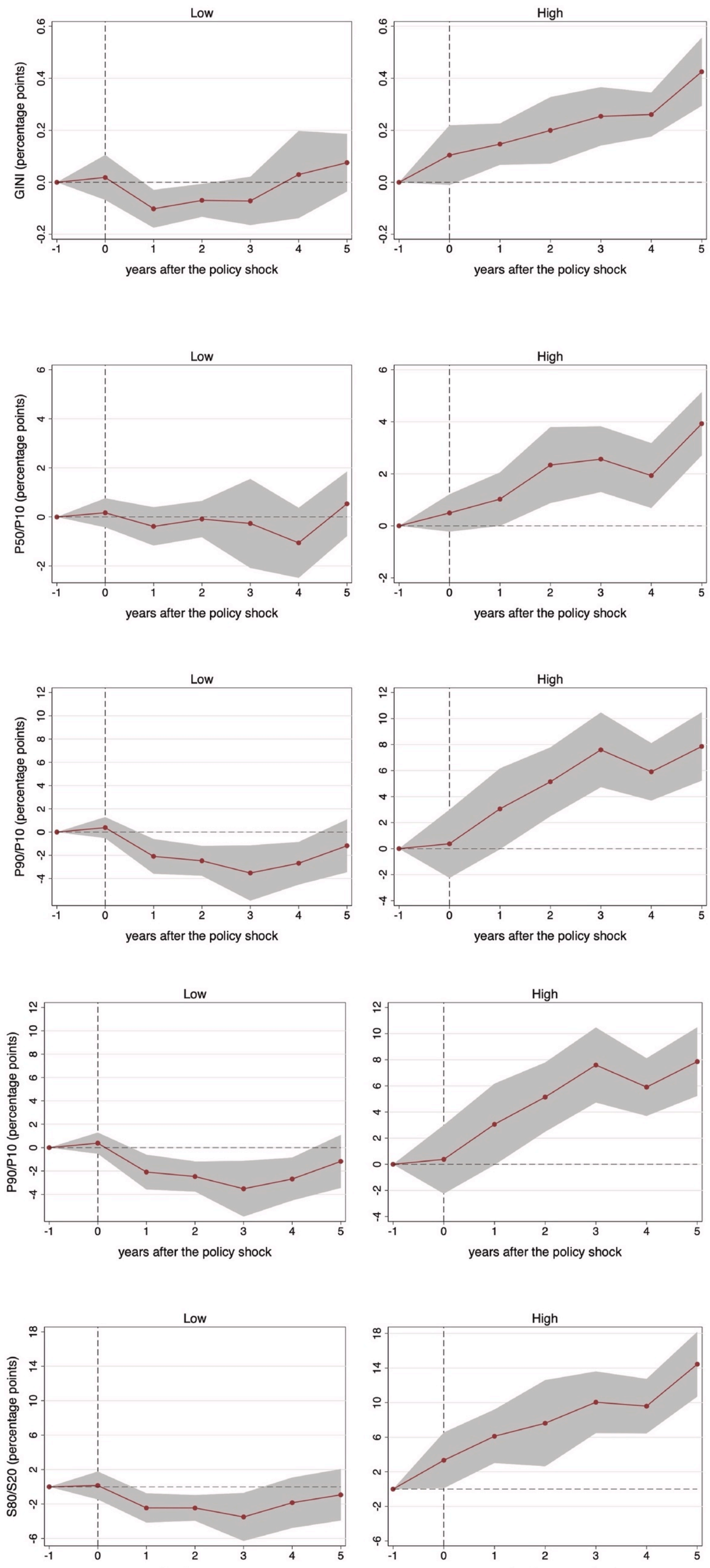

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Fig. 8. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on the smooth transition local projection approach, as described in equation (3), with the initial level of inequality as mediating factor. Left chart reports the low-scenario (i.e., low initial level of inequality); right chart reports the high-scenario (i.e., high initial level of inequality).

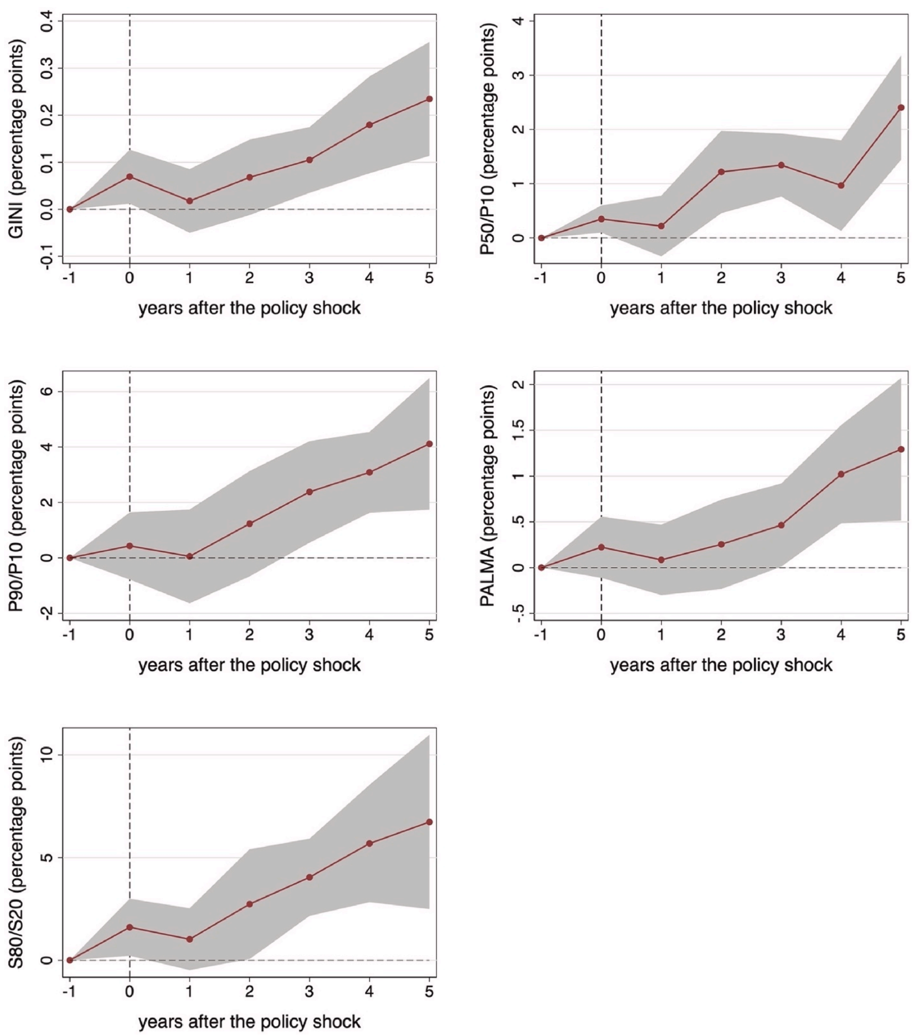

Fig. A1. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates include unemployment as additional control.

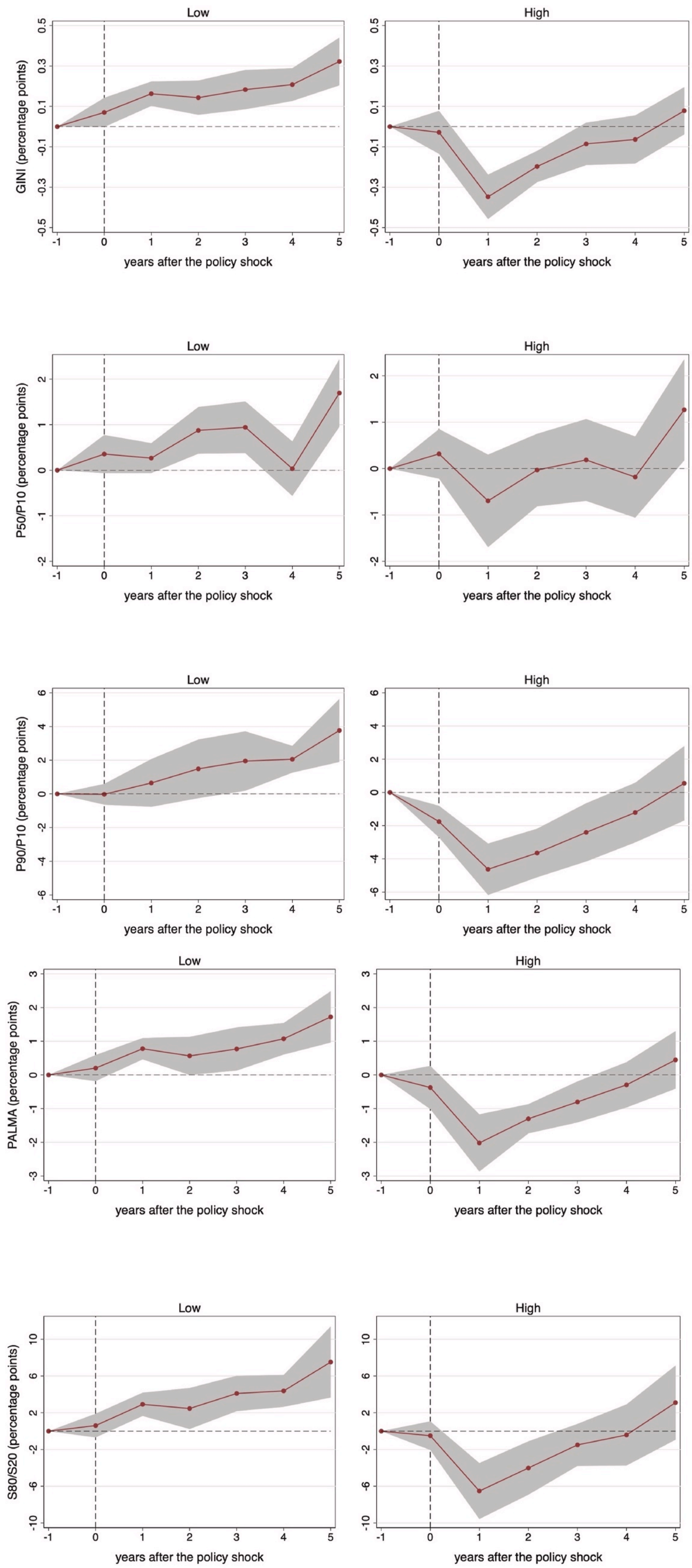

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Fig. 9. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on the smooth transition local projection approach, as described in equation (3), with per-capita GDP growth as mediating factor. Left chart reports the low-scenario (i.e., low GDP growth); right chart reports the high-scenario (i.e., high GDP growth).

