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The winds of inequalities: How hurricanes affect inequalities at the macro level

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ABSTRACT

While the consequences of natural disasters are relatively well studied, little is known about their macroeconomic impact on inequality. Following Yang (2008), we use an exogenous hurricane index, considering the average "affectedness" of individuals, based on meteorological data. Our empirical approach uses local projection (Jordà, 2005) to measure the cumulative impact of hurricanes on pre- and post-transfer Gini indices (Solt, 2020) five years after the hurricane event for a sample of 114 countries from 1995 to 2014. We find that the impact of hurricanes on inequality, is conditional on the level of a country's per capita GDP. In particular, the poorest countries tend to experience a reduction in disposable inequality following a hurricane. This study highlights the possible presence of a Schumpeterian effect in high income countries, where they experience a decline in the pre-redistribution Gini in the first few years as capital at the top of the income distribution is destroyed. Subsequently, the pre-tax and transfer Gini rises, reflecting a possible "build-back-better" mechanism as individuals at the top of the income distribution increase their income from capital via reconstruction. In the case of the post-redistribution Gini, we observe a decrease in the first years after a hurricane, underlining the positive impact of redistribution. We identify potential channels such as ODA, remittances and subsidies through which hurricanes may reduce inequality in these countries.

1. Introduction

Today's global environment is undergoing profound transformations, marked by challenges such as global warming, deforestation, pollution on a global scale, and the erosion of biodiversity. Within the scientific community, the anthropogenic origins of these disruptions are widely acknowledged. The significant alterations in our biosphere are attributed to the consequences of economic growth and industrialization. One of the most conspicuous manifestations of the disruption of nature is witnessed through natural disasters, which impact an estimated 3.5 billion people, as Dilley (2005) indicates. The toll exacted by such disasters encompasses a staggering cost in loss of life and property, as well as in shifts in power dynamics within societies. The Intergovernmental Panel on Climate Change (IPCC) warns of an impending escalation in the frequency and intensity of these events due to the rising concentration of greenhouse gases in the atmosphere (IPCC, 2018).[1]

While the economic consequences of natural disasters have stimulated a growing literature in economics, a consensus remains elusive, leading to a lively debate encompassing three distinct perspectives.

The first hypothesis involves a catch-up dynamic based on neoclassical growth theories. It claims that disasters have only a temporary impact on economic activity. According to this view, after a few years, per capita income will have recovered to its initial level, and the economy will have returned to its regular state (Brata et al., 2014; Cavallo et al., 2013; Jaramillo, 2009).

A second perspective argues that a disaster can throw a country into a poverty trap, preventing the economy from recovering to its initial level of GDP (Carter et al., 2008). Diamond (2006) even suggests that natural disasters have contributed to the collapse of societies in the past.

A more optimistic third view sees these upheavals as opportunities for countries to modernize, in line with a Schumpeterian conception of creative destruction. After a few years, per capita income will rise above its initial level, thanks to a "build-back-better" phenomenon leading to increased productivity (Hallegatte & Dumas, 2009; Loayza et al., 2012).

The conflicting conclusions that support these three perspectives underline the high level of heterogeneity of the effects of natural

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[1] It is worth noting that political considerations also influence the increase in disaster declarations. Literature on the politics of disaster declarations highlights that the designation of an event as a disaster can significantly affect resource allocation and political influence, and this strategic use appears to be increasingly common (Reeves, 2011; Schmidtlein et al., 2008).

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disasters, the analysis of which requires a focused analysis of potential transmission channels.

The impact of disasters on various economic variables, including GDP and growth (Berlemann & Wenzel, 2018; Hsiang & Jina, 2014), international trade (Pelli & Tschopp, 2017), and inequality (Cappelli et al., 2021; Paglialunga et al., 2022; Yamamura, 2015) has been widely studied. However, despite the centrality of inequality in economic discussions, the literature on climate shocks and inequality is dominated by microeconomic studies. Macro-level studies often fail to account for the temporal depth of impacts, rely on potentially biased disaster data, and overlook the descriptions of potential transmission channels. In particular, redistributive policies do not seem to have been sufficiently studied to understand impact on the dynamics of inequality following a macro-level shock. Moreover, macroeconomic studies often overlook the highly differentiated impacts of disasters, which depend on the particular event and country under consideration.

This paper addresses the existing gaps in the macroeconomic literature by posing the following questions: What is the medium-term impact of hurricanes on macro-level income inequality? Does the impact of hurricanes differ between pre-tax/transfer and post-tax/transfer inequality? Do the dynamics of hurricane impact on inequality differ according to a country's level of development? Furthermore, through what channels might hurricanes affect inequality, and do these channels vary across country development levels?

To answer these questions, we construct a sample of 114 countries from 1995 to 2014, focusing on hurricanes as one of the most frequent and destructive disasters. Our study advances the existing literature by making several substantial contributions. First, we use Jordà (2005)'s local projections (LP) to assess the cumulative impact of hurricanes on inequality up to five years after a shock. Second, we use an exogenous measure of hurricanes developed by Yang (2008), which uses meteorological data to mitigate endogeneity bias. Third, we examine the transmission channels through which hurricanes may affect inequality, providing a deeper understanding of the mechanisms at play.

Our analysis reveals a pattern in which pre-redistributive inequalities tend to rise after one year and decline four years after an event. In particular, post-redistributive inequalities, influenced by taxes and transfers, show a more pronounced and prolonged increase, persisting up to three years after the shock, without a subsequent decline. This result is particularly true when we focus solely on large hurricanes, and it is robust when we exclude the countries most heavily impacted by them in intensity or frequency. It is essential to recognize, however, that these results vary according to a country's levels of development and democracy. Developing countries show a reduction in inequality after redistribution, which can be attributed to the influx of official development assistance (ODA) and remittances. For high-income countries, both market and disposable inequality tend to decrease in the initial years following a hurricane. However, we observe an increase in the market Gini coefficient four and five years after the event, suggesting a possible Schumpeterian effect of creative destruction, where the wealthiest fringe of the population increases its income through a "build-back-better" effect as a result of the hurricane.

The remainder of this article is structured as follows. Section 2 presents the literature review. We present the construction of our database and some descriptive statistics in Section 3. The methodology is discussed in Section 4. Section 5 presents our results. The analysis by country subgroup is presented in Section 6. We discuss the channels in Section 7. Finally, we conclude and offer policy recommendations in Section 8.

2. Literature review

2.1. The impact of natural disasters under debate

In the current era of extreme weather events increasing on a global scale, there is a growing concern worldwide about adapting to climate change. Natural disasters, as emblematic expressions of the disruption of nature 's balance overwhelmingly cause substantial material devastation, primarily targeting capital, with a comparatively lesser impact on human labor. The growing literature on the economic impact of natural disasters seeks to unravel the complex consequences of these events. Despite these efforts, a consensus remains elusive, fostering an ongoing debate around three dominant perspectives.

One strand of the literature finds the presence of a catch-up dynamic in which the impact of disasters diminishes over time. Drawing on neoclassical growth models, proponents argue that if disasters undermine capital per capita in a given period, subsequent increases in savings and investment are expected to restore the economy to its steady state. Empirically, at the macro-level, Cavallo et al. (2013) and Jaramillo (2009) find that natural disasters have no long-term impact. At the regional level, Brata et al. (2014) find that the effects of the 2004 tsunami in North Sumatra faded after several years.

Conversely, another view characterizes natural disasters as shocks that can push a country or region into a situation where per capita income is too low to support an increase in per capita capital, a phenomenon known as the poverty-trap dynamic. Historical evidence, such as the severe droughts experienced by the Mayan civilization between 800 and 910, illustrates how these shocks can lead to significant human loss and societal collapse.[2] Nowadays, poverty traps seem to be observable only at the microeconomic level. For example, Carter et al. (2008)'s examination of droughts in Ethiopia and of hurricanes in Honduras find affected households struggled to recover pre-disaster assets.

In contrast, a third, more optimistic view sees disasters as catalysts for renewal and improved productivity. In line with Schumpeter's idea of creative destruction, this perspective sees the long-term benefits of replacing obsolete technology with more productive capital. A natural disaster destroys machines with obsolete technology, which are replaced by more productive capital, ultimately allowing for a better productivity source of growth (Albala-Bertrand, 1993; Benson & Clay, 2004; Hallegatte & Dumas, 2009; Hallegatte & Ghil, 2008; Loayza et al., 2012; Okuyama, 2003; Stewart et al., 2001).

However, the ability to turn post-disaster challenges into opportunities is not universal, as financial and technological constraints limit some countries. Moreover, GDP growth, often seen as a sign of shared prosperity, does not always benefit all segments of society equally. As highlighted by Noy (2009), structural shocks tend to favor the ruling classes, especially in developing countries and smaller economies. The impact on different variables varies, as illustrated by Yang (2008)'s findings that official development assistance (ODA) and remittances increase after the hurricane, while foreign direct investments (FDI) and portfolio investments decrease. Given this heterogeneity, focused analysis on specific variables or countries is essential for analytical precision.

2.2. The impact of natural disasters on inequality

The growing literature on the relationship between climate shocks and inequality constitutes an empirical discourse, which either validates or challenges the above-mentioned theories. Many studies' findings are consistent with the notion that shocks permanently trap parts of the population in poverty. Lynham et al. (2017) find that wages remained constant after a tsunami hit Hawaii in 1960 but that unemployment increased. Many family businesses went bankrupt, and much of the population was displaced. Bui et al. (2014) show that a series of natural disasters in Vietnam over 60 months resulted in adverse effects on wages, contributing to exacerbating poverty and inequality. Carter et al. (2008) focus on the long-term rebuilding of

[2] Some regions would have known losses of up to 99% of their population, contributing to the decline of this civilization.

assets after 1998's Hurricane Mitch in Honduras and the prolonged drought in Ethiopia. The authors report a critical threshold of asset ownership below which recovery is not possible, and poor households are irreparably trapped in poverty. Similar results emerge from studies in other parts of the world, such as Mexico (Rodriguez-Oreggia et al., 2013), rural India (Sedova & Kalkuhl, 2020), and Nepal (Pradhan et al., 2007). Furthermore, in societies with significant income gaps, lack of access to resources pushes households at the bottom of the distribution not to seek insurance but to resort to other means of coping with the shock, such as child labor, the sale of productive assets (Sawada & Takasaki, 2017), changes in agricultural practices and diet, and emigration of varying lengths of time (De Waal, 2005; Mahajan & Yang, 2020). However, these solutions often push households further into poverty (Banerjee et al., 2011; Lybbert & Barrett, 2011).

