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The winds of inequalities: How hurricanes impact inequalities at the macro level?

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Abstract

While the consequences of natural disasters are comparatively well studied, little is known about their macroeconomics impact on inequalities. Following Yang 2008, we use an exogenous hurricane index, considering the average "affectness" based on meteorological data. The empirical approach uses Local Projection (Jordà, 2005) to gauge the impact on two Gini indexes (pre and post-transfer) (Solt, 2020) five years after the hurricane for a sample composed of 115 countries from 1995 to 2014. Our results prove that hurricanes have a conditional effect on inequalities depending on the level of GDP per capita. The poorest countries tend to see their post-redistribution inequalities decrease. Our paper discloses the existence of the kind of Schumpeterian effect for high-income countries. In the first years, they know a decrease in their pre-redistribution Gini as the capital owned by the top of the income distribution is destroyed. Then, pre-tax and transfer Gini increases with a built-back better mechanism as individuals at the top of the income distribution will increase their revenue from capital. For post-redistribution Gini, we only see a decrease in the first years following the hurricane and underline the positive effect of redistribution. We describe OAD, remittances, and subsidies channels through which hurricanes could lower inequalities in these countries.

Keywords: Hurricane; Inequality; Natural disasters, Redistribution

1 Introduction

Our environment is undergoing a phase of profound changes: global warming, deforestation, global pollution, and erosion of biodiversity. There is no more extended debate about the anthropogenic origins of these upheavals within the scientific community. Growth and economic development have caused significant transformations in our biosphere. The consequences of global warming, the destruction of forests, and global pollution no longer appear as distant hypotheses. Do humanity and the economy have the capacity to adapt and cope with these disruptions? The risk is accurate, and the first effects are already being felt. Natural disasters are one of the most striking manifestations of nature's power. Dilley (2005) estimates that 3.5 billion people can be affected by a disaster. Natural disasters devastate societies with an exorbitant cost of loss of life, property, and altered power relations. Since the 1970s, the frequency of natural disasters worldwide has increased dramatically (Yamamura, 2015), as has the economic damage attributed to them, despite improvements in early warning systems (Coronese et al., 2019). According to the Intergovernmental Panel on Climate Change (IPCC), these events will become even more recurrent and intense due to the increasing concentration of greenhouse gases in the atmosphere (IPCC, 2018).

The analysis of the consequences of natural cataclysms is a growing literature in economics. However, no consensus is emerging, and a lively debate occurs between the three visions.

A first vision of the literature defends a catch-up dynamic based on neoclassical theories of growth, in which the disaster has only a transitory effect on economic activity. Per capita income recovers its initial level after a few years. The economy regains its Regular state (Jaramillo, 2009; Cavallo et al., 2013; Brata et al., 2014).

Conversely, a second vision believes that a disaster can plunge the country into a poverty trap, where the economy does not recover its initial level of Gross Domestic Product (Carter et al., 2008). Diamond (2006) goes further, stating that climate change is one of the factors that has contributed to the collapse of some societies in the past.

Finally, a more optimistic vision sees these phenomena as an opportunity for countries to modernize. This argument is a Schumpeterian conception of creative destruction. Machines with better technology replace the capital destroyed by the catastrophe. The economy improves productivity, which is the built-back better mechanism (Hallegatte and Dumas, 2009; Loayza et al., 2012). These conflicting conclusions depend on the level of analysis. The effects of natural disasters are characterized by high heterogeneity depending on the countries affected and the disaster studied (Klomp, 2016). The transmission channels are numerous, and it is appropriate for the rigor of the analysis to focus on only one of them.

From an empirical point of view, the effect of cataclysms is studied on many economic variables:

GDP and growth (Berlemann and Wenzel, 2018; Hsiang and Jina, 2014), international trade (Pelli and Tschopp, 2017) but also on inequality (Yamamura, 2015; Cappelli et al., 2021).

Indeed, the issue of inequality is central in economics, and the literature studying climate shocks and inequality is growing. It is mainly composed of microeconomic studies. The few studies that deal with this issue at the macroeconomic level do not consider the temporal depth of the impact, use data based on declarations that may be biased, and do not describe the channels. In particular, the role of redistribution policies can explain the dynamics of inequality after the shock. There is no clear consensus in the literature that articulates between Schumpeterian theory and permanent shock. Moreover, the impact of disasters is highly heterogeneous depending on the type of event studied and the country, which is rarely taken into account in macroeconomic studies.

Given this gap, it is legitimate to ask: What is the medium-term impact of the hurricanes on income inequality at the macro level? Is there a difference in the impact of the hurricanes between pre-tax/transfer and post-tax/transfer inequality? Are there different dynamics of the impact of hurricanes on inequality depending on the level of development? What might be the channels through which hurricanes impact inequality, and are they different by the level of development?

To answer these questions, we built a sample of 117 countries from 1995 to 2014 to test the impact of hurricanes on inequalities. Hurricanes are one of the most frequent and destructive disasters. They predominantly impact capital. This analysis has several advantages: firstly, our measure of hurricanes constructed from Yang (2008)'s methodology with meteorological data allows us to have an index of destructive potential that is as free from endogeneity bias; Secondly, we use the local projections of Jordà (2005), allowing us to look at the impact of hurricanes five years after the shock. Thirdly, we do an analysis by a subgroup of countries, looking at the impacts for two Gini coefficients: pre-and post-reallocation; Finally, we attempt to highlight some channels that explain the dynamics of inequality.

Our analysis highlights the critical role of redistribution policies. It shows that pre-redistribution inequalities tend to increase up to one year and even decrease four years after the shock. Indeed, inequality after taxes and transfers increases more vigorously and for longer (up to three years) after the shock, without decreasing after this period. This finding must, however, be balanced, as the results differ according to the level of development. The poorest and wealthiest countries would experience a decrease in post-redistribution inequalities. This result could be explained for the developing countries by the influx of official development assistance and remittances and increased subsidies for developed countries.

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 develop the channels in section 7. Finally, we develop the conclusion and policy recommendations in section 8.

2 Literature review

2.1 The impact of natural disasters under debate

In the age of climate change and the disruption of the natural balance, there is growing concern about the future of humanity. Natural disasters are the most striking examples of the indomitable essence of nature. Generally speaking, these disasters cause far more material damage (destruction of capital) than human losses (destruction of work). The growing literature on the impact of natural disasters on the economy attempts to provide answers on their consequences. However, no consensus on the issue has emerged, and a debate between the three main theses persists.