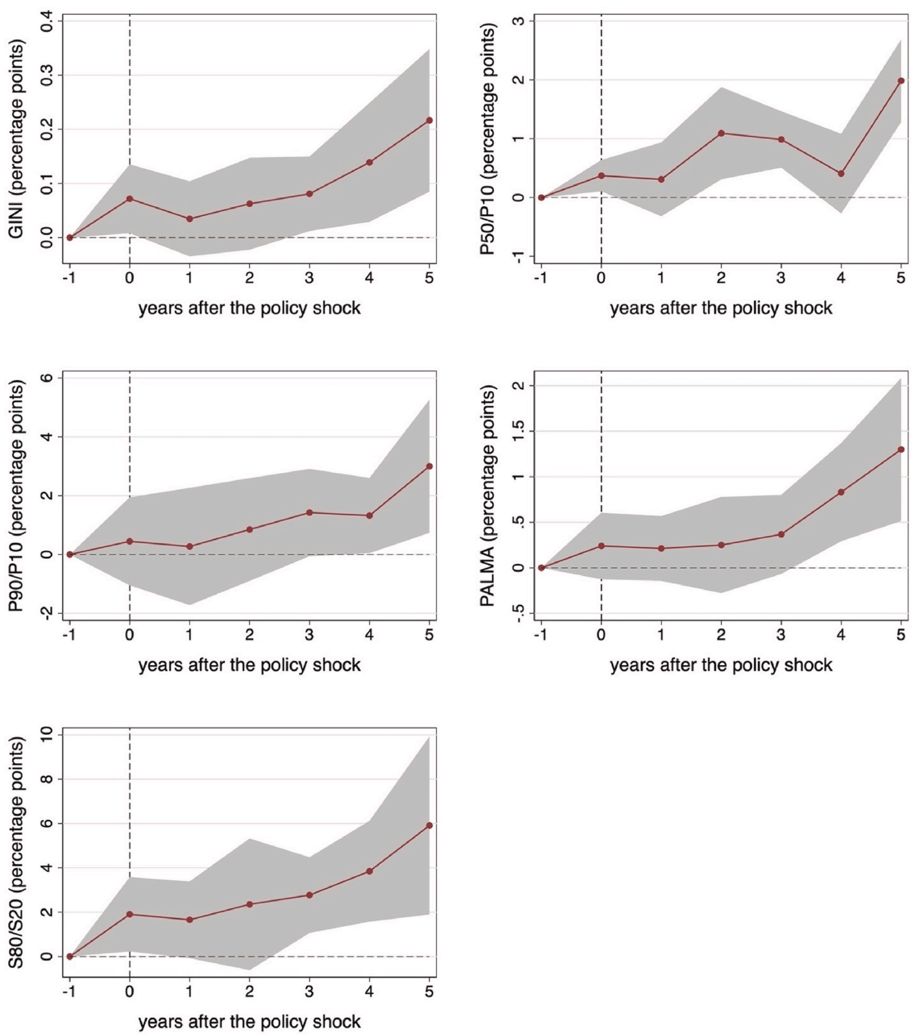

Fig. A2. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates include inflation as additional control.

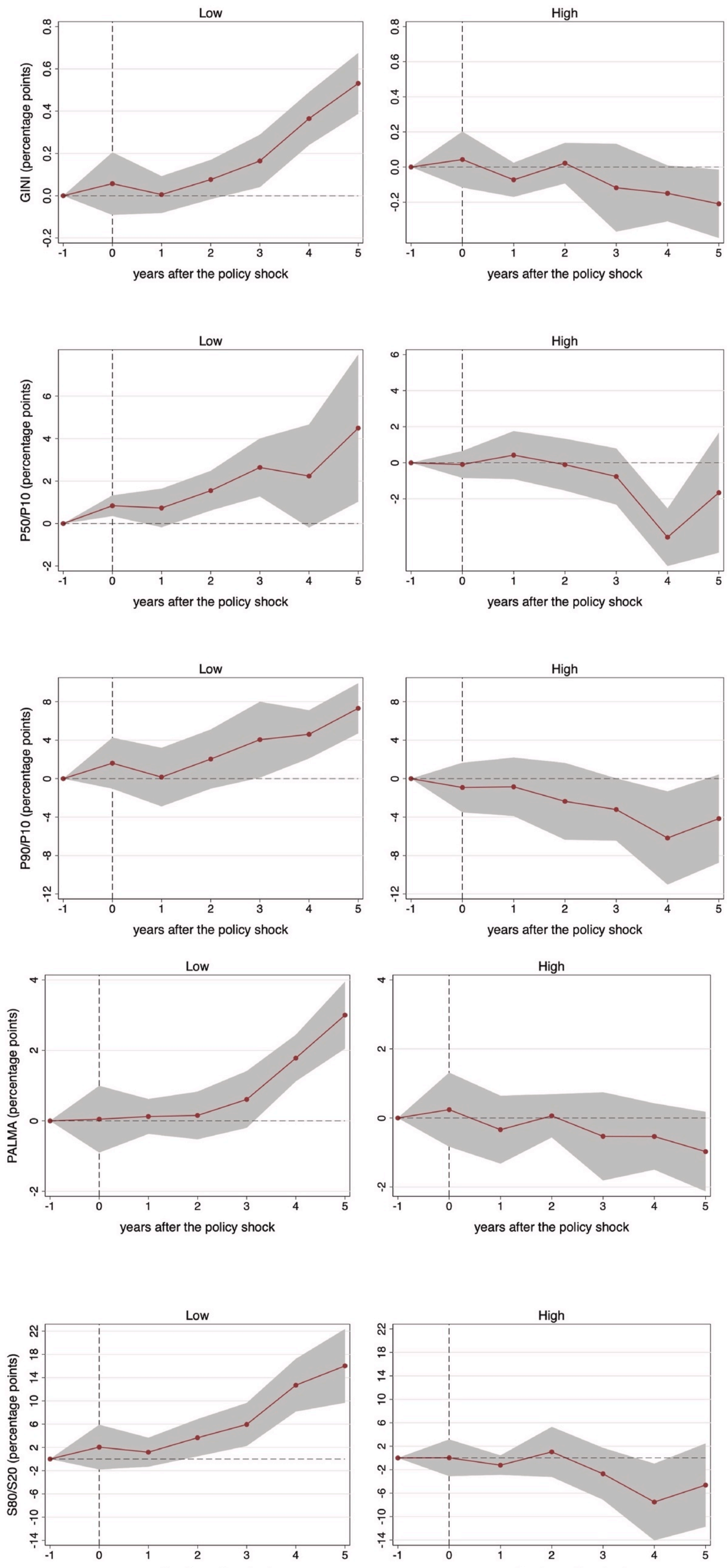

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Fig. 10. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on the smooth transition local projection approach, as described in equation (3), with expansionary fiscal policy shock as mediating factor. Left chart reports the low-scenario (i.e., low expansionary fiscal policy shock); right chart reports the high-scenario (i.e., high expansionary fiscal policy shock).

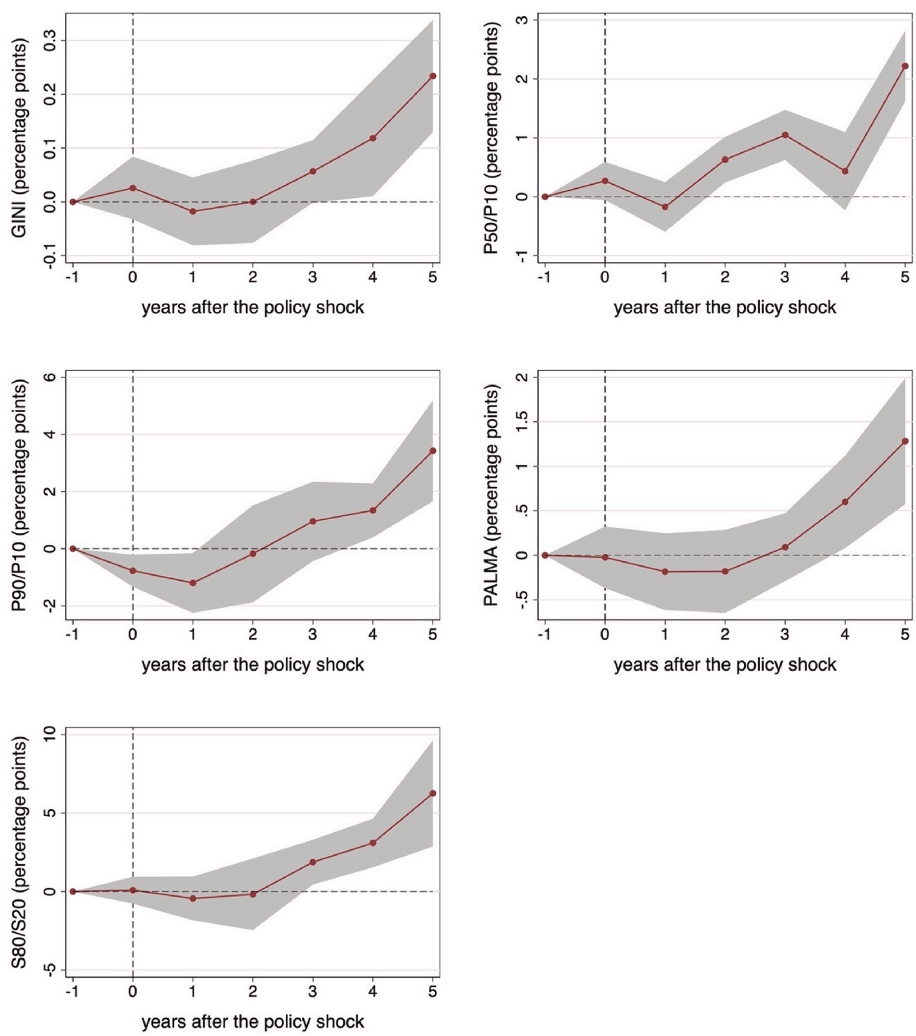

Fig. A3. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates include per-capita GDP growth as additional control.