Conversely, some authors argue for the existence of Schumpeterian creative destruction. Natural disasters can lead to the adoption of adaptive measures such as income diversification (Adger, 2006; Eriksen et al., 2005). In some countries, farmers choose drought-resistant crops or alternative storage strategies (Eakin & Conley, 2002; Thomas et al., 2007) that are effective against one-off events but less so for repeated shocks (Kallis, 2008). Finally, and most importantly, the pressure exerted in the aftermath of a disaster is often fertile ground for collateral effects such as the outbreak of armed conflict (Ide, 2020) and unrest among the civilian population in the struggle for access to humanitarian aid (Hendrix & Salehyan, 2012). However, it should be noted that structural shocks primarily benefit the ruling classes (Klein, 2007; Loewenstein, 2015). In addition, the time required for reconstruction, as well as its effectiveness, may be subject to financial or technical constraints that can widen the gap between those affected (Hallegatte & Przyluski, 2010). Again, there is no consensus, and conclusions differ depending on the country and disasters studied.

At the macro-level, the literature on inequality is rich. Many works in the line of Kuznets (1955) investigate the links between GDP, growth, and inequality. Bodea et al. (2021), Baiardi and Morana (2018), and Gokmen and Morin (2019) focus on the impact of financial crises on income inequality. A growing body of literature also explains the links between pandemics and inequality (Furceri et al., 2020; Galletta & Giommoni, 2022; Karlsson et al., 2014).

Despite extensive research, there remains a significant gap in the literature concerning the impact of natural disasters on inequality. Yamamura (2015) examines this relationship, finding that the Gini coefficient tends to increase in the short run but that these effects dissipate in the long run. Cappelli et al. (2021) identify a vicious cycle, wherein high levels of inequality exacerbate the impact of subsequent inequality-enhancing natural disasters. Both of these studies underscore the importance of addressing endogeneity in macro-level analyses of inequality. While natural disasters are erratic, their measurement can still be endogenous. The literature frequently relies on the EM-DAT database, which records financial losses regarding property damage and deaths based on declarations. Yang (2008) argue that these data can be upwardly biased as countries may inflate figures to secure more financial aid. Moreover, in contrast to Paglialunga et al. (2022), who examine the transmission channels through which natural disasters affect inequality, focusing on adverse effects using an exogenous measure of heat waves and extreme precipitation, few studies focus on describing the transmission channels through which disasters can affect inequality. Finally, most studies on the subject are limited to a short-term analysis of the impact of disasters on inequality.

To address these gaps, our study adopts a novel approach that integrates the above mentioned issues. We analyze the impact of hurricanes on inequality using meteorological data to ensure exogeneity, examining the cumulative medium-term effects at the macroeconomic level. Our study also differentiates between pre- and post-redistributive inequality and investigates the transmission channels through which hurricanes influence it. By incorporating the development and democracy level of the affected countries, our research provides a more nuanced understanding of these dynamics.

3. Data

Our main sample covers 114 countries over 20 years (1995–2014). Our sample selection results from a trade-off between temporal depth and a large sample of countries. Indeed, data on inequality in emerging and developing countries before 1995 are rarely available. In addition, the available data on hurricanes ends in 2014. According to the World Bank's classification of countries by income, we can divide our sample into four groups: 26 countries are low income, 34 are lower-middle income, 24 are upper-middle income, and 30 are high income. This classification allows us to test the differences in impact on countries according to their respective income levels.[3]

3.1. Dependent variable: Gini index

Like others in the literature (Baiardi & Morana, 2018; Cappelli et al., 2021; Gokmen & Morin, 2019; Yamamura, 2015), we use the Gini coefficient from the Standardized World Income Inequality Database (SWIID, version 4.1). As Solt (2020) points out, the SWIID, "seeks to maximize comparability while providing the broadest possible coverage of countries and years". The author estimates the relationships between Gini coefficients from multiple sources (e.g. the Global Income Inequality Database) and the baseline Gini from the Luxembourg Income Study (LIS). This methodology allows him to calculate what the LIS Gini, for country years not included, would have been. If Solt does not have enough information on a given relationship for a country, he uses information from other countries in the same region. Therefore, our dependent variable is the market Gini coefficient, calculated by country and year, from income before taxes and transfers. We also use the disposable Gini, calculated with income after taxes and transfers. The availability of these two indicators allows us to compare the potential effect of redistribution policies following a disaster.[4]

Table 1 presents descriptive statistics on the two Gini variables. Inequality without redistribution (Market) exceeds that with redistribution (Disposable), underlining the effectiveness of such policies, especially in developed countries. In line with the Kuznets curve theory of inequalities, we observe that these inequalities tend to escalate as income levels rise, before declining in developed countries.

3.2. Variable of interest: Hurricane index

Hurricanes, typhoons, and cyclones are the same disasters. The difference in the name comes from the affected areas.[5] As defined by Mahajan and Yang (2020), hurricanes are "storms that originate over tropical oceans with wind speeds greater than 33 knots" (62 km/h). These meteorological phenomena occur when two elements come together. First, the ocean temperature must be at least 26.5 degrees Celsius. The process involves the evaporation of water, followed by its condensation into large thunderclouds. The second condition is the presence of a low wind shear, which makes a storm more powerful. This heat transfer mechanism generates considerable energy, eventually forming the violent winds characteristic of hurricanes.

Hurricanes wreak significant economic impact, primarily by destroying capital and infrastructure through storm surges, high winds,

[3] To ensure comparability between income groups over time and to avoid a country moving from one category to another during the five-year analysis subsequent to the shock, we fix the country in its income group in the middle of the period (2005).

[4] It would have been interesting to have information on the breakdown of inequalities by gender, which can significantly impact income inequalities. However, the SWIID database does not provide this level of disaggregation.

[5] The term "hurricane" is used for North Atlantic and Northeast Pacific storms. The term "typhoon" is used in the northwestern Pacific, while "cyclone" is used for storms in the Indian Ocean and the southern Pacific and Atlantic Oceans.

and flooding. According to Hsiang and Narita (2012), these disasters affect approximately 35% of the world's population. The cumulative damage they cause is substantial: estimated at over $280 billion between 1970 and 2002, according to EM-DAT. Unfortunately, future projections are not optimistic; the Intergovernmental Panel on Climate Change (IPCC, 2018) predicts an increase in intensity of hurricanes in the future due to climate change and ocean warming.[6] In addition, Stern and Stern (2007) estimate that the annual cost of hurricanes could rise to 0.5%–1% of global GDP by 2050. This projection considers the combined effects of increased economic activity and the expected increase in the intensity of hurricanes.

As mentioned above, the measurement of natural disasters is considered to be potentially endogenous (Yang, 2008). A common source used in the literature for such measurements is the EM-DAT database, which provides information on factors such as death tolls or financial costs associated with disasters. However, this data type can be biased due to potential measurement errors. For example, a country affected by an earthquake might inflate the reported financial costs to attract more financial assistance. In addition, our analysis using this data could face challenges related to reverse causality. Countries facing major hurricanes may experience an increase in income inequality. Conversely, societies characterized by high income inequality may also be disproportionately affected by natural disasters. For example, the poorest households, who live in vulnerable housing conditions and lack access to preventive measures, may be more vulnerable to increased fatalities or financial losses.

To mitigate the challenges associated with measuring natural disasters, we, like others (Belasen & Polachek, 2009; Hsiang, 2010; Hsiang & Jina, 2014; Mahajan & Yang, 2020), have chosen to use the database developed by Yang (2008). This database contains a hurricane index (HI) constructed from meteorological data using the best tracks from the National Oceanic and Atmospheric Administration (NOAA) and the Joint Typhoon Warning Center (JTWC). The best tracks provide details about the center of a hurricane, including maximum wind speed and geographical coordinates at six-hour intervals. Fig. 1 provides a visual representation of the best hurricane tracks during our period (1995–2014). This approach aims to improve the accuracy and reliability of our natural disaster data, addressing concerns about potential biases and measurement errors inherent in other databases.

From these best tracks, Yang constructed his index as follows:

$$HI_{i,t} = \frac{\sum_j \sum_s x_{j,s,i,t}}{N_{i,t}} \tag{1}$$

$HI_{i,t}$ is the destructive potential of a hurricane for country i the year t. It is the sum of each individual j's "affectedness" ($x_{j,s,i,t}$) by each hurricane s, in the country i, year t and divided by the total population $N_{i,t}$. Normalizing by the country's total population allows the impact of hurricanes to be compared on a national scale between countries, regardless of their size. Simply looking at the number of people affected is not enough to fully understand the national scale of impact. For example, for the same number of people affected, the national impact will be much more significant in a small country where the proportion of the population affected is higher than in a large country with a larger population.

In Eq. (1), $x_{j,s,i,t}$ is unknown because there is no data source for the incidence of hurricanes at the individual level. Thus, he used Dilley (2005) model to calculate $pw_{g,s,i,t}$ the predicted wind speed for each 0.25 by 0.25-degree latitude and longitude grid point g. Finally, he obtained $x_{g,s,i,t}$ the hurricane intensity estimate at the grid point as follows:

$$x_{g,s,i,t} = \mathbb{1}\{pw_{g,s,i,t} > 33\} \left\{ \frac{(pw_{g,s,i,t} - 33)^2}{(w^{max} - 33)^2} \right\} \tag{2}$$

Yang normalized the index by the maximum wind speed (max) observed in the dataset (166.65 knots), adding a square term to the index to account for the nonlinearity of the impact (i.e., the more serious the wind, the greater the damage).