On the one hand, a current of literature defends the vision of a catch-up dynamic, where the effects of the disaster fade with time. According to neoclassical growth models, if a disaster harms the level of capital per capita in t, savings and, therefore, the investment must increase in the following years until the economy returns to its steady-state. Empirically, at the global level Jaramillo (2009) and Cavallo et al. (2013) find that natural disasters have no long-run impact. At the regional level, Brata et al. (2014) found that the effects of the 2004 tsunami in North Sumatra faded after a few years.

On the other hand, some of the literature describes natural disaster as a shock that can plunge a country (or region) into a situation where per capita income is too low to allow for an increase in per capita capital: this is a poverty trap dynamic. Diamond (2006) lists five factors leading to the demise of a civilization. Among these are climate change and natural disasters, which can be determining factors in the collapse of society. For example, the Maya, one of the most developed ancient civilizations, experienced intense droughts between 800 and 910. These shocks led to countless human losses. Some regions would have known losses of up to 99% of their population, contributing to the decline of this civilization. Nowadays, Poverty traps can only be observed at the microeconomic level. Carter et al. (2008), looking at droughts in Ethiopia and cyclones in Honduras, show that affected households never recovered their pre-disaster assets.

Finally, more optimistic economists see disasters as a new beginning, a chance to improve the economy and productivity. This theory is the dynamic of creative destruction à la Schumpeter, where the country, in the long run, will benefit from the disaster. It can be seen as a mechanism of building back better or rebuilding with improvements over the past. The disaster destroys machines with obsolete technology, which are replaced by more productive capital, allowing, in the end, better productivity, a source of growth (Hallegatte and Dumas, 2009; Hallegatte and Ghil, 2008; Loayza et al., 2012; Albala-Bertrand, 1993; Benson and Clay, 2004; Okuyama, 2003; Stewart et al., 2001).

However, not all countries have the financial and technological means to turn post-disaster pressure into an opportunity. At the same time, GDP growth does not necessarily imply widely shared prosperity. The evidence suggests that structural shocks usually benefit the ruling classes first. Noy (2009) describes the impact of natural disasters as more outstanding for developing countries and small economies. Indeed, countries with a skilled workforce and better governance are more likely to recover their pre-disaster growth performance.

Moreover, not all the variables studied are impacted in the same way. For example, Yang (2008) shows that official Development Assistance (ODA) and remittances increase after a hurricane. In contrast, other financial flows, such as Foreign Direct Investment (FDI) and portfolio investment, tend to decline. It should be noted that the results differ according to the disasters or countries studied (Klomp and Valckx, 2014). It is, therefore, appropriate to focus on one of them while dealing with the heterogeneity of its effects across countries for the accuracy of the analysis.

2.2 The impact of natural disasters on inequalities

The literature on the impacts of climate shocks on inequality is growing, with an empirical debate at its core to corroborate the three theories mentioned above. Many articles are consistent with the theory that the shock permanently leads part of the population into a poverty trap. Lynham et al. (2017) find that wages remained constant after the tsunami hit Hawaii in 1960, but 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-run rebuilding of assets after the 1998 Hurricane Mitch in Honduras and the prolonged drought in Ethiopia 1998. 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 and 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 and Takasaki, 2017), changes in agricultural practices and diet, and emigration of varying lengths of time (De Waal, 2005; Mahajan and Yang, 2020). However, these solutions often push households further into poverty (Banerjee et al., 2011; Lybbert and Barrett, 2011).

Conversely, some authors describe the existence of Schumpeterian creative destruction. Natural disasters can lead to adopting 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 and Conley, 2002; Thomas et al., 2007) that are effective against one-off events but less 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 and 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 and its effectiveness may be subject to financial or technical constraints that can widen the gap between those affected (Hallegatte and Przyluski, 2010). Again, there is no consensus, and the conclusions differ depending on the country and the 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), Gokmen and Morin (2019), and Baiardi and Morana (2018) focus on the impact of financial crises on income inequality. A growing literature also explains the links between pandemics and inequality (Galletta and Giommoni, 2022; Karlsson et al., 2014; Furceri et al., 2020).

Nerveless, there is a huge gap in the literature on the impact of natural disasters on inequalities. Yamamura (2015) studies the impact of natural disasters on inequality. He finds that the Gini coefficient tends to increase in the short run, then this effect disappears in the long run. Cappelli et al. (2021) highlight the existence of a vicious circle where high levels of inequality lead to being more affected by inequality-enhancing natural disasters. However, a significant gap remains regarding the impact of natural disasters on inequality at the macro level.

These two articles highlight the importance of taking endogeneity into account in the analysis. Indeed, the measurement of natural disasters can be endogenous even though they are erratic events. Neverless, the literature frequently uses the EM-DAT database, which records financial losses for property damage or the number of deaths based on declarations. Yang (2008) points out that these data can create endogeneity as they are often biased upwards to receive more significant financial flows. He advises using only meteorological data and proposes an index of the destructive potential for hurricanes. Moreover, they do not account of heterogeneity between countries and disasters. Finally, few authors in the macroeconomic literature explore the channels explaining the dynamics of inequality following a shock.

Thus, it appears that the literature on the impact of climate shocks on inequalities is incomplete. We propose an approach at the junction of the issues developed above in order to analyze in the most exogenous way possible, using meteorological data, the cumulative impact of hurricanes over the medium term and at the macroeconomic level, according to the level of development without forgetting to discuss the transmission channels.

3 Data

Our main sample covers 117 countries over 20 years (1995-2014). Our sample selection results from a trade-off between temporal depth and a large sample of countries. Indeed, inequality data for emerging and developing countries are rarely available before 1995. In addition, the available data for hurricanes ends in 2014. According to the World Bank classification, we can divide our sample into four income groups. Thus, 27 countries are low-income, 35 lower-middle-income, 24 upper-middle-income, and 45 high-income. This classification allows us to test the difference in impact according to their respective income level.

3.1 Dependent variable : Gini index

Like many in the literature (Baiardi and Morana, 2018; Gokmen and Morin, 2019; Yamamura, 2015; Cappelli et al., 2021), we use the Gini coefficient from the Standardized World Income Inequality Database (SWIID, version 4.1). The SWIID "seeks to maximize comparability while providing the broadest possible coverage of countries and years" (Solt, 2020). Solt (2020) 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 from data available in other sources. If Solt does not have enough information on a given relationship for a country, he uses information on that relationship 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 effect of redistribution policies after a disaster.