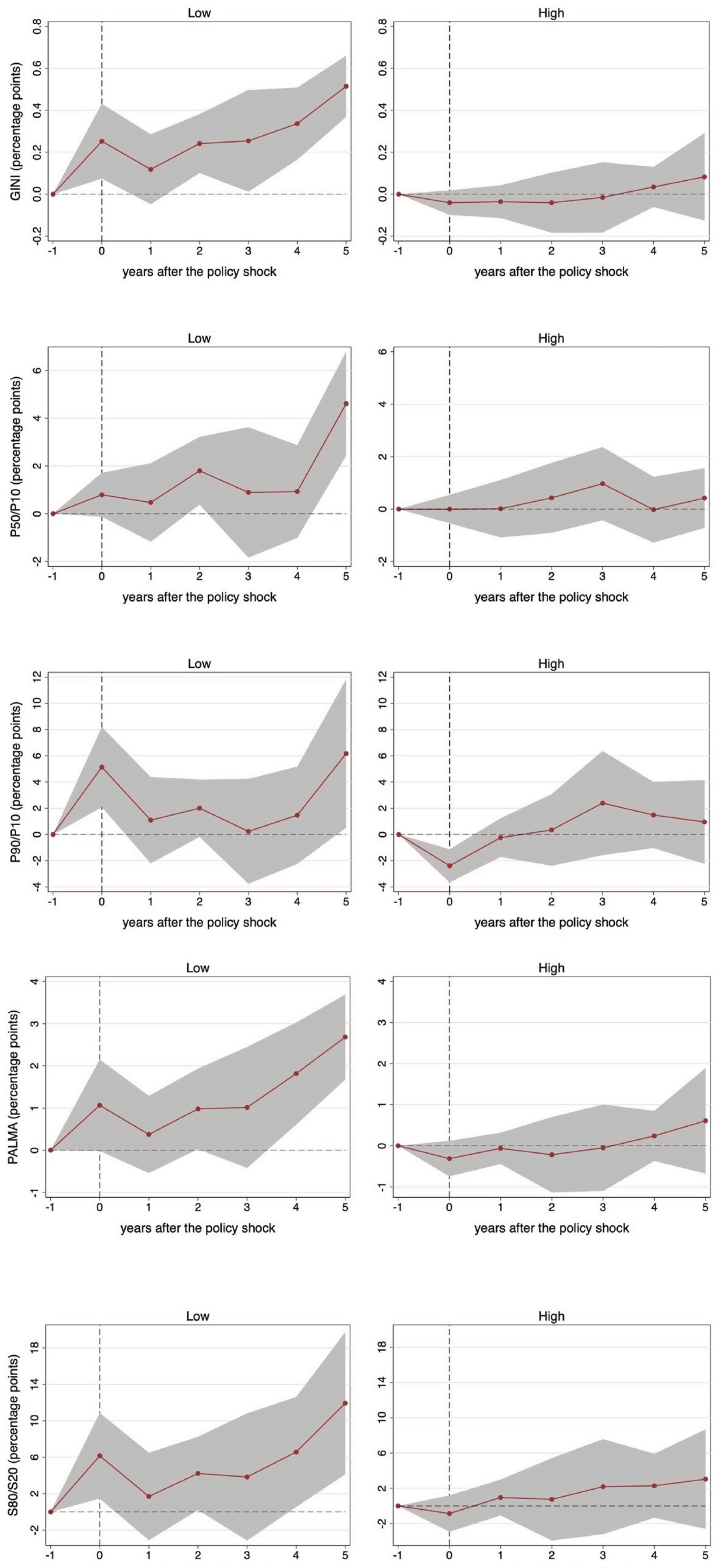

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Fig. 11. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on the smooth transition local projection approach, as described in equation (3), with redistribution policy shock as mediating factor. Left chart reports the low-scenario (i.e., low redistribution policy shock); right chart reports the high-scenario (i.e., high redistribution policy shock).

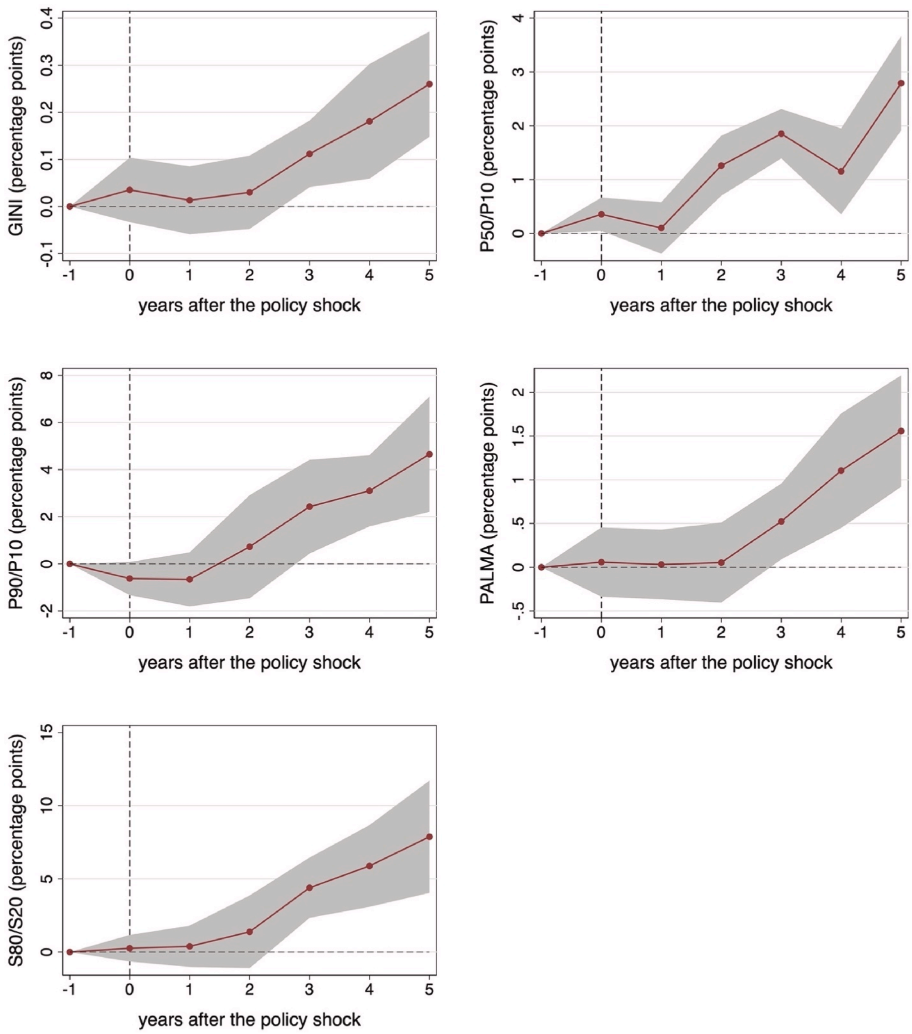

Fig. A4. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates include unemployment, inflation and per-capita GDP growth as additional controls.

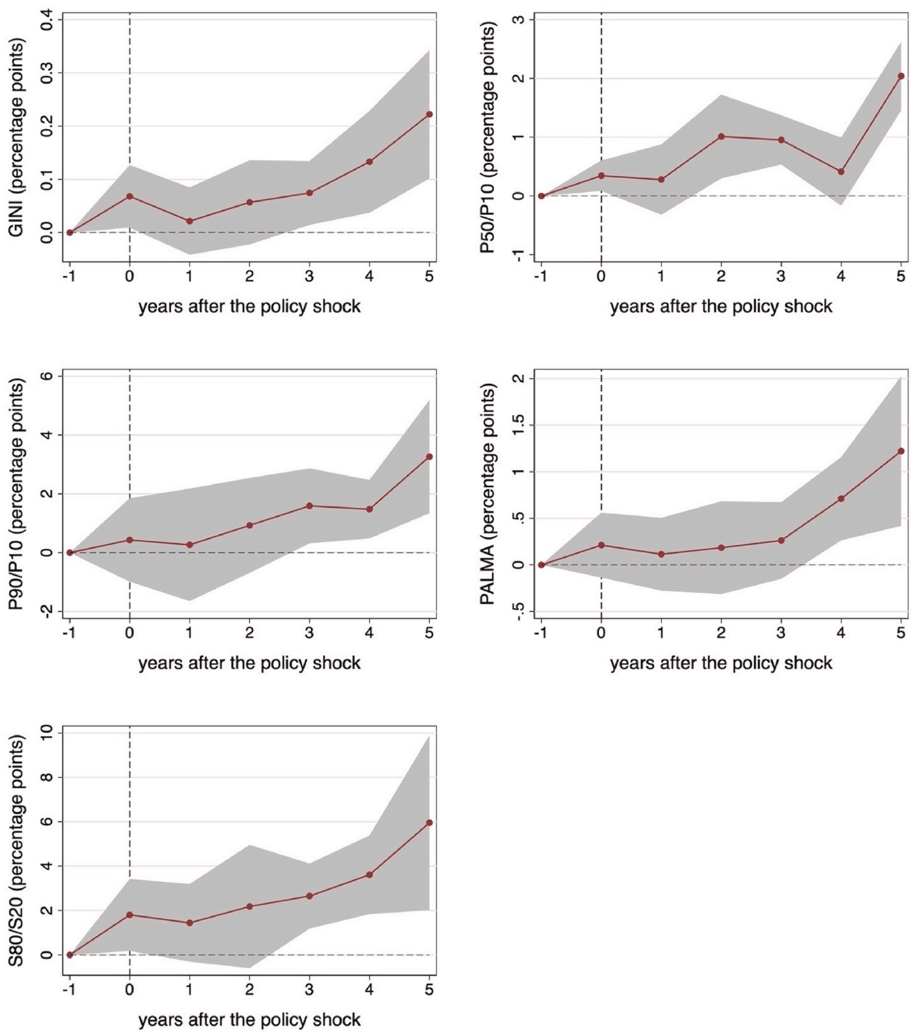

Fig. A5. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates include dummies indicating the Great Recession years.