Finally, he used 1990 gridded population data from the Socioeconomic Data and Applications Center (SEDAC) at Columbia University for each 0.25-degree N_g grid point:

$$HI_{i,t} = \frac{\sum_g \sum_s x_{g,s,i,t} N_{g,1990}}{\sum_g N_{g,1990}} \tag{3}$$

This methodology allows for the measurement of hurricane events per capita and weighted by intensity, which could be seen as an exogenous variable.[7]

Table 1 presents some descriptive statistics for our HI variable. We note that countries are affected regardless of their income level. Forty-five countries in our sample experienced at least one hurricane between 1995 and 2014.[8] Contrary to expectations, developed countries appear to have a higher hurricane index on average. Looking only at countries that experienced a hurricane in a given year (HI > 0) and categorizing them by country income group, lower-middle income countries have a higher average coefficient. Although developed countries are more frequently affected (N = 149), the effect seems a little less pronounced. Furthermore, within the subset of affected countries, the large standard deviation indicates significant heterogeneity in the magnitude of hurricane impact.

3.3. Control variables

We use a set of control variables to build a structural model as Bodea et al. (2021) and Reuveny and Li (2003). First, the level of democracy could play a role, as highly democratic states could more easily reduce inequality due to better tax systems and redistributive fiscal policies (Acemoglu et al., 2015). We use the variable "POLITY" (Marshall et al., 2017), which rates the governance of countries from −10 (complete autocracy) to +10 (complete democracy) based on a set of variables such as the competitiveness of executive recruitment or the constraint on the chief executive. We also include three variables that control for economic openness. First, we control for trade openness, measured as the value of exports and imports divided by GDP (World Bank). Many authors have argued that trade increases (Rodrik, 1998) or decreases (Birdsall, 1998) inequality. Second, we control FDI flows (net FDI flows as a percentage of GDP; World Bank). As with trade, the literature on the effect of FDI on inequality is mixed. Third, we include a variable for portfolio investment flows (net portfolio investment as a percentage of GDP; World Bank). Finally, we control for (log) GDP per capita (World Bank). Furthermore, in line with the Kuznets curve, which suggests an inverted U-shaped relationship between income per capita and inequality, we have included a squared term for the GDP per capita variable. This assumption considers that inequality tends to increase with economic development up to a certain threshold, after which it decreases. The squared term allows for a more nuanced representation of the complex dynamics involved in the relationship between income per capita and inequality.

[6] It is worth noting that future climate models suggest that increased wind shear is likely to reduce the overall number of hurricanes. However, the warming of ocean waters due to climate change is expected to favor the formation of large thunderclouds. This will increases the likelihood that they will intensify into high-category storms and extend their paths further from the tropics, suggesting a future scenario of fewer but more intense hurricanes.

[7] It should be noted that we have reintegrated the overseas departments that were not originally part of France in the database (Réunion, Martinique, Guadeloupe, French Guiana and Mayotte) as they are not independent states.

[8] See Table A.1 for more details on the sample.

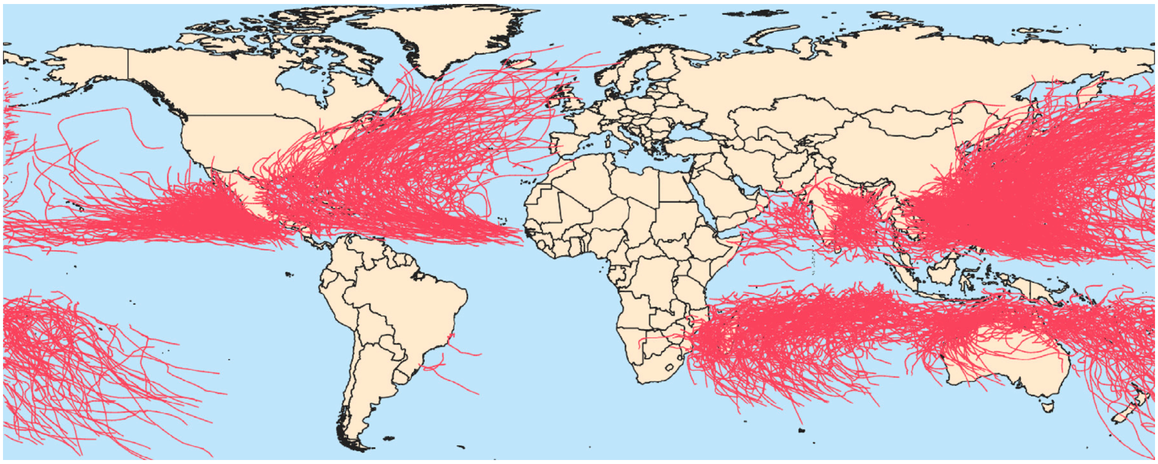

Fig. 1. World map of hurricane best tracks: 1995–2014.
Source: Author's elaboration from IBTrACS database.

Table 1
Descriptive statistics.
Source: Authors' elaboration.

	N	Mean	SD	Min	Max
Full sample					
Hurricane index	2280	.001506	.0108932	0	.201552
Hurricane index (>0)	369	.0093052	.0257311	4.04e−10	.201552
Disposable Gini	2280	.3890018	.0911964	.22	.671
Market Gini	2280	.4661487	.0682745	.219	.724
Low income countries					
Hurricane index	520	.0003882	.0037629	0	.0798339
Hurricane index (>0)	69	.0029253	.0100269	4.04e−10	.0798339
Disposable Gini	520	.4201769	.0622018	.329	.563
Market Gini	520	.4450269	.0611221	.349	.596
Lower-middle income countries					
Hurricane index	680	.0021058	.0144593	0	.201552
Hurricane index (>0)	107	.0133829	.0344513	4.12e−09	.201552
Disposable Gini	680	.4310338	.0860214	.237	.671
Market Gini	680	.4696	.0838401	.219	.708
Upper-middle income countries					
Hurricane index	480	.0006016	.0053547	0	.0770514
Hurricane index (>0)	44	.0065626	.0167143	1.07e−07	.0770514
Disposable Gini	480	.3949792	.0971289	.22	.636
Market Gini	480	.4818958	.0694218	.369	.724
High income countries					
Hurricane index	600	.0025184	.0132704	0	.1634536
Hurricane index (>0)	149	.0101412	.0251975	2.85e−08	.1634536
Disposable Gini	600	.309565	.0562102	.22	.507
Market Gini	600	.467945	.0455365	.31	.563

Notes: Descriptive statistics of hurricane index, disposable Gini (post-tax & transfers), market Gini (pre-tax & transfers) according to subgroup from the World Bank.

4. Empirical strategy

Our empirical strategy is based on ordinary least squares (OLS) estimation of a structural model explaining income inequality with Jordà (2005)'s local projections. LP are constructed as a local impulse response estimated at each time horizon, in contrast to a Vector Autoregression (VAR) model that extrapolates results from data based on a distant horizon. This method has several advantages: (i) it is easy to estimate with OLS; (ii) it is more robust to model misspecification; (iii) it lends itself more readily to point or joint inference; and (iv) it is more amenable to highly non-linear models (Jordà, 2005). This model is increasingly used in the literature and is well suited to our approach, as it could be compared to the impact analysis method in the presence of an orthogonal independent variable (here: the hurricane index). The model is constructed as follows:

$$Y_{i,t+h} - Y_{i,t-1} = \beta^h HI_{i,t} + \omega^h [HI \times GDPcap_{i,t-1}] + \theta^h X_{i,t-1} + \alpha_i^h + \rho_t^h + \Omega_i^h \times t + \epsilon_{i,t+h} \tag{4}$$

The LP is made from the year before the hurricane $t-1$ to $h = 0,\dots,5$, time horizon of 5 years after the storm. Given the temporal depth of our sample (20 years), we can only analyze the impact of hurricanes over the medium term. The Left-Hand Side (LHS) variable gives the cumulative change from $t-1$ (before the impact) to $t+h$ of the Gini index. The coefficient associated with the hurricane index is $\beta^h HI_{i,t}$. $HI \times GDPcap_{i,t-1}$ is the multiplicative variable between the hurricane index and the logarithm of GDP per capita, used to test whether the impact is different depending on the wealth level of the affected country. $X_{i,t-1}$ is a set of control variables described above and GDP squared to test the Kuznets inequality curve. All control variables are lagged to minimize a potential reverse causality problem. α_i^h and ρ_t^h are, respectively, the country and time-fixed effects. $\Omega_i^h \times t$ allows us to account for country-specific patterns of inequality growth and its relative inertia (Hsiang & Jina, 2014). Finally, $\epsilon_{i,t+h}$, the idiosyncratic error term for each time horizon, is clustered by country to correct for heteroscedasticity and serial autocorrelation.

5. Results

5.1. The effect of hurricanes on pre-redistribution inequalities

Table 2 presents the results of the impact of hurricanes on the market Gini, providing insight into the impact of inequality without redistribution. The regression results show a cumulative increase in inequality up to one year after the hurricane. To provide a more concrete interpretation, an increase of one standard deviation in HI (Table 1: 0.026) corresponds to a cumulative increase of 0.003 in the market Gini one year after the shock.[9] Although seemingly modest, this translates into a cumulative increase of 0.65% in the market Gini.[10]

[9] The coefficient is calculated as follows: $0.112 \times 0.026 = 0.003$.

[10] Given that the average market Gini is 0.466 (Table 1).

Looking at the time dynamics of this impact, the significance diminishes two years after the hurricane. Interestingly, the cumulative inequalities decrease four and five years after the hurricane.