Table 1 presents some descriptive statistics about the two Gini variables. Inequality without redistribution is higher than with it, which indicates the usefulness of these policies, especially for developed countries. In connection with the Kuznets curve of inequalities, we note that they increase with the level of income and then decrease for developed countries.

3.2 Variable of interest: hurricane index

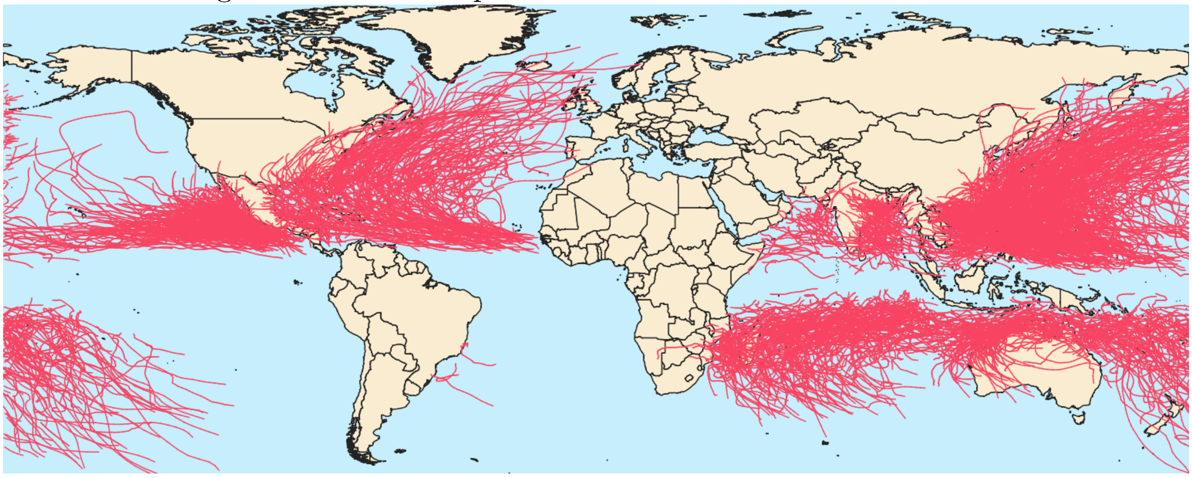
Hurricanes, typhoons, and cyclones are the same natural disasters. The difference in the name comes from the affected areas. The word hurricane is used for the North Atlantic and Northeast Pacific Oceans; typhoon for the Northwest Pacific Ocean; and cyclone for the Indian Ocean and the southern Pacific and Atlantic Oceans. Mahajan and Yang (2020) defines hurricanes as "storms that originate over tropical oceans with wind speeds greater than 33 knots" (62 km/h). They are born when the ocean's temperature is at least 26.5 degrees Celsius. The water will first evaporate and then condense into huge clouds. This heat transfer creates much energy and will cause strong winds.

Hurricanes primarily have an economic impact by destroying capital and infrastructure through storm surges, high winds, and flooding. According to Hsiang and Narita (2012), about 35% of the world's population is affected by these disasters. It is estimated to have caused more than $280 billion in damage between 1970 and 2002 (EM-DAT). The predictions are not much better: the Intergovernmental Panel on Climate Change IPCC (2018) considers that the frequency and intensity of hurricanes will increase in the coming years due to climate change and ocean warming. In addition, due to increased economic activity, N. Stern and N. H. Stern (2007) estimate that by 2050, the cost of hurricanes could reach 0.5-1% of global GDP by 2050.

As discussed above, the measurement of a natural disaster can be endogenous (Yang, 2008). Indeed, many in the literature use the EM-DAT database. It provides information on the number of deaths or the cost of natural disasters. This data type is subject to bias because it will likely suffer measurement errors. For example, a country that experiences an earthquake may overestimate the financial cost to increase the aid received. In addition, our analysis would suffer from a reverse causality problem. Countries experiencing large hurricanes might see income inequality increase. On the other hand, unequal societies are also likely to experience a more significant impact. Many of the poorest households live in precarious housing, cannot access preventive measures, and may increase the number of deaths or financial damage.

For these reasons, we decided to use others Belasen and Polachek (2009); Hsiang (2010); Hsiang and Jina (2014); Mahajan and Yang (2020) the database of Yang (2008). Yang constructed a hurricane index (HI) from meteorological data, which compiled the best tracks from the National Oceanic and Atmospheric Administration (NOAA) and the Joint Typhoon Warning Center (JTWC). The best tracks provide information about the center's maximum wind speed and geographic coordinates at six-hour intervals for each hurricane. Figure 1 shows the best tracks of hurricane for our period (1995-2014).

Figure 1: World map of Hurricane Best Tracks: 1995–2014



Source: Author's elaboration from IBTrACS database

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

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

$HI_{i,t}$ is the destructive potential of the 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 divide by the total population $N_{i,t}$. In this equation $x_{j,s,i,t}$ 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:

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

He normalized the index by the maximum wind speed (max) observed in the dataset (166.65 knots). He added 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 for each 0.25 degree N_g grid point from the Socioeconomic Data and Applications Center (SEDAC) at Columbia University :

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

This methodology allows to measure hurricane events per capita weighted by intensity, which is an exogenous variable.

Table 1 presents some descriptive statistics for our variable HI. We note that there is a significant disparity in the impact between countries. Forty-six countries in our sample experienced over the period from 1995 to 2014 at least one hurricane. Countries are affected regardless of their income level. However, the developed ones experience, in absolute and in proportion, more hurricanes. Moreover, among the affected countries, the high standard deviation indicates substantial heterogeneity in the 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, democratic states are more likely to reduce inequality because they provide the right to vote and give a voice to poor individuals. 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 the value of 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 is mixed on the effect of FDI on inequality. Third, we include a variable for portfolio investment flows (net portfolio investment as a percentage of GDP; World Bank). Finally, according to the Kuznets curve, inequality first increases with economic development. It then decreases when a country reaches a given level of development, meaning that there is an inverted U-shaped relationship between per capita income and inequality. We, therefore, control for (log) GDP per capita (World Bank).