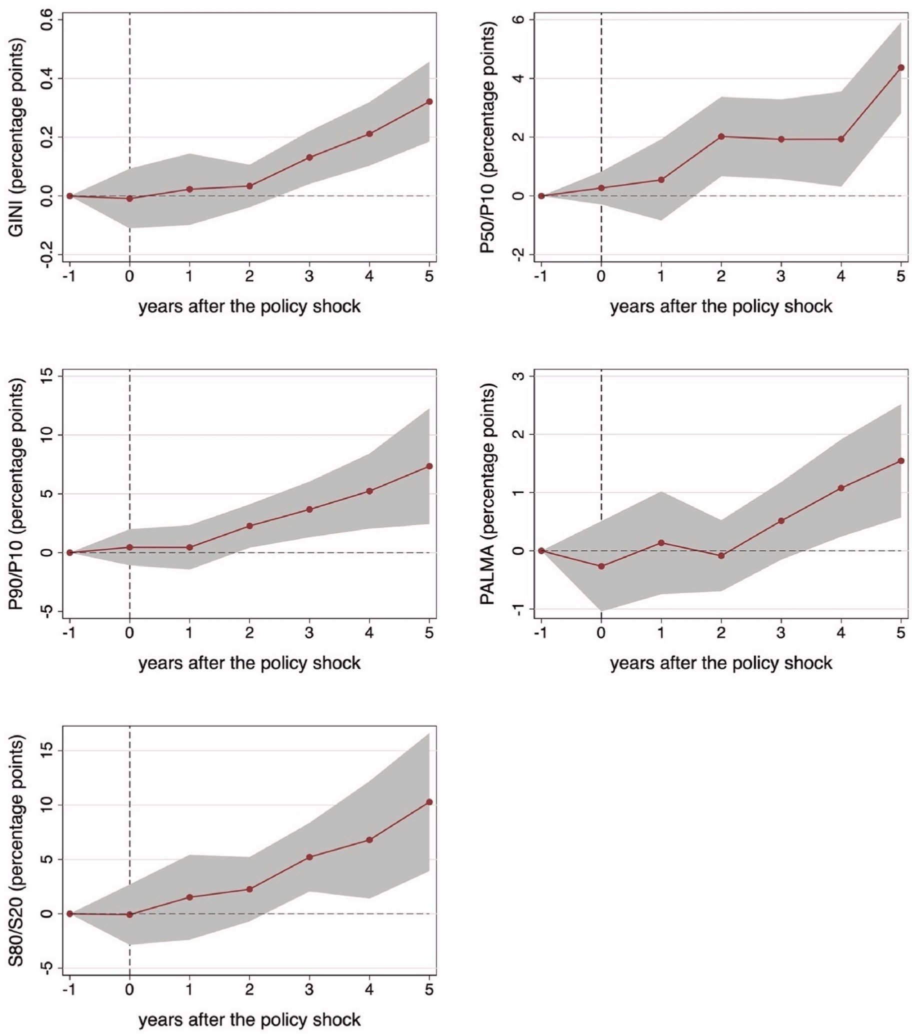

Fig. A6. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates control for fiscal policy shocks.

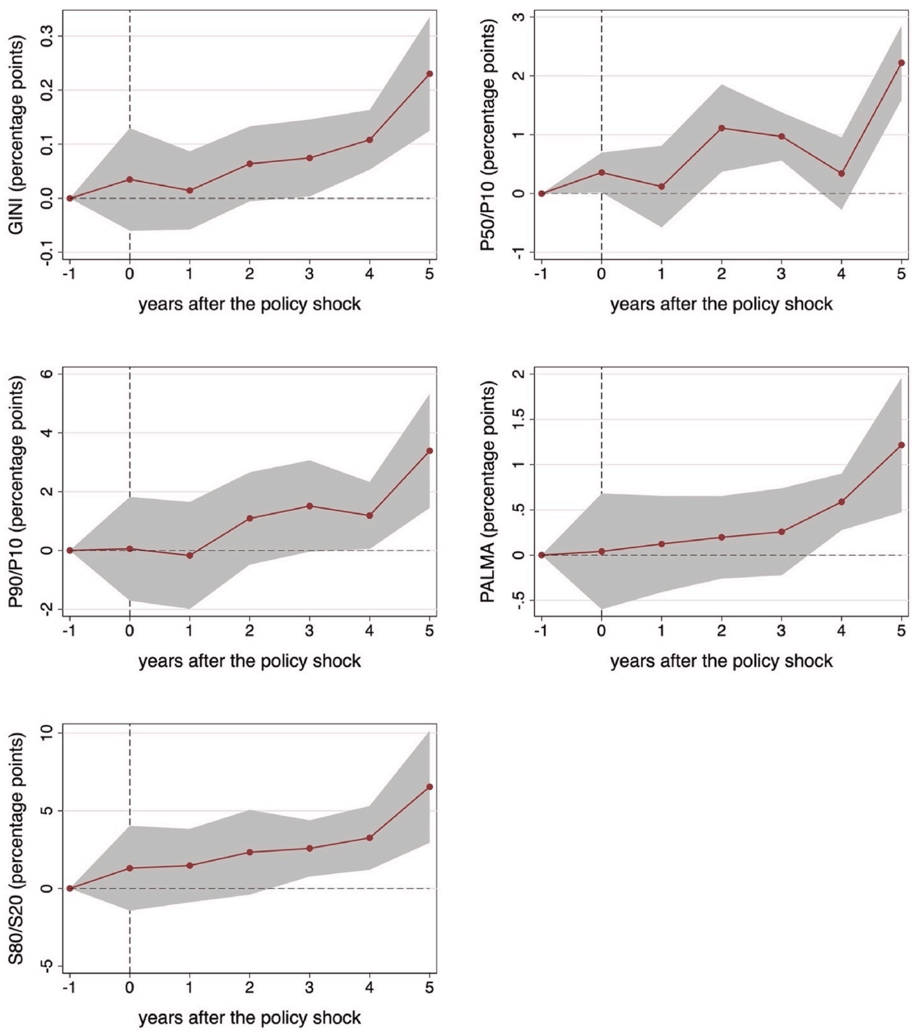

Fig. A7. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates control for the degree of uncertainty.

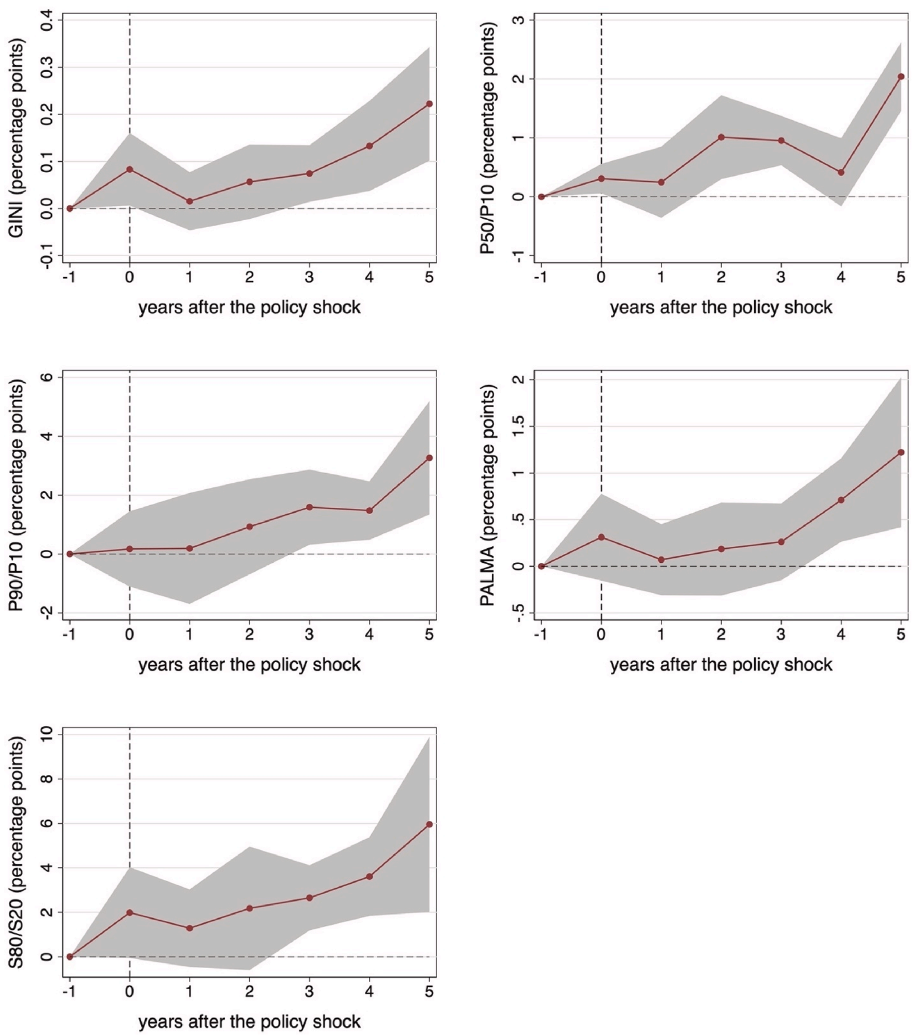

Fig. A8. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates exclude years 2019 and 2020.

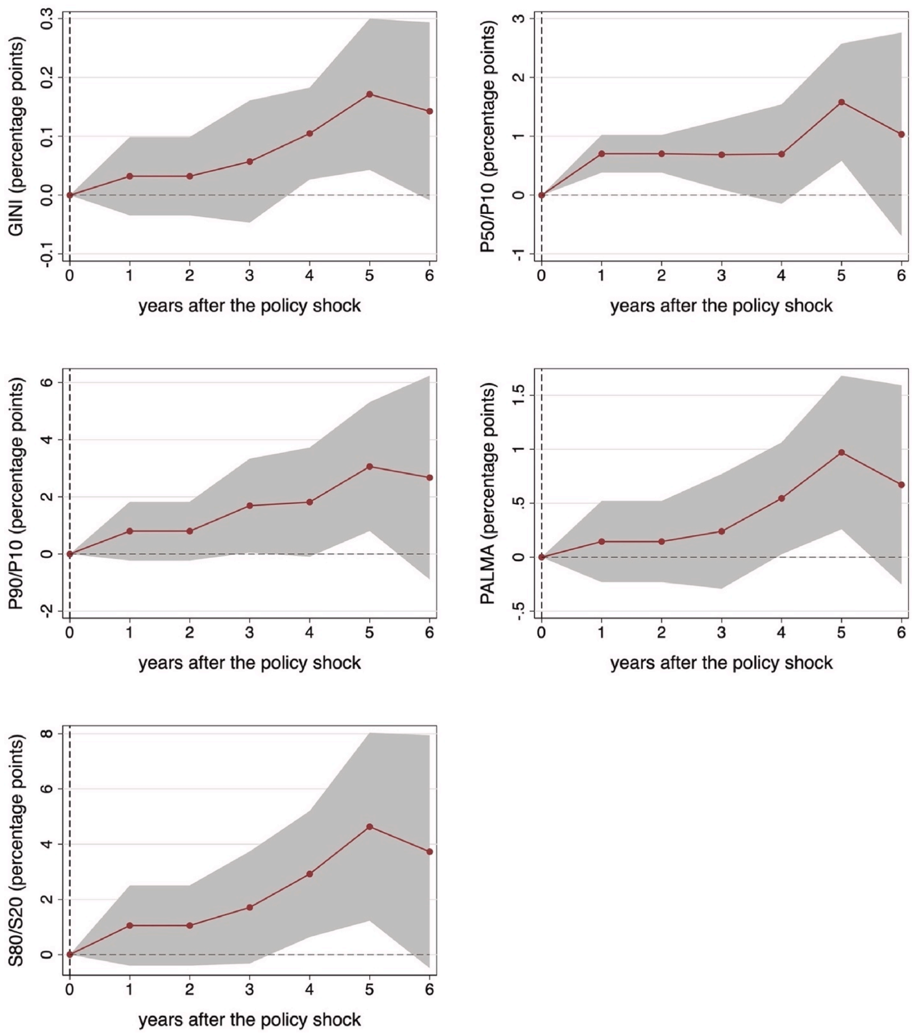

Fig. A9. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates exclude the contemporaneous effect.