Introducing the multiplicative variable between HI and GDP per capita allows us to examine heterogeneity across countries, based on income levels. Its significant and positive (negative) coefficient in years with a negative (positive) HI coefficient shows that countries with a higher GDP per capita experience a smaller increase, or even a decrease, in inequality one year after the hurricane. The threshold at which inequality decreases after a hurricane is around $1750 for the market Gini. Almost 25% of our observations fall below this threshold.

We could interpret this as owing to the fact that the poorest countries are essentially agricultural economies that often have precarious infrastructure and housing that are less resistant to hurricanes. This is particularly true for the poorest sections of the populations of these countries. Therefore, these countries would be more likely to suffer significant damage after a hurricane and adopt adaptation strategies to increase their income in the subsequent years.

Conversely, we find that the increase in market inequalities four years after the shock only affects the richer countries. Indeed, the positive and significant coefficient of the multiplicative variable indicates that above a certain level of GDP per capita, the impact of a hurricane increases inequality for the wealthiest countries four years after the shock. This result is intriguing and would suggest a Schumpeterian effect with a "build-back-better" mechanism: After a hurricane, capital is destroyed. It is then replaced by more efficient capital, allowing for an increase in capital income, which tends to go to the richest fringe of the population.[11] Indeed, modern economies are more capital intensive. Capital is mainly held by the richest individuals in the population, who likely then experience, a greater reduction in their income from capital in the initial years after a hurricane, which could explain why inequalities tend to decrease in the richest countries.

Like others in the literature (Bodea et al., 2021), we find that few of our control variables have a strong and consistent effect on inequality. This is probably because inequality is highly sticky, and our empirical approach takes into account country-specific patterns of inequality growth.

It would be interesting to observe what happens in the presence of a redistributive policy, to see to what extent it tends to smooth out the evolution of inequalities following a hurricane.

5.2. The effect of hurricanes on post-redistribution inequalities

Table 3 presents the results of the impact of hurricanes on the disposable Gini for our full sample. The results show a significant cumulative increase in the disposable Gini up to three years after the shock associated with the HI. The magnitude of the coefficients is more substantial compared to the market Gini, with a value of 0.166 compared to 0.112 one year after the shock. Four years after the hurricane, the effect is no longer significant.

These results are, therefore, surprising and counter-intuitive when compared with the Gini market. They tend to suggest that the redistribution policy exacerbates inequalities since, in its absence, market inequalities would have increased less and even decreased four years after the hurricane. There are several potential reasons for this poor redistribution policy: a reduction in social transfers, a reduction in taxes for the richest, and the capture of resources by a section of the population (cartels, corruption).

However, these results must be tempered by the multiplicative variable between HI and GDP per capita. In the regressions for the disposable Gini index, the coefficient of the multiplicative variable is negative and significant for the first three years. This suggests that the higher the GDP per capita of the country, the less significant the impact of storms on the Gini index. Similarly, after a certain level of GDP per capita, the effect seems to be reversed: high income countries tend to experience a decrease in disposable income inequality. It is important to note that the coefficient on the multiplicative variable is higher for the disposable Gini than for the market Gini (−0.021 vs. −0.015), so the poor redistribution would only affect the least wealthy countries.[12]

In developed countries, disposable inequalities decrease more than market inequalities. Thus, redistributive policies are more efficient in wealthier countries, because they have more flexible budget constraints, a better borrowing, capacity, and a better tax system, allowing them to better smooth the shock and sometimes even reduce inequalities.[13]

This global analysis of the results highlights potentially poor redistributive policies, but only in the least wealthy countries in our sample. It would therefore seem worthwhile to analyze subgroups of countries according to their income levels.[14]

5.3. Hurricane intensity and frequency

Hurricanes are erratic events. It is difficult to predict the areas that will be affected, the intensity of the disasters, and their frequency. Nevertheless, some countries are affected more frequently because of their geography (large coastal areas, islands) and some countries are less affected but systematically experience high-intensity cyclones. It is, therefore, important to look at the distribution of the cumulative frequency and intensity of shocks.

Yang (2008)'s database provides the number of hurricanes by country and year since 1950, as well as the HI variable. We have summed each variable, by country, between 1950 and 2014. Table 4 shows the descriptive statistics for these variables.

Analyzing the distribution of cumulative hurricane frequency and intensity across countries over the period, we find that the countries in our sample experienced an average of twenty hurricanes. The high standard deviation nuances the previous result and highlights a significant disparity among countries. Furthermore, the countries that experienced more than 320 hurricanes (almost 5 per year) are concentrated at the 99th percentile. The same observation holds for cumulative intensity. These results suggest that hurricanes disproportionately affect the top 1% of our sample in terms of frequency and intensity.

It is therefore logical to believe that there could be unobservable heterogeneity for these countries (i.e., poverty traps, more resilient infrastructure, and better resilience), leading to the dynamics of hurricanes not being the same for all countries.

To ensure this is not the case, we re-estimate our model for disposable and market Gini by excluding from our sample the 99th percentile of the most affected countries and of those that experienced the largest

[11] The "build-back-better" effect would mainly concern individuals at the top of the income distribution since they are not only potentially more affected due to the capitalist intensity of their income but also have better access to insurance, which allows them to rebuild more efficiently compared to those at the bottom of the distribution.

[12] Tables A.2 and A.3 display the results of population-weighted regressions for market and disposable Gini. Despite varying significance for some years, the overall post-hurricane dynamics and their coefficients for market and disposable inequality remain consistent.

[13] More flexible budget constraints are a first-order condition for reducing inequality; the second would be good implementation efficiency, which could be undermined by poor institutional quality or corruption.

[14] Following a reviewer's suggestion, we estimate the baseline models for the market and disposable Gini to account for regional heterogeneity. We successively add, interacting with our HI variable of interest, a binary variable (taking the value 1 if the country belongs to the region, 0 otherwise) for seven regions: East Asia and the Pacific, South Asia, North America, Middle East and North Africa, Sub-Saharan Africa, Latin America and the Caribbean, Europe and Central Asia. The results (available upon request) for our variable of interest, HI, are similar to those in Tables 2 and 3.

Table 2
Cumulative effect of Hurricane index on market Gini.

	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Hurricane index	0.109***	0.112***	0.081	−0.033	−0.231*	−0.234***
	(0.026)	(0.042)	(0.064)	(0.091)	(0.125)	(0.089)
HI × (log) GDP per capita	−0.014***	−0.015***	−0.011	0.003	0.028*	0.029***
	(0.003)	(0.005)	(0.008)	(0.011)	(0.015)	(0.011)
(Log) GDP per capita	−0.029*	−0.063**	−0.098**	−0.131**	−0.164***	−0.176**
	(0.016)	(0.031)	(0.045)	(0.053)	(0.057)	(0.074)
(Log) GDP per capita^2	0.002*	0.004**	0.006**	0.008**	0.010***	0.011**
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
FDI	0.000	0.000	0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Portfolio investments	−0.000	−0.000	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trade	−0.000	−0.000	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Polity	0.000	0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.406	0.504	0.590	0.659	0.723	0.784
Observations	1784	1683	1582	1481	1381	1282

Notes: Market Gini refers to pre-taxes and transfers Gini index. All the coefficients are expressed in cumulative form. All our variables (except HI) are lagged by one period. Standard errors are in parentheses.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 3
Cumulative effect of Hurricane index on disposable Gini.

	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Hurricane index	0.160***	0.166***	0.207***	0.174***	−0.024	−0.057
	(0.034)	(0.042)	(0.048)	(0.062)	(0.066)	(0.076)
HI × (log) GDP per capita	−0.020***	−0.021***	−0.026***	−0.022***	0.002	0.007
	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)
(Log) GDP per capita	−0.022	−0.043	−0.062	−0.079	−0.114	−0.148
	(0.019)	(0.039)	(0.056)	(0.066)	(0.072)	(0.093)
(Log) GDP per capita^2	0.001	0.002	0.003	0.005	0.007	0.009*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)
FDI	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Portfolio investments	0.000	0.000**	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trade	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Polity	0.000	0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.373	0.453	0.530	0.594	0.660	0.726
Observations	1784	1683	1582	1481	1381	1282

Notes: Disposable Gini refers to post-taxes and transfers Gini index. All the coefficients are expressed in cumulative form. All our variables (except HI) are lagged by one period. Standard errors are in parentheses.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4
Descriptive statistics of the cumulative occurrence & intensity of hurricanes.
Source: Authors' elaboration.

	Mean	SD	Min	p50	p75	p90	p95	p99	Max	N
Cumulative occurrence of storms	20.49	60.13	0.00	0.00	5.00	36.00	151.00	320.00	342.00	2280
Cumulative intensity of storms	0.07	0.20	0.00	0.00	0.00	0.17	0.46	1.09	1.17	2280

Notes: Storms from 1950 to 2014 for the countries of our sample.

hurricanes. As shown in Fig. 2, the post-hurricane inequality dynamics remain stable, neither the coefficients nor their magnitudes or significance change.

One possible explanation for this is that countries more affected in frequency or intensity have developed a resilience to hurricanes, so these phenomena no longer impact inequality.