4 Empirical strategy

Our empirical strategy is based on ordinary least squares (OLS) estimation of a structural model explaining income inequality with the Local Projections (LP) method of Jordà (2005). 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 we employ an orthogonal measure of the hurricane

Table 1: Descriptive statistics

	Descriptive statistics				
	N	Mean	SD	Min	Max
			All sample		
Hurricane Index	2,280	0.001506	0.0108932	0	0.201552
Hurricane Index (>0)	369	0.0093052	0.0257311	4.04e-10	0.201552
Disposable Gini	2,280	0.3890018	0.0911964	0.22	0.671
Market Gini	2,280	0.4661487	0.0682745	0.219	0.724
GDP per capita	2,280	13365.36	17822.81	215.7467	105454.7
			Low income countries		
Hurricane Index	496	0.0003801	0.0038282	0	0.0798339
Hurricane Index (>0)	61	0.003091	0.0106013	1.69e-08	0.0798339
Disposable Gini	496	0.4216734	0.0604526	0.296	0.555
Market Gini	496	0.4503024	0.0641439	0.243	0.604
			Lower-middle income countries		
Hurricane Index	640	0.0019121	0.0139422	0	0.201552
Hurricane Index (>0)	105	0.0116549	0.0328588	4.04e-10	0.2015529
Disposable Gini	640	0.4283453	0.085703	0.22	0.671
Market Gini	640	0.4643453	0.079077	0.219	0.708
			Upper-middle income countries		
Hurricane Index	483	0.0014225	0.0106408	0	0.1518784
Hurricane Index (>0)	60	0.0114514	0.0284292	2.18e-06	0.1518784
Disposable Gini	483	0.4117723	0.0971431	0.232	0.664
Market Gini	483	0.483029	0.0805679	0.324	0.724
			High income countries		
Hurricane Index	661	0.0020185	0.0112463	0	0.1634536
Hurricane Index (>0)	143	0.0093301	0.0227851	2.85e-08	0.1634536
Disposable Gini	661	0.3097534	0.0547881	0.22	0.507
Market Gini	661	0.4674508	0.042583	0.31	0.563

Notes: Descriptive statistics of hurricane index, disposable Gini (post-tax transfers), market Gini (pre-tax transfers) and GDP per capita according to subgroup from the World Bank.
Source: Authors' elaboration.

to the Gini index. The model is constructed as follows:

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

The LP is made from the year before the hurricane to $h = 0, ..., 5$ time horizon of 5 years after the storm. Given the temporal depth of our sample, we can only analyze the impact of hurricanes over the medium term. The left-hand variable gives the cumulative change from $t-1$ to $t+h$ of the Gini index. $\beta^h HI_{i,t}$ is the coefficient associated with the hurricane index. $HI \times GDP_{i,t-1}$ is the multiplicative variable between the hurricane index and the logarithm of GDP per capita to test whether the impact is different depending on the wealth level of the affected country. X is a set of control variables described above plus GDP squared to test the Kuznets inequality curve. All control variables are lagged to minimize the reverse causality problem. α_i^h, ρ_t^h are respectively the country and time fixed effects. $\Omega_i^h \times t$ t allows us to account for country-specific patterns of inequality growth (Hsiang and 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 gives us the results for the impact of the hurricanes on the market Gini. These regressions allow us to see the impact of the shock on inequality without redistribution. We find that following a hurricane, inequalities increase cumulatively up to one year after the impact. We can interpret the coefficient as follows: an increase of one standard deviation of HI (0.026) would cumulatively increase the market Gini by 0.003 (0.112/38.46) after the shock. This seems relatively small, but it corresponds to a cumulative increase of 0.65% in the market Gini one year after the storm (as the average market Gini=0.466).

Looking at the dynamics of the impact, the effect of the hurricane is no longer significant three years after the impact. Moreover, we notice that the inequalities decrease four years after the hurricane.

The multiplicative variable between HI and GDP per capita allows us to test whether there is heterogeneity between countries' income levels. Its coefficient is positive (negative) in years when the coefficient of HI is negative (positive). One year after the cyclone, countries with a higher GDP per capita experienced a lesser increase in inequality or even a reduction. The threshold at which inequality decreases after the hurricane is 1748 dollars for the market Gini. Almost 25% of observations of our sample fall below this threshold.

Poorest countries often have precarious infrastructures, housing less resistant to natural disasters, and are essentially agricultural economies. This is especially true for the poorest part of the population in these countries. Thus, they would be more likely to suffer more significant damage following a hurricane and adopt adaptation strategies to increase their incomes in the following years.

Conversely, the increase in market inequalities four years after the shock would only concern the more wealthy countries. Indeed, the positive and significant coefficient of the multiplicative variable indicates that beyond this level of GDP per capita, the impact of a hurricane would increase inequality for the wealthiest countries four years after the shock. This result is fascinating and suggests a Schumpeterian effect with a "built back better" mechanism: following a hurricane, the capital is destroyed. Then it is replaced by more efficient capital, allowing an increase in capital income, which generally goes to the wealthiest fringe of the population. Indeed, modern economies are more intense in capital. It is mainly held by the wealthiest individuals in the population, who would then experience a more significant reduction in their income from capital, which could explain why inequalities tend to decrease in the wealthiest countries.

Like others in the literature (Bodea et al., 2021), few control variables have a strong and consistent effect on inequality. This is likely because inequality is highly sticky, and our empirical approach considers country-specific inequality growth patterns.

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.

Table 2: Cumulative effect of Hurricane index on market Gini

	(Market Gini)					
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)
Hurricane index × (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	1,784	1,683	1,582	1,481	1,381	1,282

Notes: Market Gini refers to pre taxes and transfers Gini index. All the coefficients are expressed in cumulative form. Average and standard deviation (in parentheses); *** p <0.01, ** p <0.05, * p <0.1.
Source: Authors' elaboration.

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 entire sample. Thus, we can see a positive impact, increasing and significant at 1%, of the hurricane on the Gini disposable up to 3 years after the shock. The magnitude of the coefficients is more considerable than for the market Gini (0.176 vs. 0.119 one year after the shock). Looking at the dynamics of the impact, the effect of the hurricane is no longer significant three years after the impact.