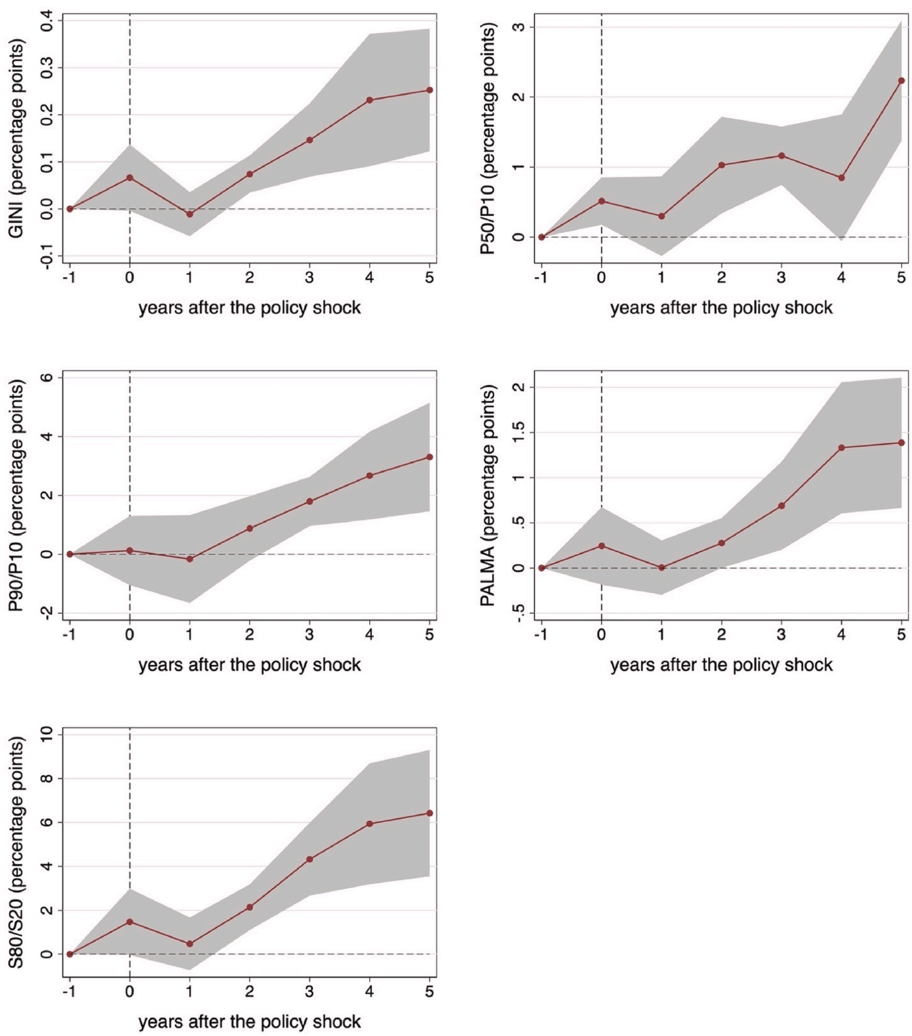

Fig. A10. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates include country-specific time trend.

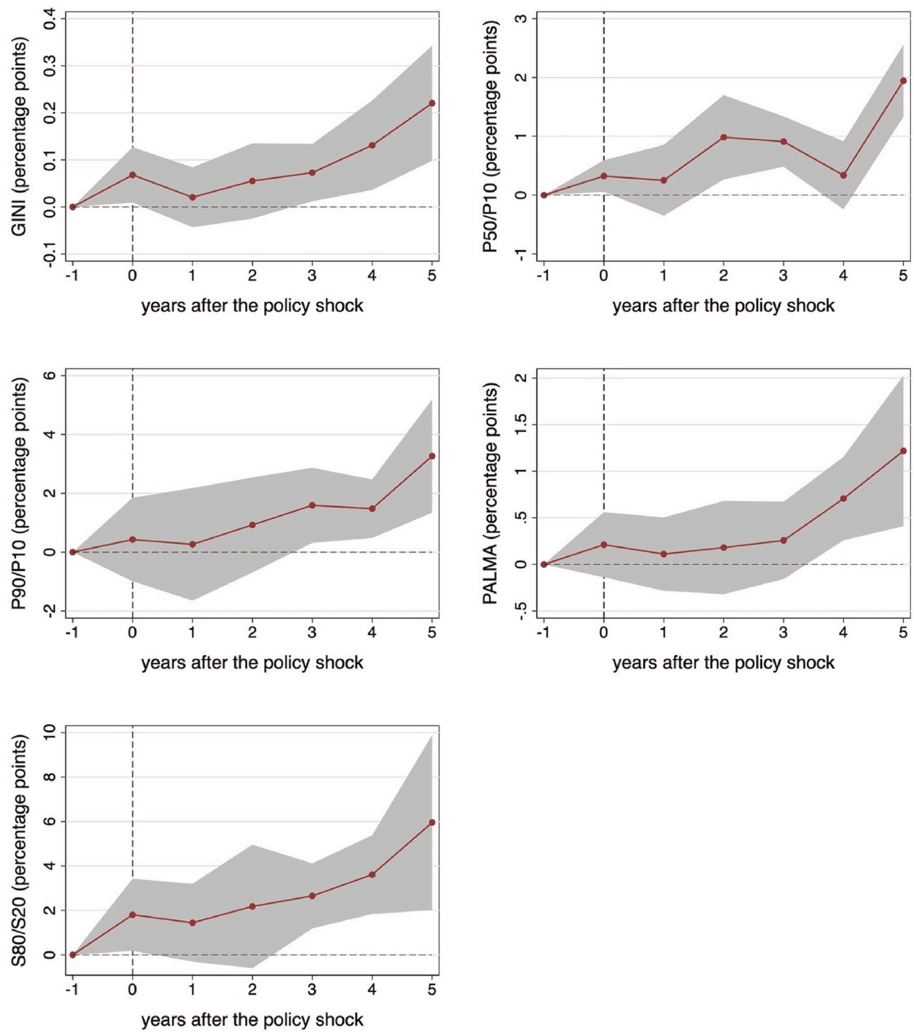

Fig. A11. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates exclude outliers.

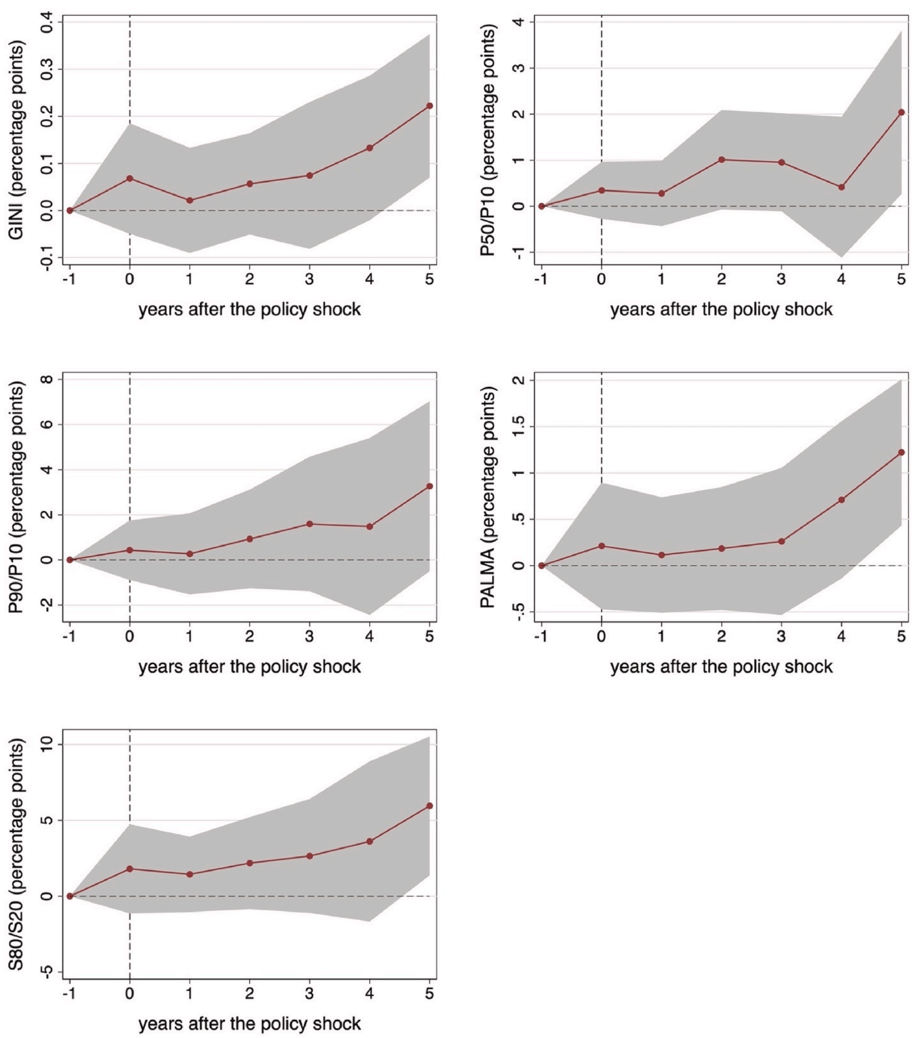

Fig. A12. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on standard errors clustered at the country level.