5.4. *Low versus high destructive potential of hurricanes*

It is also possible that a hurricane's impact on inequality varies according to its strength. A hurricane's strength is indicated by the Saffir-Simpson scale, which ranks hurricanes according to wind speed. However, strength alone is not enough to determine a hurricane's

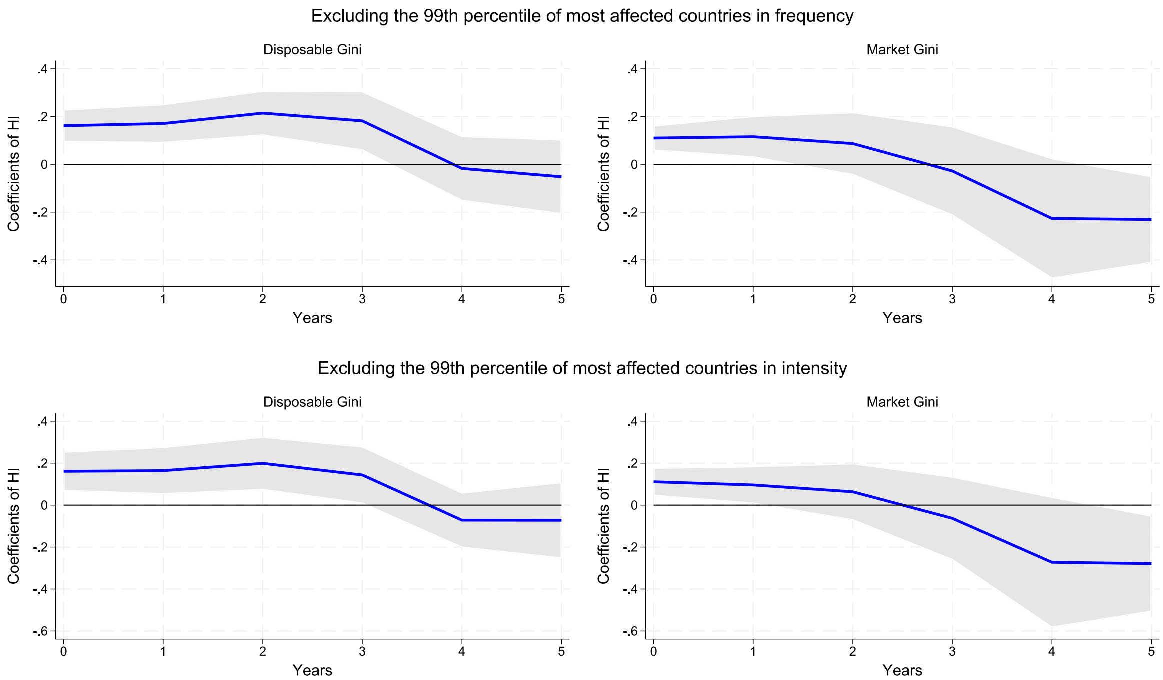

Fig. 2. Cumulative effect of hurricane index on disposable and market Gini excluding countries most affected in frequency and intensity. Notes: Full country sample, two-way FE panel regression with controls. Point estimators and 95%-confidence intervals.

impact, as this also depends on the number of people affected. By calculating its destructive potential, Yang's database allows us to identify hurricanes that are considered the most highly destructive. We therefore chose to classify hurricanes into two categories, strong and weak, using the median of the hurricane index for values above zero. Using this threshold, we estimate the impact of hurricanes on disposable and market inequality. The upper (lower) part of Fig. 3 shows the effects of hurricanes on disposable and market inequality, keeping in our estimate only hurricanes below (above) the median of the hurricane index.

We observe that when a country is hit by a hurricane with low destructive potential, there is no impact on inequality. This result is understandable, as such a hurricane causes little or no material destruction that could affect inequality. On the other hand, when a hurricane has a high destructive potential, we find the results described above. This threshold effect in the destructive power of hurricanes supports the hypothesis described above of a possible Schumpeterian phenomenon in rich countries. Indeed, only a powerful hurricane could cause significant material destruction, especially of capital, which would affect the richest incomes and initially reduce inequality. Subsequently, the richest incomes are likely to rise with reconstruction and a "build-back-better" phenomenon, leading to an ultimate increase in market inequalities.

Thus, post-transfer and tax inequalities increase more after a hurricane than do market inequalities, which tend to decrease after four years. This poor redistribution mainly affects the less wealthy countries, as indicated by our significant multiplicative variable with GDP per capita, which is opposite to the HI coefficient. Conversely, we highlight the possible existence of a "build-back-better" mechanism in high income countries. These results remain robust even when the most affected countries (in frequency and intensity) are excluded and when we focus on hurricanes with a high destructive potential. Given these results, an analysis by subgroups of countries seems highly relevant.

6. Heterogeneity of impact, by democracy and development levels

6.1. Hurricanes, democracy and corruption levels

As discussed above, the impact of hurricanes varies according to a country's level of wealth. The literature on inequality also examines the effects of political variables on its evolution. Aidt and Jensen (2009) point out that more democratic countries are better equipped to reduce inequality thanks to higher public spending and a more redistributive tax system. This condition seems particularly relevant to our analysis. After a disaster, a country needs to be able to mobilize its budget for reconstruction and mitigate the potential impact of inequality. Conversely, more authoritarian countries may find it more challenging to implement these policies because of corruption.

To test for this possible heterogeneity of impact, we repeat our regressions using the same model but dividing our sample in two, according to the median of our polity variable. In addition, to strengthen the robustness of our model, we include the World Bank's control of corruption variable, which measures a country's level of corruption. The amount of foreign aid a country can receive and how it is used may depend on this level. Donors may be more reluctant to provide aid when corruption is high, as in the aftermath of Hurricane Nargis in Myanmar or the 2010 earthquake in Haiti. Similarly, high levels of corruption could make redistributive policies less effective because of the monopolization of resources by an elite.

Fig. 4 shows the results for countries considered less democratic (top) and more democratic (bottom). For the more democratic countries, we observe the effect of our baseline with a more substantial amplitude, underlining the positive impact of democracy on reducing inequality, especially in developed countries.[15] For less democratic countries, however, the dynamic is quite different. Inequality before

[15] As our interaction variable between the hurricane index and the GDP per capita remains significant and of opposite sign.

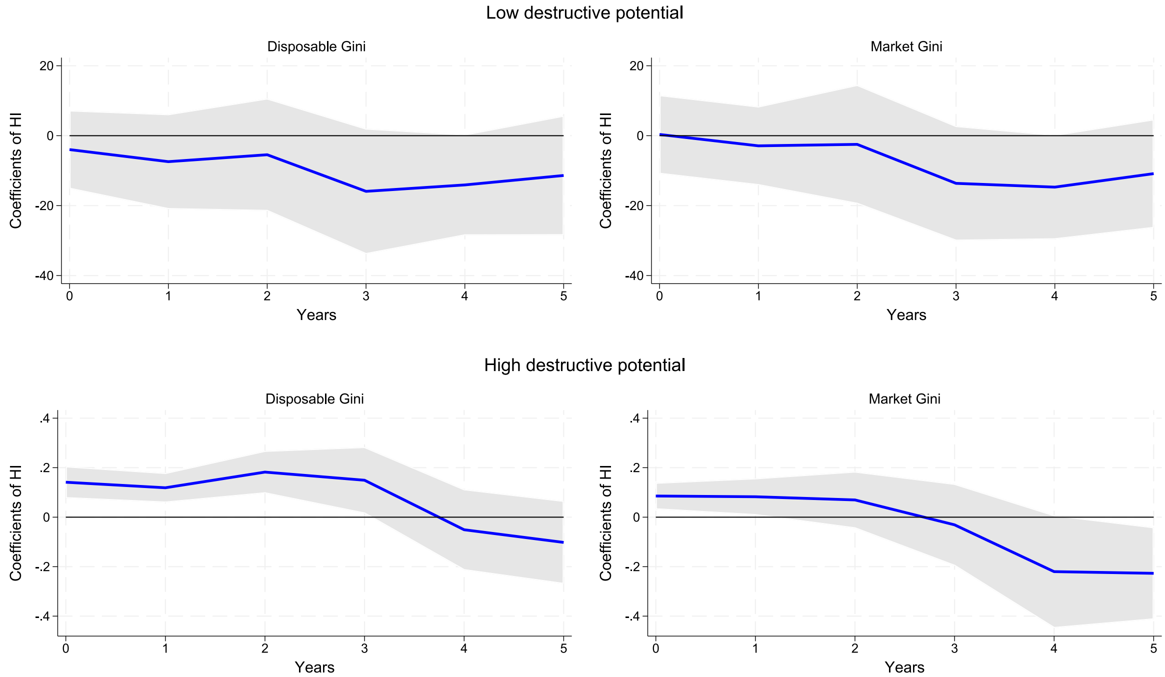

Fig. 3. Cumulative effect of hurricane index on disposable and market Gini by hurricane force. Notes: Country sub sample divided around the median of HI, two-way FE panel regression with controls. Point estimators and 95%-confidence intervals.

taxes and transfers increases up to three years after a hurricane. By comparison, disposable inequality rises more sharply in the immediate aftermath of a hurricane, reflecting the difficulty of implementing effective redistributive policies. These results suggest that in addition to a country's level of development, democracy and corruption are essential factors in reducing inequalities. More democratic countries can more easily implement reconstruction and redistribution policies without these funds being diverted by high corruption levels.

6.2. The effect of hurricanes on pre-redistribution inequalities by country subgroup

We use the World Bank country income classification to create four groups: low income, lower-middle income, upper-middle income, and high income countries. As we work on subsamples of countries according to their income, we remove from our model the multiplicative variable between GDP per capita and HI, and GDP squared.

Fig. 5 presents a subgroup analysis for the market Gini to consider the dynamics of inequality in the absence of redistributive policies. Without redistribution, the hurricane has no effect on inequality for the low income group, except for a slight increase four and five years after the shock. For the upper-middle income group, there is a slight decrease after one year, which can be explained by the inflow of foreign aid. A useful example of the importance of remittances is Puerto Rico. As an unincorporated territory of the United States, Puerto Rico received no official development assistance after Hurricane Maria. In this context, remittances played a critical role, providing most of the personal assistance to residents who remained on the island.

More interestingly, for high income countries, we see that inequality decreases one year after the hurricane hits and rises four years later. This result could be seen as a Schumpeterian effect of creative destruction, which could explain this inequality dynamic. After the shock, the destroyed capital is replaced by more productive capital, allowing the income of the richest part of the population to rise.