Thus, these results compared with those of the Gini market are surprising and counterintuitive and tend to suggest that the redistribution policy accentuates inequalities since, in its absence, market inequalities would increase less and even decrease four years after the hurricane. There are several reasons for this poor redistribution policy: a reduction in social transfers, a reduction in taxes for the richest, and the capture of resources by one part of the population (cartel, corruption).

However, these results must be qualified by the presence of the multiplicative variable between HI and GDP per capita. As for the market Gini's regressions, the coefficient in front of the multiplicative variable is negative and significant for the first three years. This suggests that the impact of storms on the Gini disposable is less intense the higher the country's GDP per capita. It is important to note that the coefficient in front of the multiplicative variable is higher for the disposable Gini than for the Market Gini (-0.021 vs. -0.015), the poor redistribution would concern only the least wealthy countries.

In developed countries, disposable inequalities would decrease more than market ones. So, redistribution policies are more efficient in more prosperous countries because they have more flexible budget constraints, a better borrowing capacity, or a better taxation system. This element would allow them to smooth the shock better and even reduce inequalities.

This global analysis of the results shows that there is a lousy redistribution policy but that this only concerns the least wealthy countries in our sample. It, therefore, appears attractive to analyze by sub-group of countries according to their income levels.

Figure I.1 in appendix give us the regression without the interaction term between HI and the level of GDP per capita. We notice that hurricane no longer impact disposable inequalities. That underline that our results are conditional to the GDP per capita.

5.3 Hurricane intensity and frequency

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

The Yang (2008) database allows us to know the number of hurricanes, by country and year, since 1950. The same is true for the HI variable. We summed up each variable by country between

Table 3: Cumulative effect of Hurricane index on disposable Gini

	(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)
Hurricane index × (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	1,784	1,683	1,582	1,481	1,381	1,282

Notes: Disposable Gini refers to after taxes and transfers Gini index. All the coefficients are expressed in cumulative form. Average and standard deviation (in parentheses); *** p <0.01, ** p <0.05, * p <0.1.
Source: Authors' elaboration.

1950 and 2014. Table 4 presents the descriptive statistics for these variables.

Analyzing the distribution of cumulative hurricane frequency and intensity across countries over the period tells us that, on average, countries experienced twenty hurricanes. The high standard deviation nuances the previous result and highlights a substantial disparity between countries. In addition, the countries that have experienced more than 300 hurricanes (almost 5 per year) are concentrated in the 99th percentile. The observation is the same for the cumulative intensity. These results suggest that hurricanes disproportionately affect the top 1% of our sample by their occurrence and intensity.

Thus, it is logical to think that there could be an unobservable heterogeneity for these countries (i.e., poverty traps, more resistant infrastructures, and better resilience), leading to the dynamics

Table 4: Descriptive statistics of the cumulative occurrence frequency of hurricane

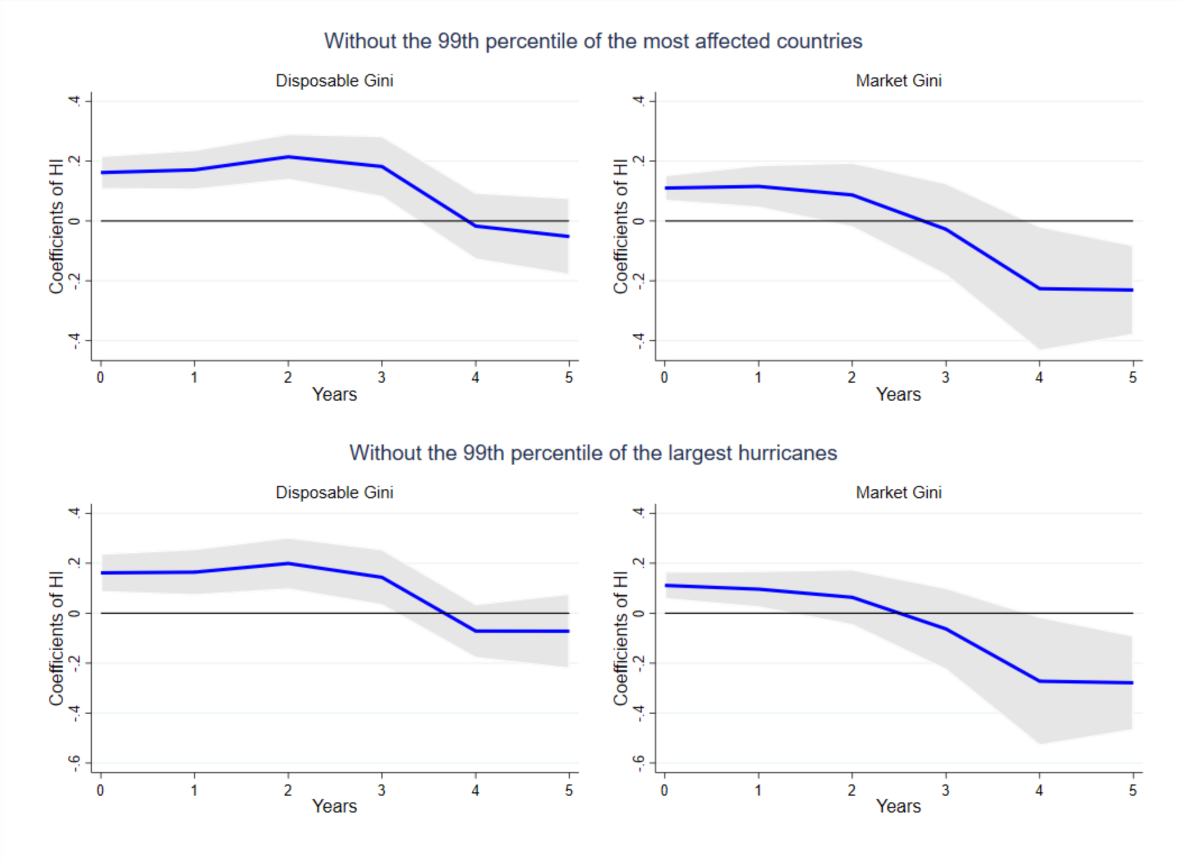
	Mean	SD	Min	p50	p75	p90	p95	p99	Max	N
Cumulative occurence of storms	20.49	60.13	0.00	0.00	5.00	36.00	151.00	320.00	342.00	2280
Cumulative intensity of storms	0.07	0.20	0.00	0.00	0.00	0.17	0.46	1.09	1.17	2280

of the hurricanes are not 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 the 99th percentile of the countries that experienced the largest hurricanes. As shown in Figure 2, the dynamics of inequality after hurricanes remain stable; neither the coefficients nor their magnitudes and significances change.