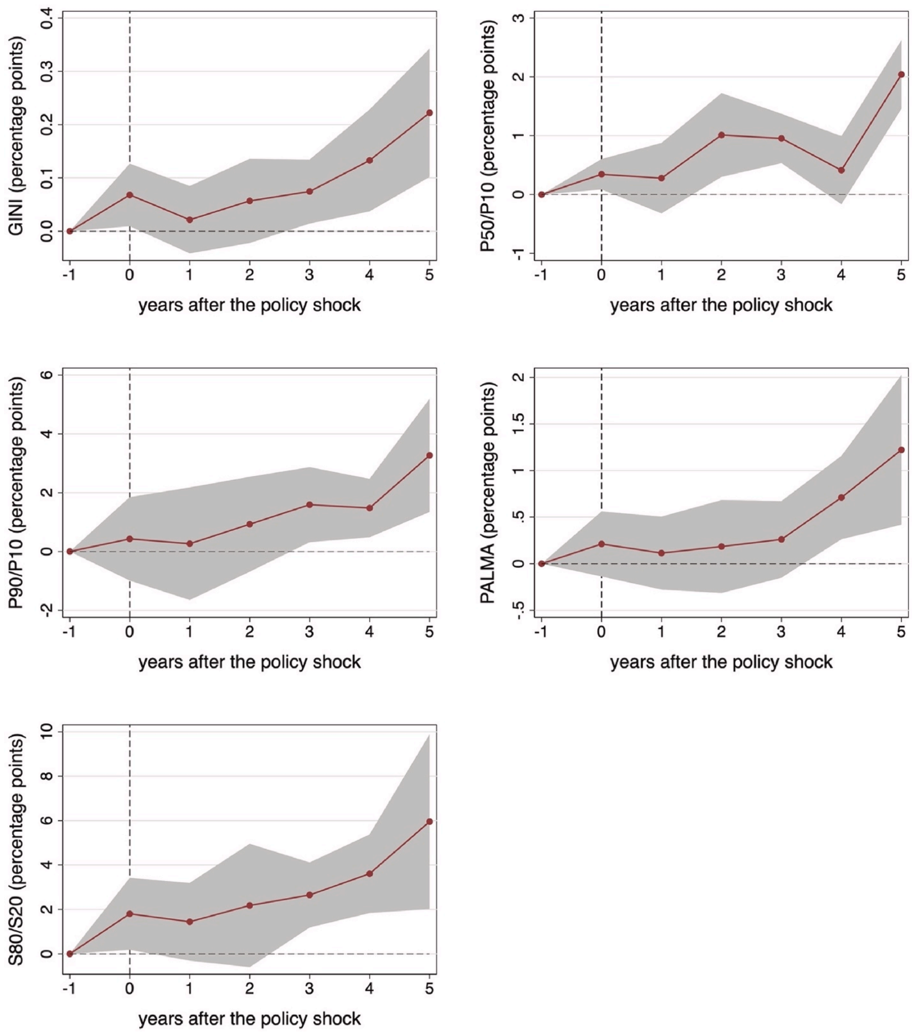

Fig. A13. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on a different lags' structure in equation (1) (i.e., 4 lags).

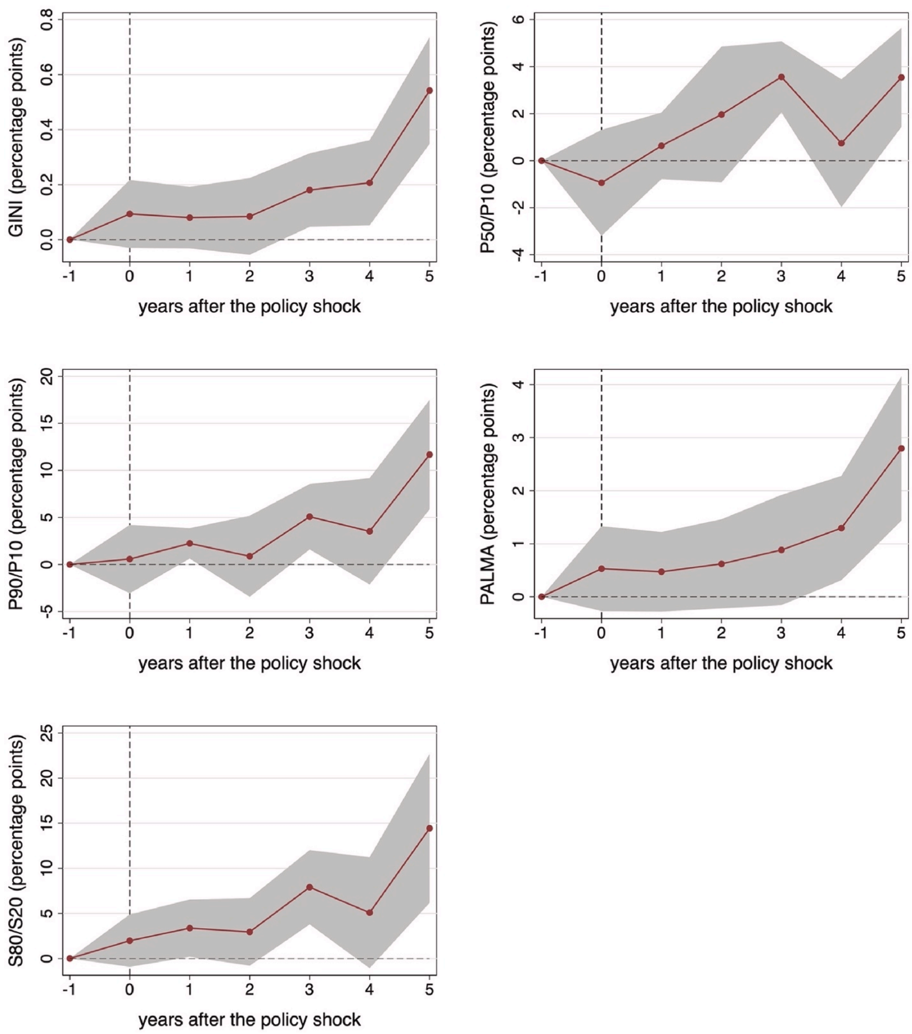

Fig. A14. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on an Instrumental Variable (IV) approach, where the instrument is the product between the minimum distance of a country's centroid to the coast, and the number of hurricanes at the global level.

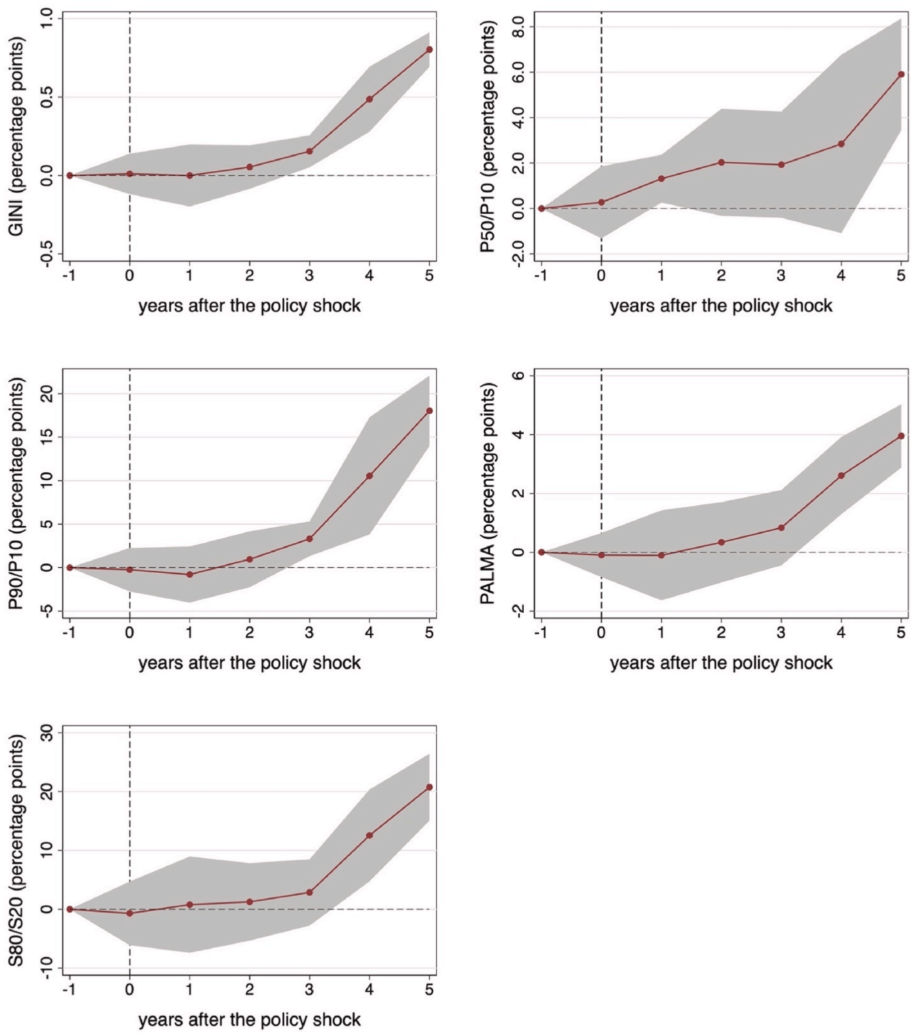

Fig. A15. The charts show the impulse response functions of income inequality—based on different inequality indicators—to an increase of 1 standard deviation of the change of the Environmental Policy Stringency (EPS) index in our sample. GINI compares the cumulative proportions of population and income, 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 is 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 all received by the 40% with the lowest income. The shaded areas represent the 90 percent confidence intervals; y-axes indicate percentage points; x-axes indicate time (year); t = 0 is the year of the shock. Estimates are based on an Instrumental Variable (IV) approach, where the instrument is the product between the country’s agricultural land (km2) per capita, and the number of droughts at the global level.