6.3. The effect of hurricanes on post-redistribution inequality by country subgroup

Fig. 6 displays the results for the disposable Gini according to the four groups. We can see that inequality in low income countries decreases cumulatively four to five years after the shock. This result could be explained by an influx of ODA, remittances from migrants who left after the disaster, or the adoption of adaptive strategies such as diversifying crops.[16] We find no hurricane effect on the disposable Gini for the lower- and upper-middle income groups.

For the high income group, there is a cumulative decline in inequality up to three years after the shock. As noted above, this result may be because rich countries have a highly capital-intensive production system. As the hurricane destroys mostly capital, which is the primary source of income for the richest part of the population, inequality would tend to fall.

In addition, the positive impact of transfers should be emphasized, as the fall in inequality is more remarkable for the disposable Gini than for the market Gini. In addition, transfer policies avoid a surge in inequality, as is the case with the market Gini. Developed countries have the resources to pursue efficient redistribution policies. They also often have an effective redistributive system, because they have fewer budget constraints, a more developed tax system, and a greater capacity to borrow.

Our findings on the impact of hurricanes on post redistribution inequality for high income countries are consistent with Barbieri and

[16] Although individual migration mainly affects the middle part of the income distribution (Borjas, 1987), it is also an insurance mechanism at the household and even village levels in developing countries (Chort & Senne, 2015; Stark & Bloom, 1985). In the event of a shock, the migrant, who maintains links with those left behind, can play a counter-cyclical role by sending remittances and helping those left behind, who are often lower in the income distribution than they are.

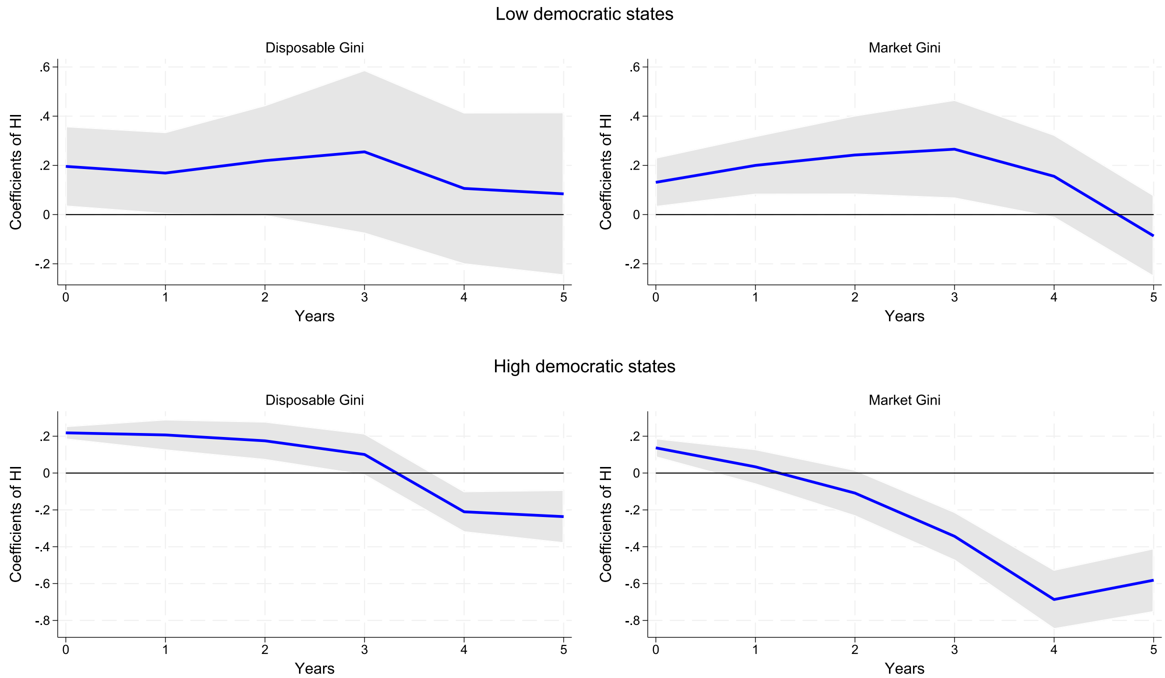

Fig. 4. Cumulative effect of hurricane index on disposable and market Gini depending on level of democracy. Notes: Country sub sample divided by their level of democracy, two-way FE panel regression with controls. Point estimators and 95%-confidence intervals.

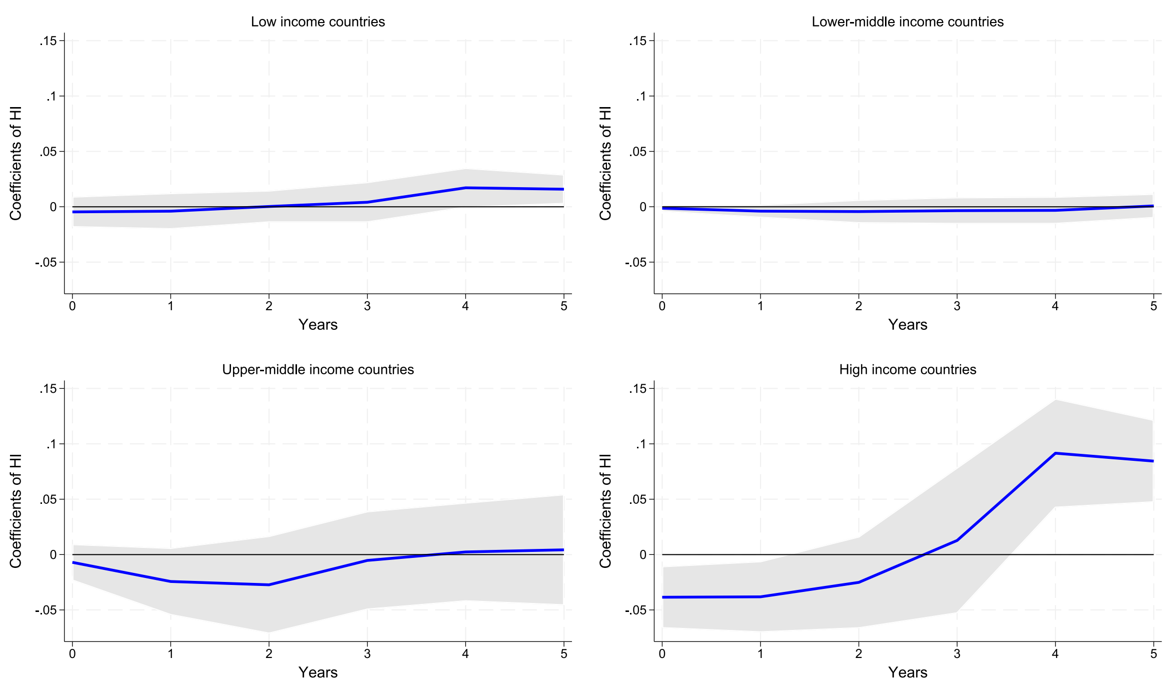

Fig. 5. Cumulative effect of hurricane index on market Gini by level of development. Notes: Country sub sample with World Bank's income groups, two-way FE panel regression with controls. Point estimators and 95%-confidence intervals.

Edwards (2017), who examine the effects of Hurricane Katerina in New Orleans. Before Hurricane Katrina, New Orleans had high levels of concentrated poverty and inequality, despite being part of a wealthy nation. Post-Katrina socio-economic restructuring has reduced inequality, supported by a more equitable distribution of skills and income; these changes have contributed to a positive outcome for the post-Katrina New Orleans, making it a more prosperous and less unequal city.

There are different dynamics of inequality at different income levels. For low and high income countries, redistribution and transfers are

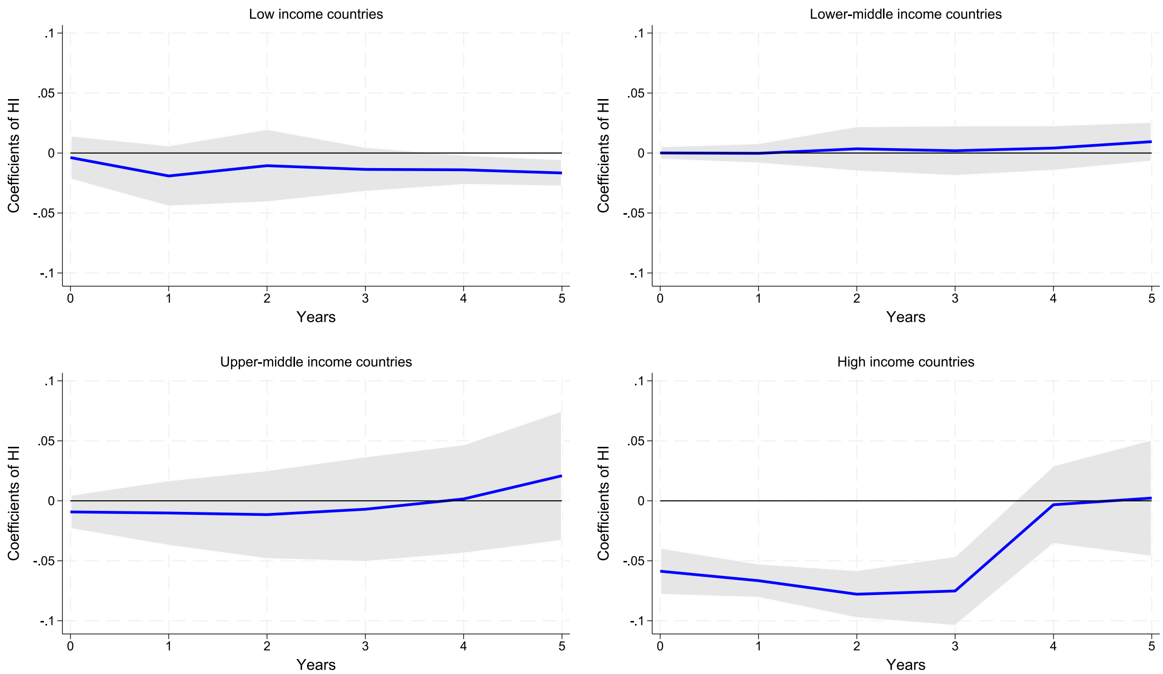

Fig. 6. Cumulative effect of hurricane index on disposable Gini by level of development. Notes: Country sub sample with World Bank's income groups, two-way FE panel regression with controls. Point estimators and 95%-confidence intervals.