One reason that could explain this is that countries that are more frequently affected in terms of occurrence or intensity have adopted a resilience to hurricanes so that these phenomena no longer impact inequalities.

Figure 2: Cumulative Effect of Hurricane Index on disposable and market Gini



Point Estimators and 90%-Confidence Intervals (Full Country Sample, Twoway FE Panel Regression with Controls)

Thus we have seen that post-transfer and tax inequalities increase more after a hurricane than market inequalities, which tend to decrease after four years. This poor redistribution only concerns the least wealthy countries since our multiplicative variable with GDP per capita is significant and of the opposite sign with the HI coefficient. According to these results, an analysis by the subgroups of countries seems more than relevant.

6 Heterogeneity of impact by the level of development.

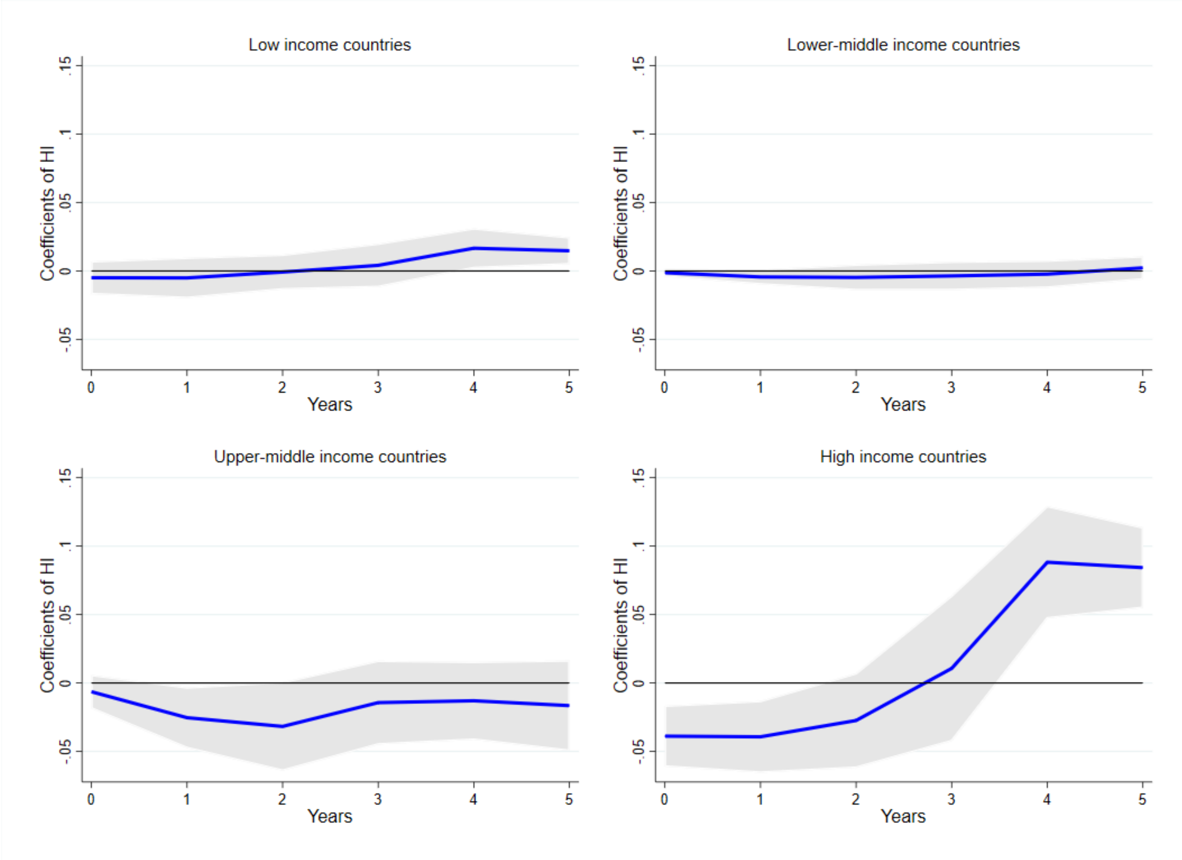
6.1 The effect of hurricanes on pre-redistribution inequalities by country subgroup

We use the World Bank classification to create four groups of countries: 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.

Figure 3 presents a subgroup analysis for the market Gini to see the dynamics of inequality in the absence of a redistribution policy. Without redistribution, the hurricane does not affect inequality for the group of low-income countries. We see a slight decline one year after the storm for the upper-middle-income group. This can be explained by capital destruction but without a rebuilding effect.

For the high-income countries, we see that inequality falls one year after the shock and increases four years later. This result could be seen as a Schumpeterian effect of creative destruction can explain this inequality dynamic. After the shock, the destroyed capital is replaced by a more productive one, allowing the income of the richest to increase.

Figure 3: Cumulative Effect of Hurricane Index on market Gini



Point Estimators and 90%-Confidence Intervals (Country Sub samples, Twoway FE Panel Regression with Controls)

6.2 The effect of hurricanes on post redistribution inequality by country subgroup

Figure 4 presents the results for the Gini disposable according to the four groups. We can see that inequality decreases cumulatively in low-income countries one year and, three to five years after the shock. This result could be explained by an inflow of official development assistance or migrant transfers to the poorest part of the population to smooth out the shock's adverse effects and reduce inequality.