Appendix. Tables

Table A1
The impact of the Environmental Policy Stringency (EPS) index on income inequality, based on different inequality indicators

		k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	EPS	0.068*	0.021	0.057	0.074*	0.133**	0.222***
		(0.036)	(0.038)	(0.048)	(0.036)	(0.058)	(0.073)
	L1.EPS	−0.112*	−0.039	−0.047	0.016	0.063	−0.077
		(0.064)	(0.074)	(0.059)	(0.059)	(0.116)	(0.066)
	L2.EPS	0.112***	0.134**	0.156**	0.135***	0.039	0.008
		(0.027)	(0.059)	(0.059)	(0.042)	(0.085)	(0.088)
	L1.Gini	−0.237***	−0.279***	−0.434***	−0.527***	−0.543***	−0.754***
		(0.062)	(0.085)	(0.074)	(0.123)	(0.124)	(0.040)
	L2.Gini	−0.089*	−0.164***	−0.280**	−0.296*	−0.475***	−0.537***
		(0.049)	(0.056)	(0.109)	(0.154)	(0.065)	(0.095)
P90/10	EPS	0.430	0.266	0.927	1.592*	1.478**	3.267**

(continued on next page)

Table A1 (*continued*)

		k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		(0.862)	(1.162)	(0.980)	(0.774)	(0.603)	(1.169)
	L1.EPS	−0.656	0.133	0.146	−0.003	1.542	−0.626
		(0.947)	(1.651)	(1.146)	(0.976)	(1.863)	(1.409)
	L2.EPS	1.202	1.535**	1.820**	2.917**	1.028	−0.837
		(0.804)	(0.647)	(0.694)	(1.198)	(1.111)	(2.207)
	L1.P90/P10	−0.215***	−0.141**	−0.235***	−0.565***	−0.696***	−0.996***
		(0.050)	(0.069)	(0.061)	(0.085)	(0.108)	(0.098)
	L2.P90/P10	0.010	0.089	−0.224*	−0.265	−0.613***	−0.546***
		(0.051)	(0.065)	(0.124)	(0.173)	(0.062)	(0.094)
P50/10	EPS	0.345**	0.278	1.012**	0.954***	0.414	2.041***
		(0.157)	(0.363)	(0.432)	(0.254)	(0.351)	(0.354)
	L1.EPS	−0.424	0.294	−0.385	−0.291	1.197	−0.408
		(0.370)	(0.331)	(0.585)	(0.421)	(0.793)	(0.752)
	L2.EPS	0.726***	0.319	0.640**	1.302**	0.057	−0.525
		(0.210)	(0.369)	(0.287)	(0.468)	(0.607)	(1.121)
	L1.P50/P10	−0.415***	−0.345***	−0.314***	−0.559***	−0.709***	−0.950***
		(0.080)	(0.034)	(0.096)	(0.163)	(0.077)	(0.058)
	L2.P50/P10.	−0.103***	0.028	−0.217	−0.291**	−0.562***	−0.501***
		(0.024)	(0.107)	(0.177)	(0.134)	(0.082)	(0.102)
Palma	EPS	0.212	0.114	0.185	0.262	0.711**	1.223**
		(0.212)	(0.238)	(0.303)	(0.250)	(0.272)	(0.488)
	L1.EPS	−0.428	−0.196	−0.282	0.215	0.444	−0.634
		(0.370)	(0.394)	(0.363)	(0.315)	(0.637)	(0.386)
	L2.EPS	0.521***	0.664**	0.873**	0.623**	−0.179	−0.380
		(0.178)	(0.322)	(0.336)	(0.254)	(0.515)	(0.532)
	L1.PALMA	−0.249***	−0.282***	−0.461***	−0.514***	−0.516***	−0.684***
		(0.049)	(0.092)	(0.060)	(0.093)	(0.136)	(0.037)
	L2.PALMA	−0.075	−0.157***	−0.269***	−0.254*	−0.370***	−0.466***
		(0.066)	(0.042)	(0.091)	(0.136)	(0.075)	(0.075)
S80/S20	EPS	1.802*	1.443	2.179	2.653***	3.610***	5.954**
		(0.984)	(1.064)	(1.689)	(0.889)	(1.076)	(2.392)
	L1.EPS	−2.141	−0.969	−1.158	0.513	2.028	−2.595
		(1.328)	(1.775)	(1.562)	(1.034)	(2.412)	(1.803)
	L2.EPS	2.044***	2.533	3.428**	3.183**	0.241	−1.338
		(0.686)	(1.645)	(1.415)	(1.423)	(2.442)	(2.638)
	L1.S80/S20	−0.177***	−0.172*	−0.341***	−0.483***	−0.466**	−0.767***
		(0.057)	(0.092)	(0.066)	(0.105)	(0.195)	(0.040)
	L2.S80/S20	−0.004	−0.065	−0.253**	−0.176	−0.423***	−0.527***
		(0.055)	(0.053)	(0.101)	(0.234)	(0.122)	(0.088)

Notes: Columns show estimates of equation (1) for different horizons *k,* with *k*=0, …,5 (years), for different inequality indicators—as indicated in column (1). GINI 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 is 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 all received by the 40% with the lowest income. L1 indicates one lag of the variable. L2 indicates two lags of the variable. Coefficients have been multiplied by 100 and by 1 standard deviation of the yearly change of EPS in our sample. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A2
Instrumental Variable (IV) results when using the length of coastline in country *i* by the number of floods at the global level as instrument, and the GINI inequality indicator as dependent variable

	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
EPS	0.213*	0.192*	0.225	0.246**	0.390***	0.503***
	(0.111)	(0.097)	(0.137)	(0.113)	(0.135)	(0.126)
L1.EPS	−0.192*	−0.110	−0.127	−0.097	−0.086	−0.243*
	(0.099)	(0.077)	(0.117)	(0.099)	(0.136)	(0.122)
L2.EPS	0.107***	0.102***	0.141***	0.140***	0.008	−0.031
	(0.023)	(0.022)	(0.029)	(0.042)	(0.051)	(0.071)
L1.GINI	−0.296***	−0.284***	−0.421***	−0.559***	−0.529***	−0.744***
	(0.066)	(0.068)	(0.071)	(0.092)	(0.147)	(0.090)
L2.GINI	−0.068	−0.134*	−0.261***	−0.234	−0.387***	−0.382**
	(0.060)	(0.075)	(0.076)	(0.152)	(0.076)	(0.140)
Observations	267	244	221	198	172	150
R-squared	0.061	0.051	0.121	0.184	0.143	0.221
Kleibergen-Paap_rk_Wald_F_statistic	25.77	25.95	24.40	26.41	27.41	28.19
Stock-Yoko 5% critical value	19.93	19.93	19.93	19.93	19.93	19.93
Overidentification Hansen J stat.	0.484	1.421	0.0438	0.819	0.0722	0.136
p-value	0.487	0.233	0.834	0.318	0.788	0.712

Notes: Columns show estimates of equation (2)—headline equation—for different horizons *k,* with *k*=0, …,5 (years). GINI compares the cumulative proportions of population and income, and it ranges between 0 (perfect equality) and 1 (perfect inequality). L1 indicates one lag of the variable. L2 indicates two lags of the variable. Coefficients have been multiplied by 100 and by 1 standard deviation of the yearly change of EPS in our sample. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A3
Instrumental Variable (IV) results when using the length of coastline in country *i* by the number of floods at the global level as instrument, and the P50/P10 inequality indicator as dependent variable

	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
EPS	−0.015	1.104	3.779***	3.495***	2.241	3.793*
	(0.858)	(1.417)	(1.344)	(0.980)	(1.724)	(2.085)
L1.EPS	−0.302	−0.325	−2.093*	−2.216***	0.000	−1.598
	(0.820)	(1.052)	(1.154)	(0.525)	(0.891)	(1.811)
L2.EPS	0.718***	0.301	0.425	1.333**	0.065	−0.716
	(0.224)	(0.368)	(0.339)	(0.555)	(0.441)	(1.118)
L1.P50/P10	−0.391***	−0.318***	−0.297*	−0.487**	−0.710***	−0.987***
	(0.072)	(0.059)	(0.156)	(0.200)	(0.096)	(0.065)
L2.P50/P10	−0.074	0.020	−0.123	−0.226*	−0.528***	−0.466***
	(0.044)	(0.124)	(0.184)	(0.127)	(0.080)	(0.117)
Observations	266	243	220	197	171	149
R-squared	0.147	0.077	−0.020	0.071	0.166	0.268
Kleibergen-Paap_rk_Wald_F_statistic	30.50	30.98	27.53	30.91	34.26	30.08
Stock-Yoko 5% critical value	19.93	19.93	19.93	19.93	19.93	19.93
Overidentification Hansen J stat.	0.0233	1.343	0.354	0.378	0.300	0.416
p-value	0.879	0.247	0.552	0.539	0.306	0.519

Notes: Columns show estimates of equation (2)—headline equation—for different horizons *k*, with *k*=0, …,5 (years). P50/P10 is the median income to the upper bound value of the first decile. L1 indicates one lag of the variable. L2 indicates two lags of the variable. Coefficients have been multiplied by 100 and by 1 standard deviation of the yearly change of EPS in our sample. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A4
Instrumental Variable (IV) results when using the length of coastline in country *i* by the number of floods at the global level as instrument, and the P90/P10 inequality indicator as dependent variable

	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
EPS	4.613***	4.427**	4.442	6.517**	9.281***	12.517***
	(1.661)	(1.977)	(2.909)	(2.784)	(2.204)	(3.133)
L1.EPS	−3.713**	−2.359**	−1.951	−3.542**	−3.810**	−6.797**
	(1.604)	(0.877)	(1.443)	(1.578)	(1.706)	(2.918)
L2.EPS	1.370	1.209*	1.648*	3.155**	0.902	−1.247
	(0.954)	(0.620)	(0.833)	(1.508)	(1.117)	(2.105)
L1.P90/P10	−0.209***	−0.089	−0.201**	−0.576***	−0.732***	−1.061***
	(0.056)	(0.067)	(0.085)	(0.102)	(0.121)	(0.143)
L2.P90/P10	0.041	0.139*	−0.172	−0.198	−0.580***	−0.474***
	(0.068)	(0.071)	(0.133)	(0.184)	(0.070)	(0.113)
Observations	267	244	221	198	172	150
R-squared	0.027	0.029	0.015	0.080	0.091	0.150
Kleibergen-Paap_rk_Wald_F_statistic	24.59	24.58	22.11	24.22	25.07	27.55
Stock-Yoko 5% critical value	19.93	19.93	19.93	19.93	19.93	19.93
Overidentification Hansen J stat.	0.0751	0.144	0.138	0.122	0.521	0.355
p-value	0.784	0.704	0.315	0.318	0.324	0.294