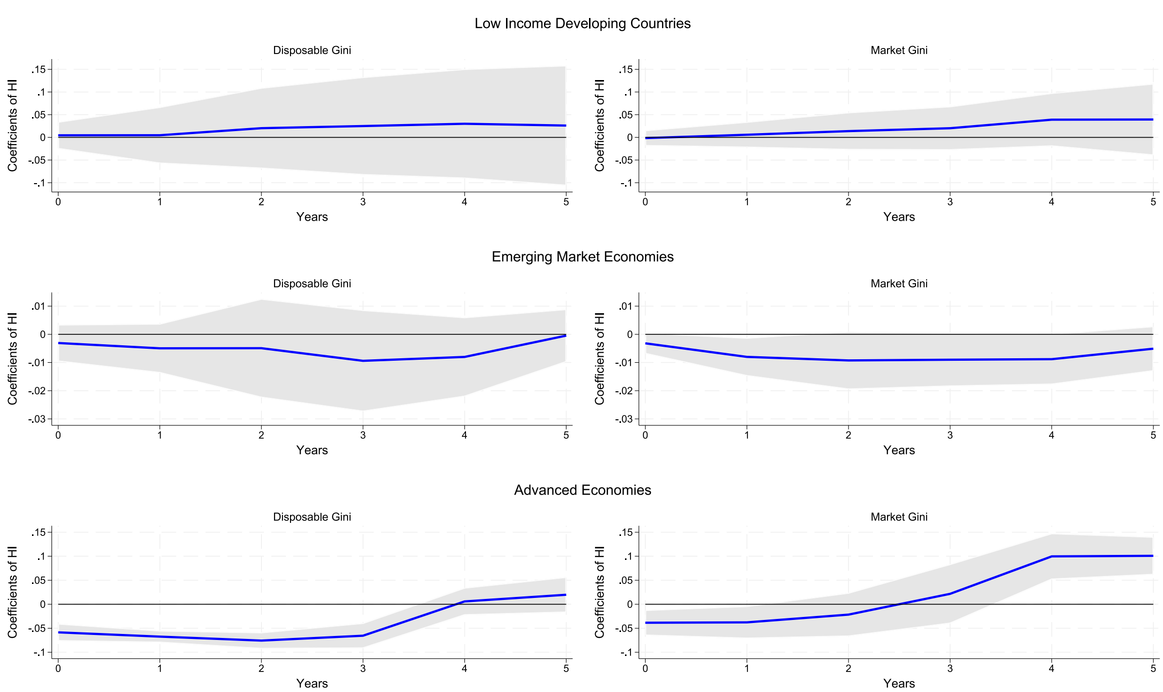

Fig. 7. Cumulative effect of hurricane index on disposable & market Gini with IMF's classification. Notes: Country sub sample with IMF's classification, two-way FE panel regression with controls. Point estimators and 95%-confidence intervals.

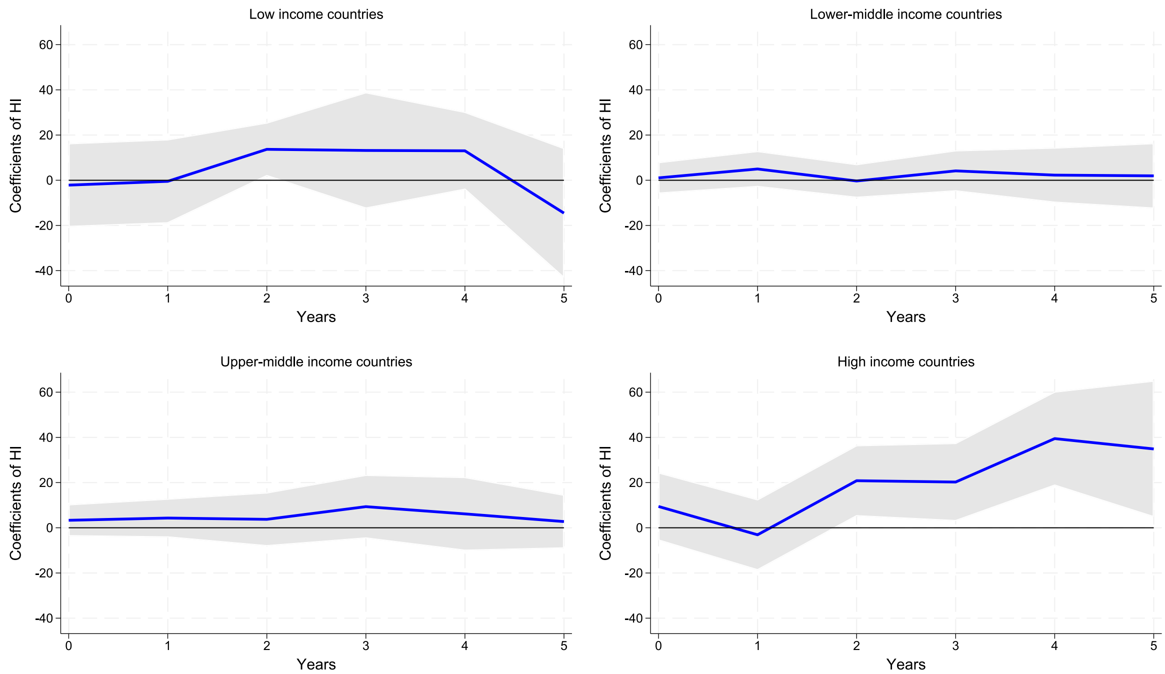

Fig. 8. Cumulative effect of hurricane index on subsidies and other transfers. Notes: Country sub samples with World Bank's income groups, two-way FE panel regression with controls Point estimators and 95%-confidence intervals.

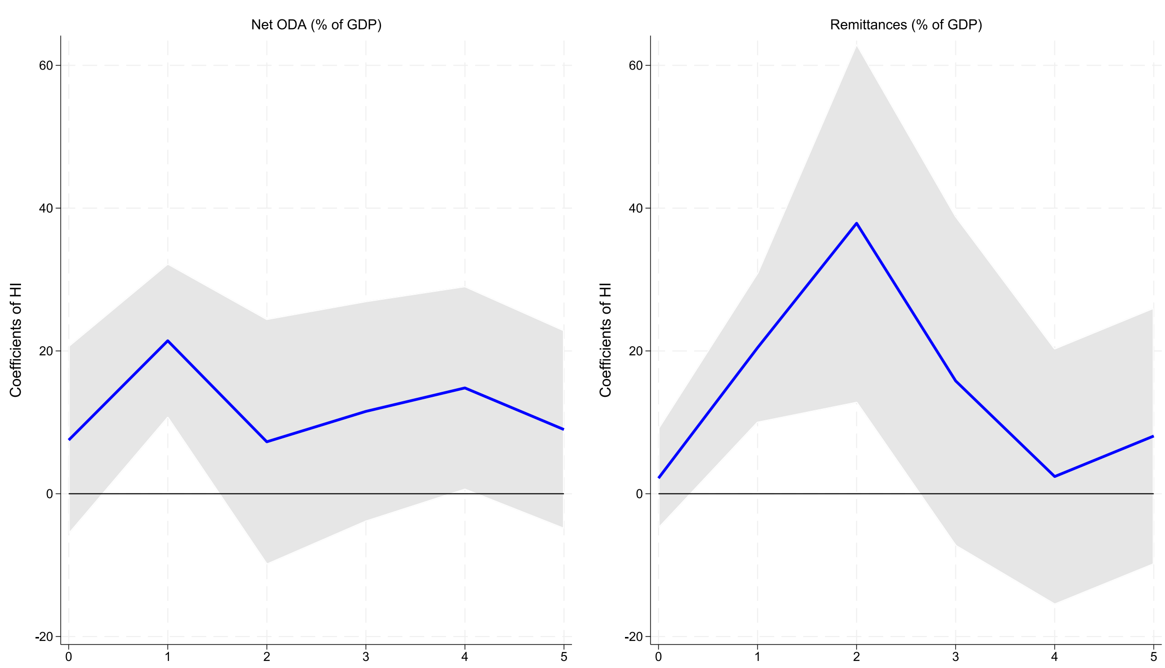

Fig. 9. Cumulative effect of hurricane index on ODA & remittances. Notes: Low income countries, two-way FE panel regression with controls. Point estimators and 95%-confidence intervals.

essential, without which inequalities would remain unaffected or even increase. These conclusions are similar to those drawn for the full sample.[17]

6.4. Change in classification

Fig. 7 represents the disposable and market Gini results for which we have replaced the World Bank's country income classification with that of the IMF. This information allows us to test the sensitivity of our results across groups. The IMF classifies countries into three categories: low income developing countries, emerging market economies, and advanced economies. Our sample countries are divided into groups of 27, 52 and 35 countries, respectively.[18] As we can see, this classification change does not alter our results: we find the above effect for the advanced economies group. We can thus conclude that our results are relatively robust to a change in classification.

7. Transmission channels and discussion

As we have seen, post-tax and post-transfer inequality declines for low and high income countries. However, what are the possible channels through which this decline takes place? We present three different potential channels which can explain this dynamic after a hurricane: social transfers, ODA, and remittances. We maintain the subgroup analysis to consider the specific dynamics of each income level outlined above. To do this, we alternatively change our dependent variable in our structural model to include subsidies and other transfers, remittances, and ODA. These variables are expressed as a percentage of GDP and are taken from the World Bank.