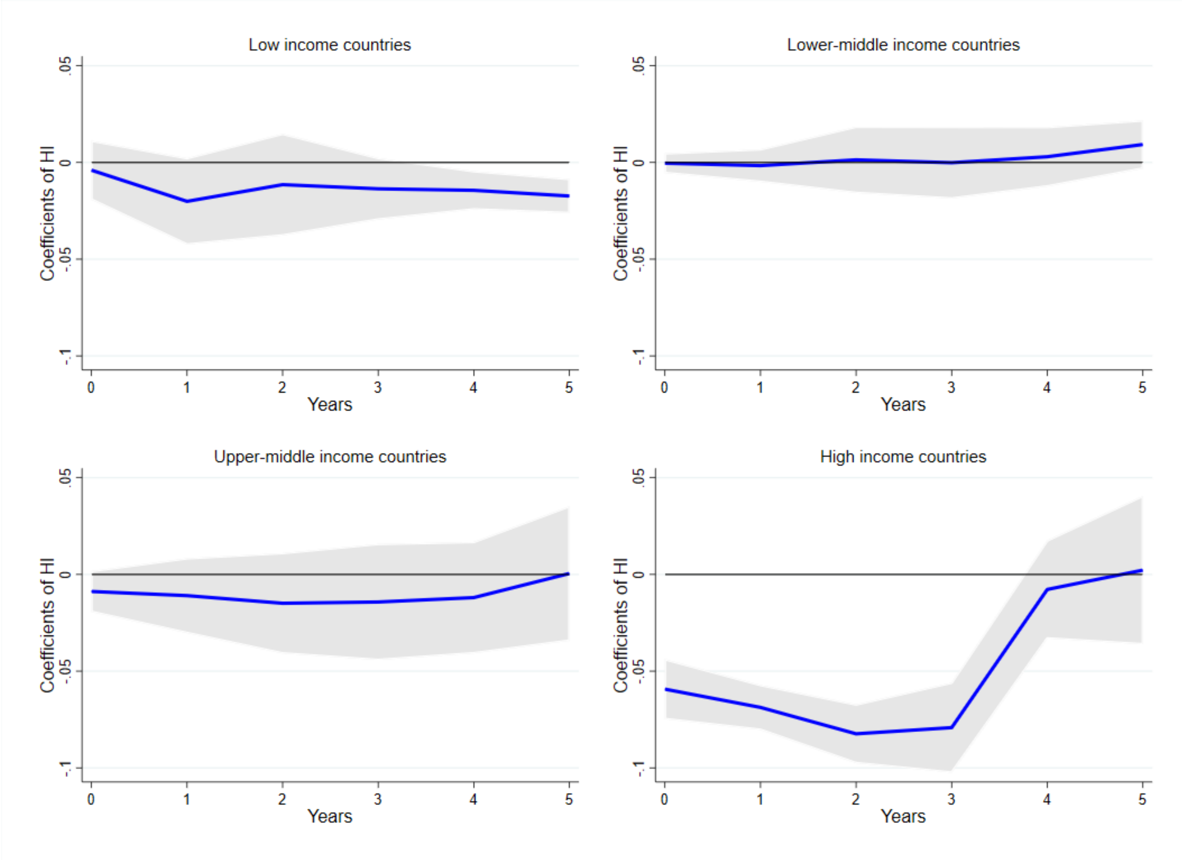
We find no effect of the hurricane on the disposable Gini for the lower and upper-middle-income groups. For the upper-middle-income group, we find the paradox developed in the main results where inequality only decreases in the absence of transfers. Thus, we can conclude that redistribution is poorly used, but it is difficult to explain the mechanism by which this happens. Transfers may be misdirected or captured by a group of individuals.

For the high-income group, there is a cumulative decline in inequality up to three years after the shock. As said before, this result may come from rich countries having a highly capital-intensive productive system. As the hurricane destroys mostly capital, the primary income source for the wealthiest part of the population, inequality would tend to fall.

In addition, the positive impact of transfers should be emphasized since the fall in inequality is more remarkable for the disposable Gini than for the market. Also, the transfer policy avoids a surge in inequality, as is the case for the market Gini. Developed countries have the means to pursue an efficient redistribution policy. They often have a complete redistribution system because of a lesser budget constraint, a more developed tax system, and a greater capacity to borrow.

There are different dynamics of inequality depending on the level of income. The role of redistribution and transfers is essential for low and high-income countries, without which inequalities would not be impacted or even increase. For upper-middle-income countries, it seems that redistribution is not efficient. Thus, we find the conclusions developed for the total sample results.

Figure 4: Cumulative Effect of Hurricane Index on disposable Gini

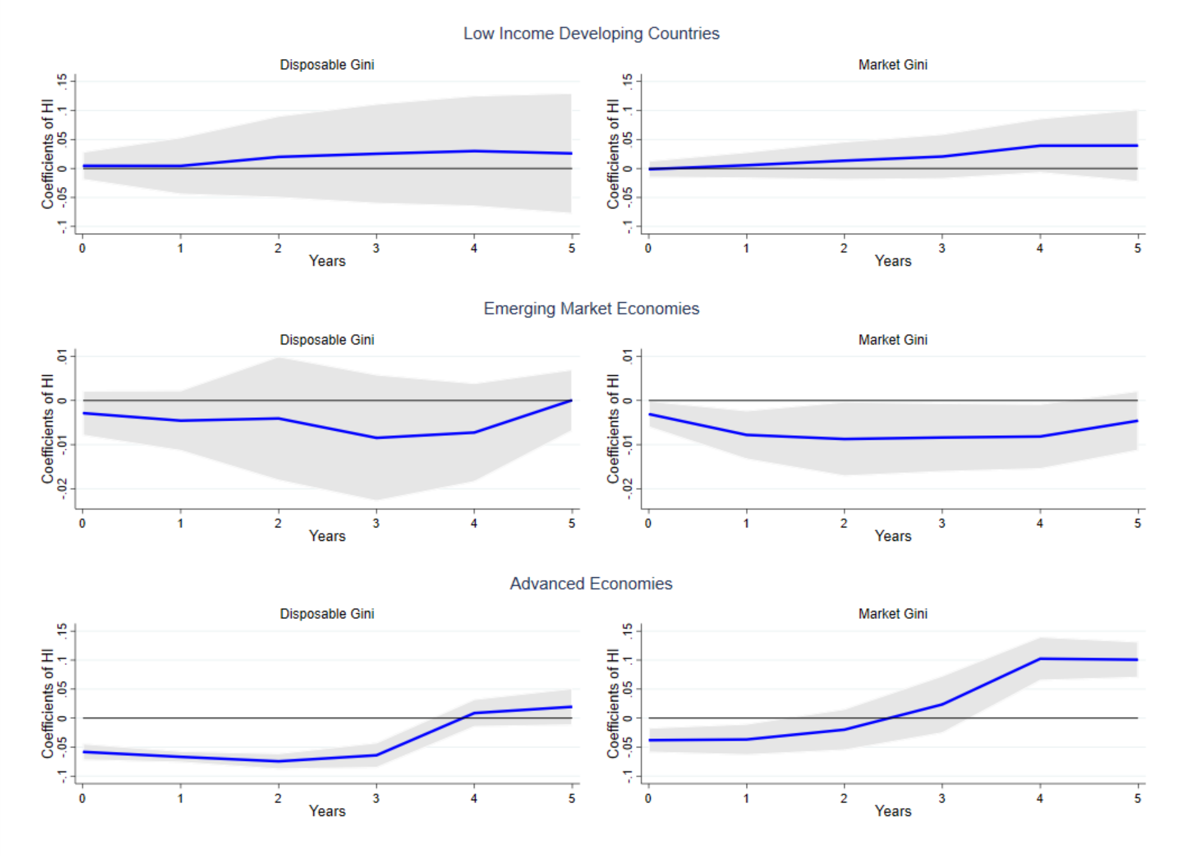


Point Estimators and 90%-Confidence Intervals (Country Sub samples, Twoway FE Panel Regression with Controls)