Notes: Columns show estimates of equation (2)—headline equation—for different horizons *k*, with *k*=0, …,5 (years). 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. L1 indicates one lag of the variable. L2 indicates two lags of the variable. Coefficients have been multiplied by 100 and by 1 standard deviation of the yearly change of EPS in our sample. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A5
Instrumental Variable (IV) results when using the length of coastline in country *i* by the number of floods at the global level as instrument, and PALMA inequality indicator as dependent variable

	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
EPS	1.035	0.993	1.279	0.943	2.206***	2.485***
	(0.754)	(0.674)	(0.805)	(0.722)	(0.736)	(0.593)
L1.EPS	−0.830	−0.556	−0.822	−0.170	−0.504	−1.334**
	(0.682)	(0.503)	(0.707)	(0.592)	(0.779)	(0.554)
L2.EPS	0.417**	0.461***	0.771***	0.553**	−0.349	−0.616
	(0.165)	(0.139)	(0.168)	(0.226)	(0.339)	(0.420)
L1.PALMA	−0.302***	−0.247***	−0.413***	−0.534***	−0.525***	−0.630***
	(0.057)	(0.058)	(0.059)	(0.065)	(0.139)	(0.074)
L2.PALMA	−0.045	−0.098*	−0.231***	−0.231*	−0.283***	−0.324***
	(0.054)	(0.053)	(0.066)	(0.130)	(0.080)	(0.105)
Observations	267	244	221	198	172	150
R-squared	0.060	0.040	0.096	0.183	0.128	0.189
Kleibergen-Paap_rk_Wald_F_statistic	25.46	25.65	23.50	25.80	27.77	29.68
Stock-Yoko 5% critical value	19.93	19.93	19.93	19.93	19.93	19.93
Overidentification Hansen J stat.	0.605	1.658	0.257	1.230	0.410	0.188
p-value	0.437	0.198	0.612	0.267	0.522	0.301

Notes: Columns show estimates of equation (2)—headline equation—for different horizons *k,* with *k*=0, …,5 (years). PALMA ratio is the share of all income received by the 10% people with highest income, divided by the share of all received by the 40% with the lowest income. L1 indicates one lag of the variable. L2 indicates two lags of the variable. Coefficients have been multiplied by 100 and by 1 standard deviation of the yearly change of EPS in our sample. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A6
Instrumental Variable (IV) results when using the length of coastline in country *i* by the number of floods at the global level as instrument, and the S80/S20 inequality indicator as dependent variable

	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
EPS	3.683	4.944*	6.081*	6.606**	8.428**	10.654***
	(3.121)	(2.487)	(3.380)	(3.173)	(3.207)	(3.654)
L1.EPS	−3.295	−2.925	−3.199	−2.165	−0.552	−5.538*
	(2.809)	(2.365)	(2.615)	(2.413)	(3.230)	(3.013)
L2.EPS	2.158***	2.481***	3.388***	3.301**	−0.781	−2.045
	(0.685)	(0.706)	(1.136)	(1.503)	(1.726)	(2.646)
L1.S80/S20	−0.183**	−0.081	−0.228**	−0.474***	−0.460**	−0.758***
	(0.073)	(0.078)	(0.086)	(0.105)	(0.190)	(0.048)
L2.S80/S20	0.065	0.044	−0.186	−0.121	−0.392***	−0.455***
	(0.059)	(0.109)	(0.120)	(0.254)	(0.137)	(0.115)
Observations	267	244	221	198	172	150
R-squared	0.044	0.019	0.043	0.106	0.114	0.207
Kleibergen-Paap_rk_Wald_F_statistic	25.15	25.26	22.13	23.91	24.85	26.74
Stock-Yoko 5% critical value	19.93	19.93	19.93	19.93	19.93	19.93
Overidentification Hansen J stat.	0.294	1.645	0.0737	0.504	0.0319	0.880
p-value	0.588	0.200	0.786	0.317	0.858	0.427

Notes: Columns show estimates of equation (2)—headline equation—for different horizons *k,* with *k*=0, …,5 (years). S80/S20 represents the ratio of the average income of the 20% richest to the 20% poorest. L1 indicates one lag of the variable. L2 indicates two lags of the variable. Coefficients have been multiplied by 100 and by 1 standard deviation of the yearly change of EPS in our sample. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A7
Checking the exclusion restriction by adding the instrument—i.e., the length of coastline in country *i*, by the number of floods at global level—in the baseline specification

DEP. VAR.	Gini			P90/P10			P50/P10			Palma			S80/S20		
	k = 0	k = 2	k = 5	k = 0	k = 2	k = 5	k = 0	k = 2	k = 5	k = 0	k = 2	k = 5	k = 0	k = 2	k = 5
EPS	0.002	0.002	0.010***	−0.001	0.029	0.134**	0.025**	0.041**	0.097***	0.003	0.005	0.055**	0.052	0.066	0.290**
	(0.003)	(0.002)	(0.003)	(0.051)	(0.042)	(0.059)	(0.010)	(0.019)	(0.016)	(0.020)	(0.015)	(0.023)	(0.080)	(0.074)	(0.112)
L1.EPS	−0.004*	−0.001	−0.003	−0.036	0.025	−0.044	−0.031	−0.016	−0.028	−0.012	−0.006	−0.024	−0.082	−0.017	−0.126
	(0.002)	(0.002)	(0.003)	(0.040)	(0.055)	(0.081)	(0.020)	(0.026)	(0.047)	(0.011)	(0.015)	(0.020)	(0.054)	(0.081)	(0.092)
L2.EPS	0.006***	0.007***	−0.000	0.077**	0.083**	−0.017	0.032**	0.029**	−0.023	0.023*	0.040***	−0.023	0.111**	0.173***	−0.080
	(0.001)	(0.002)	(0.004)	(0.035)	(0.030)	(0.120)	(0.012)	(0.014)	(0.060)	(0.012)	(0.012)	(0.023)	(0.043)	(0.058)	(0.144)
L1.INEQUALITY	−0.290***	−0.406***	−0.714***	−0.223***	−0.203**	−1.075***	−0.391***	−0.291**	−0.967***	−0.300***	−0.403***	−0.604***	−0.189***	−0.239**	−0.761***
	(0.073)	(0.065)	(0.089)	(0.054)	(0.088)	(0.113)	(0.070)	(0.136)	(0.068)	(0.063)	(0.052)	(0.077)	(0.067)	(0.096)	(0.059)
L2.INEQUALITY	−0.067	−0.261***	−0.384**	0.041	−0.184	−0.553***	−0.071*	−0.150	−0.499***	−0.041	−0.227***	−0.321**	0.067	−0.191	−0.469***
	(0.064)	(0.084)	(0.156)	(0.067)	(0.134)	(0.114)	(0.041)	(0.208)	(0.131)	(0.058)	(0.074)	(0.118)	(0.060)	(0.132)	(0.124)
INSTRUMENT	**−0.001**	**0.000**	**0.001**	**−0.008**	**−0.004**	**−0.012**	**0.016**	**0.046**	**0.006**	**−0.008**	**−0.006**	**0.001**	**−0.028**	**−0.004**	**0.028**
	(0.001)	**(0.003)**	**(0.002)**	**(0.028)**	**(0.020)**	**(0.034)**	**(0.032)**	**(0.069)**	**(0.033)**	**(0.009)**	**(0.019)**	**(0.009)**	**(0.054)**	**(0.106)**	**(0.055)**
L1. INSTRUMENT	**0.003**	**0.002**	**0.003**	**−0.000**	**0.041**	**0.033**	**0.046**	**0.009**	**0.118**	**0.020**	**0.020**	**0.015**	**0.058**	**0.064**	**0.032**
	(0.002)	**(0.004)**	**(0.003)**	**(0.032)**	**(0.027)**	**(0.024)**	**(0.037)**	**(0.048)**	**(0.153)**	**(0.014)**	**(0.024)**	**(0.013)**	**(0.079)**	**(0.113)**	**(0.089)**
Observations	267	221	150	267	221	150	266	220	149	267	221	150	267	221	150
R-squared	0.119	0.155	0.295	0.069	0.044	0.310	0.153	0.068	0.291	0.105	0.136	0.239	0.070	0.065	0.225

Notes: Columns show estimates of equation (1) for different horizons *k*, with *k*=0, 2, 5 (years). L1 indicates one lag of the variable. L2 indicates two lags of the variable. INEQUALITY refers to different inequality indicators, as in the first row of the table. GINI 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 is 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 all received by the 40% with the lowest income. Estimates include contemporaneous and lagged instrument, i.e., the length of coastline in country *i*, by the number of floods at global level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A8
Checking the exclusion restriction by regressing the residual of baseline specifications on the instrument—i.e., the length of coastline in country *i*, by the number of floods at global level

DEP. VAR.	Gini			P90/P10			P50/P10			Palma			S80/S20		
	k = 0	k = 2	k = 5	k = 0	k = 2	k = 5	k = 0	k = 2	k = 5	k = 0	k = 2	k = 5	k = 0	k = 2	k = 5
INSTRUMENT	−0.001	0.000	0.000	−0.005	−0.004	−0.010	0.016	0.042	0.009	−0.011	−0.008	−0.001	−0.032	−0.012	0.030
	(0.001)	(0.003)	(0.001)	(0.024)	(0.022)	(0.030)	(0.038)	(0.065)	(0.029)	(0.009)	(0.016)	(0.008)	(0.053)	(0.099)	(0.052)
L1. INSTRUMENT	0.003	0.002	0.003	0.000	0.040	0.032	0.038	0.011	0.104	0.019	0.021	0.018	0.051	0.065	0.037
	(0.002)	(0.003)	(0.002)	(0.025)	(0.043)	(0.020)	(0.032)	(0.043)	(0.150)	(0.016)	(0.018)	(0.012)	(0.066)	(0.092)	(0.076)
Observations	267	221	150	267	221	150	266	220	149	267	221	150	267	221	150
R-squared	0.012	0.004	0.024	0.007	0.003	0.018	0.003	0.009	0.005	0.012	0.008	0.023	0.009	0.008	0.003

Notes: Columns show estimates of the residuals of equation (1) on contemporaneous and lagged instrument, i.e., the length of coastline in country *i*, by the number of floods at global level, for different horizons *k*, with *k*=0, 2, 5 (years). L1 indicates one lag of the variable. Dependent variables are the different inequality indicators, as in the first row. GINI 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 is 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 all received by the 40% with the lowest income. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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