7.1. Channel of social transfers

Fig. 8 displays the correlation between the hurricanes on subsidies and other transfers, for each subgroup. We can see that hurricanes cumulatively increase subsidies two years after they occur, but only in rich countries. We find that this increase coincides with the time when market inequalities increase. This result seems to suggest the "build-back-better" hypothesis, according to which the destroyed capital after a hurricane mainly affects the richest fringe of the population, leading to a decrease in inequality. In their rebuilding efforts, investors replace the destroyed capital with more productive technologies, thereby increasing their income and market inequalities. Thus, social transfers are correctly used in these economies to avoid increasing inequality. The fact that hurricanes do not affect transfers to other groups is unsurprising. Social transfers are easier to mobilize in countries with looser budget constraints and a sound tax system.

7.2. ODA and remittances channel

To explain the decline in disposable income inequality in low income countries, we first analyze the effect of ODA. The left-hand side of Fig. 9 shows the impact of the hurricanes on ODA. We see that ODA in the affected country increases in the year following the event. This international solidarity smooths out the shock and is mainly directed towards the poorest part of the population. Looking at the right-hand side of Fig. 9, we see that hurricanes increase remittances during the two years following the hurricane. This counter-cyclical effect can also explain the fall in the Gini coefficient. Indeed, remittances are an essential source of access to finance for developing countries. Migrants have often maintained links with families left behind. In a context where government transfers are highly complicated, migrants fulfill this function. Thus, this double inflow of international finance could increase the income of individuals in these countries in a sustainable way, leading to a reduction in post-transfer inequalities.

8. Conclusion

While the economic consequences of natural disasters have received increasing attention over the past decade, there is limited understanding of their medium-term impact on inequality at the macro level.

This paper addresses this gap by conducting a comprehensive analysis of the impact of hurricanes on inequality. Using an exogenous hurricane index derived from meteorological data, we present compelling empirical evidence supporting the hypothesis that hurricanes have conditional effects on countries, according to their GDP levels.

We show that pre-redistribution inequalities tend to cumulatively increase the year following a hurricane and decrease four and five years after it strikes. Conversely, hurricanes tend only to cause higher disposable inequalities for up to three years. These results apply mainly to strong hurricanes and are robust to the exclusion of the most affected countries. There is also evidence of a role for the level of democracy in the management of inequality in the aftermath of a hurricane.

However, the significant contribution of the paper is its demonstration that the inequality effects of storms differ substantially among countries with different levels of development. For low income countries, we find that disposable Gini tends to decrease, which could be explained by a surge in remittances and ODA the year following the disaster strikes. For the high income group, market and disposable inequality tend to decrease in the years following a hurricane. We find an increase in the market Gini four and five years later, underlying a possible Schumpeterian effect of creative destruction. We show that subsidies and transfers increase, supporting the hypothesis that redistributive policies are central to smoothing natural disasters.

A possible extension of our work would be to look at the gender impact of hurricanes or natural disasters and how this significantly impacts income inequality in affected populations.

CRediT authorship contribution statement

Aubin Vignoboul: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

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Appendix

See Tables A.1–A.3.

Data availability

Data will be made available on request.

[17] It is worth noting that the results do not change if we allow countries to change their income category during the period. Results are available upon request.

[18] As for the World Bank classification, for the whole period, we assign countries to a group according to their classification in 2005.

Table A.1
Countries of the sample according to their income classification.

Country	Number of hurricanes	Income classification	Country	Number of hurricanes	Income classification
Argentina	0	Upper-middle income	Lithuania	0	Lower-middle income
Armenia	0	Low income	Luxembourg	0	High income
Australia	83	High income	Macedonia	0	Lower-middle income
Austria	0	High income	Malawi	0	Low income
Bangladesh	16	Low income	Malaysia	2	Upper-middle income
Barbados	5	Upper-middle income	Mauritania	0	Low income
Belarus	0	Lower-middle income	Mauritius	9	Upper-middle income
Belgium	0	High income	Mexico	121	Upper-middle income
Bolivia	0	Lower-middle income	Moldova	0	Lower-middle income
Botswana	0	Lower-middle income	Mongolia	0	Low income
Brazil	0	Upper-middle income	Morocco	1	Lower-middle income
Bulgaria	0	Lower-middle income	Namibia	0	Lower-middle income
Burkina Faso	0	Low income	Netherlands	0	High income
Canada	43	High income	New Zealand	3	High income
Chile	0	Upper-middle income	Nicaragua	8	Low income
China	136	Low income	Niger	0	Low income
Colombia	1	Lower-middle income	Nigeria	0	Low income
Costa Rica	0	Lower-middle income	Norway	1	High income
Croatia	0	Upper-middle income	Pakistan	4	Low income
Cyprus	0	High income	Panama	0	Lower-middle income
Czech Republic	0	Upper-middle income	Paraguay	0	Lower-middle income
Cote d'Ivoire	0	Low income	Peru	0	Lower-middle income
Denmark	0	High income	Philippines	92	Lower-middle income
Dominican Republic	14	Lower-middle income	Poland	0	Lower-middle income
Ecuador	0	Lower-middle income	Portugal	4	High income
Egypt	0	Lower-middle income	Puerto Rico	11	Upper-middle income
El Salvador	3	Lower-middle income	Romania	0	Lower-middle income
Estonia	0	Lower-middle income	Russia	6	Lower-middle income
Ethiopia	0	Low income	Rwanda	0	Low income
Finland	0	High income	Sierra Leone	0	Low income
France	1	High income	Singapore	1	High income
Gambia	0	Low income	Slovakia	0	Lower-middle income
Georgia	0	Low income	Slovenia	0	Upper-middle income
Germany	0	High income	South Africa	0	Upper-middle income
Ghana	0	Low income	Spain	0	High income
Greece	0	Upper-middle income	Sri Lanka	1	Low income
Guatemala	9	Lower-middle income	St. Lucia	6	Upper-middle income
Honduras	12	Low income	Sudan	0	Low income
Hong Kong	22	High income	Swaziland	0	Lower-middle income
Hungary	0	Upper-middle income	Sweden	1	High income
Iceland	4	High income	Switzerland	0	High income
India	46	Low income	Tajikistan	0	Low income
Indonesia	3	Lower-middle income	Tanzania	0	Low income
Iran	1	Lower-middle income	Thailand	17	Lower-middle income
Ireland	5	High income	Tonga	10	Lower-middle income
Israel	0	High income	Tunisia	0	Lower-middle income
Italy	0	High income	Turkey	0	Lower-middle income
Jamaica	8	Lower-middle income	Uganda	0	Low income
Japan	114	High income	Ukraine	0	Lower-middle income
Jordan	0	Lower-middle income	United Kingdom	5	High income
Kazakhstan	0	Lower-middle income	United States	90	High income
Kenya	0	Low income	Uruguay	0	Upper-middle income
Korea	22	High income	Venezuela	1	Lower-middle income
Kyrgyzstan	0	Low income	Vietnam	59	Low income
Laos	23	Low income	Yemen	1	Low income
Latvia	0	Lower-middle income	Zambia	0	Low income
Lesotho	0	Lower-middle income	Zimbabwe	3	Low income

Countries of the samples according to the World Bank's classification and the numbers of hurricanes during the period (1995–2014).

Table A.2
Cumulative effect of Hurricane index on market Gini (Population Weighted regressions).

	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Hurricane index	0.090***	0.050	0.020	−0.096*	−0.283***	−0.261***
	(0.030)	(0.043)	(0.039)	(0.054)	(0.060)	(0.060)
HI × (log) GDP per capita	−0.012***	−0.007	−0.003	0.011*	0.036***	0.034***
	(0.003)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
(Log) GDP per capita	0.007	0.035	0.033	0.022	0.003	−0.040
	(0.021)	(0.056)	(0.082)	(0.091)	(0.095)	(0.085)
(Log) GDP per capita^2	−0.001	−0.002	−0.002	−0.001	−0.000	0.002
	(0.001)	(0.003)	(0.005)	(0.005)	(0.006)	(0.005)
FDI	0.000	0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Portfolio investments	−0.000**	−0.000**	−0.000	−0.000	−0.000**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trade	−0.000***	−0.000**	−0.000**	−0.000***	−0.000***	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Polity	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.579	0.716	0.784	0.834	0.880	0.917
Observations	1784	1683	1582	1481	1381	1282

Note: Market Gini refers to post-taxes and transfers Gini index. All the coefficients are expressed in cumulative form. All our variables (except HI) are lagged by one period. Standard errors are in parentheses.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.3
Cumulative effect of Hurricane index on disposable Gini (Population Weighted regressions).

	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Hurricane index	0.151***	0.117*	0.146**	0.099	−0.094	−0.108*
	(0.039)	(0.062)	(0.064)	(0.072)	(0.059)	(0.055)
HI × (log) GDP per capita	−0.020***	−0.016**	−0.020**	−0.014*	0.011*	0.013*
	(0.004)	(0.007)	(0.008)	(0.008)	(0.006)	(0.007)
(Log) GDP per capita	0.049	0.111	0.164*	0.193*	0.162	0.087
	(0.035)	(0.077)	(0.092)	(0.100)	(0.118)	(0.125)
(Log) GDP per capita^2	−0.003	−0.007	−0.010*	−0.011*	−0.009	−0.005
	(0.002)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
FDI	0.000	0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Portfolio investments	0.000	0.000*	0.000***	0.000	0.000*	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trade	−0.000***	−0.000***	−0.000**	−0.000*	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Polity	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.538	0.666	0.735	0.781	0.832	0.882
Observations	1784	1683	1582	1481	1381	1282

Note: Disposable Gini refers to post-taxes and transfers Gini index. All the coefficients are expressed in cumulative form. All our variables (except HI) are lagged by one period. Standard errors are in parentheses.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

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