6.3 Change in classification

Figure 5 presents the disposable and market Gini results, for which we have replaced the World Bank classification with the IMF classification. This information allows us to test the sensitivity of our results across groups. The IMF classifies countries into three categories: the Low-Income Developing Countries, the Emerging Market Economies, and the Advanced Economies. Respectively, the countries are divided into groups, each of which is 28, 54, and 35 countries. As we can see, this change in classification alters our results: we do not find the significant effect of the hurricane on disposable incomes for the low-income developing countries. On the other hand, the effects described above remain identical for the other two groups. Thus, we can conclude that our results are relatively robust to a change in classification.

Figure 5: Cumulative Effect of Hurricane Index on disposable market Gini with IMF classification



Point Estimators and 90%-Confidence Intervals (Country Sub samples, Twoway FE Panel Regression with Controls)

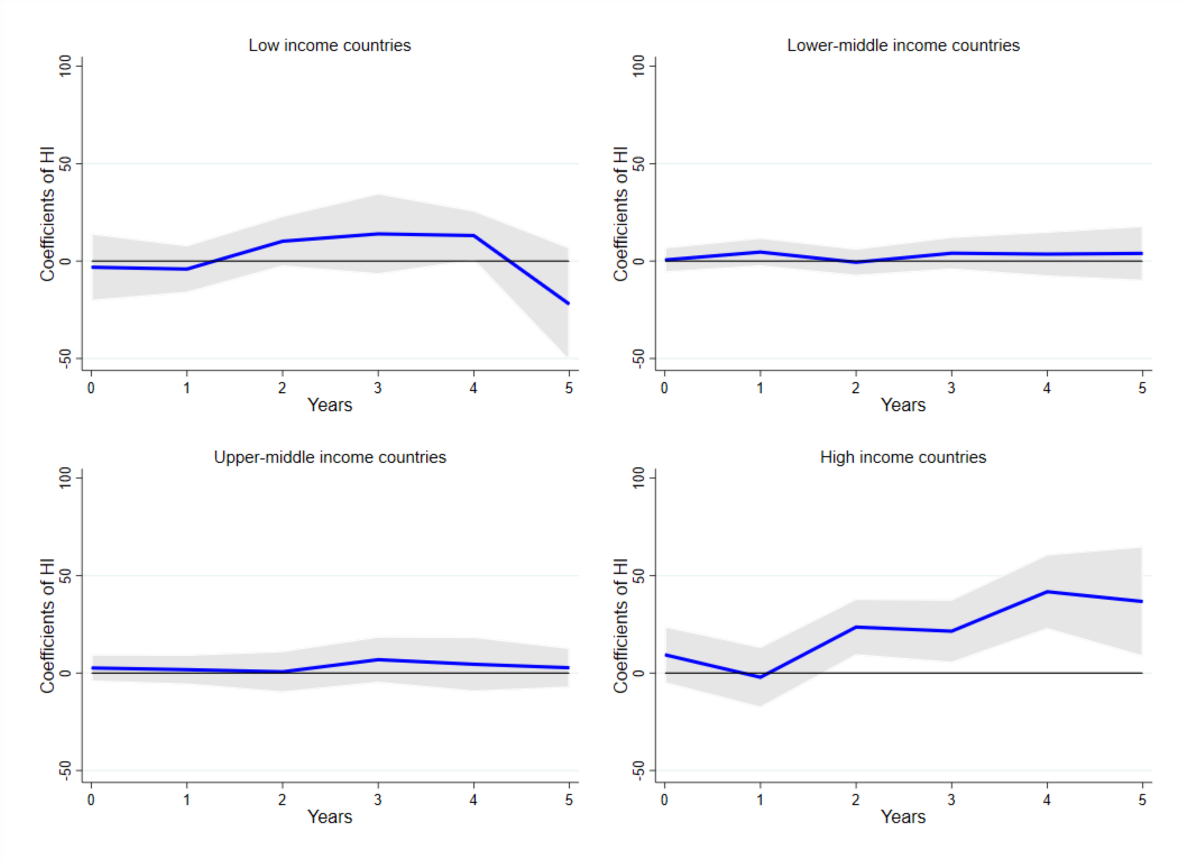
7 Transmission channels and discussion

As we have seen, post-tax and post-transfer inequality decline for low- and high-income countries. However, through what channels does this decline take place? We will present here three different channels: social transfers, ODA, and remittances that can explain this dynamic following a hurricane. We retain the subgroup analysis to account for the specific dynamics of each income level outlined above. To do this, alternatively, we change our dependent variable in our structural model by subsidies and other transfers, remittances, and ODA. These variables are expressed as a percentage of GDP and come from the World Bank

7.1 Channel of social transfers

Figure 6 shows the impact of the hurricanes on subsidies and other transfers for each subgroup. We can see that the hurricanes cumulatively increase subsidies two years after the shock, only for rich countries. We note that this increase corresponds to the time when market inequalities increase. This result corroborates the built-back better hypothesis developed earlier, according to which following a hurricane, the destroyed capital affects mainly the richest fringe of the population, leading to a decline in inequality. In their reconstruction efforts, investors replace the destroyed capital with more productive technologies, increasing their income and market inequalities. Thus, social transfers are correctly employed in these economies to avoid increasing inequality. The fact that typhoons do not affect subsidies for other groups is not surprising. Social transfers are easier to mobilize in countries with looser budget constraints and a sound tax system.

Figure 6: Cumulative Effect of Hurricane Index on subsidies and other transfers

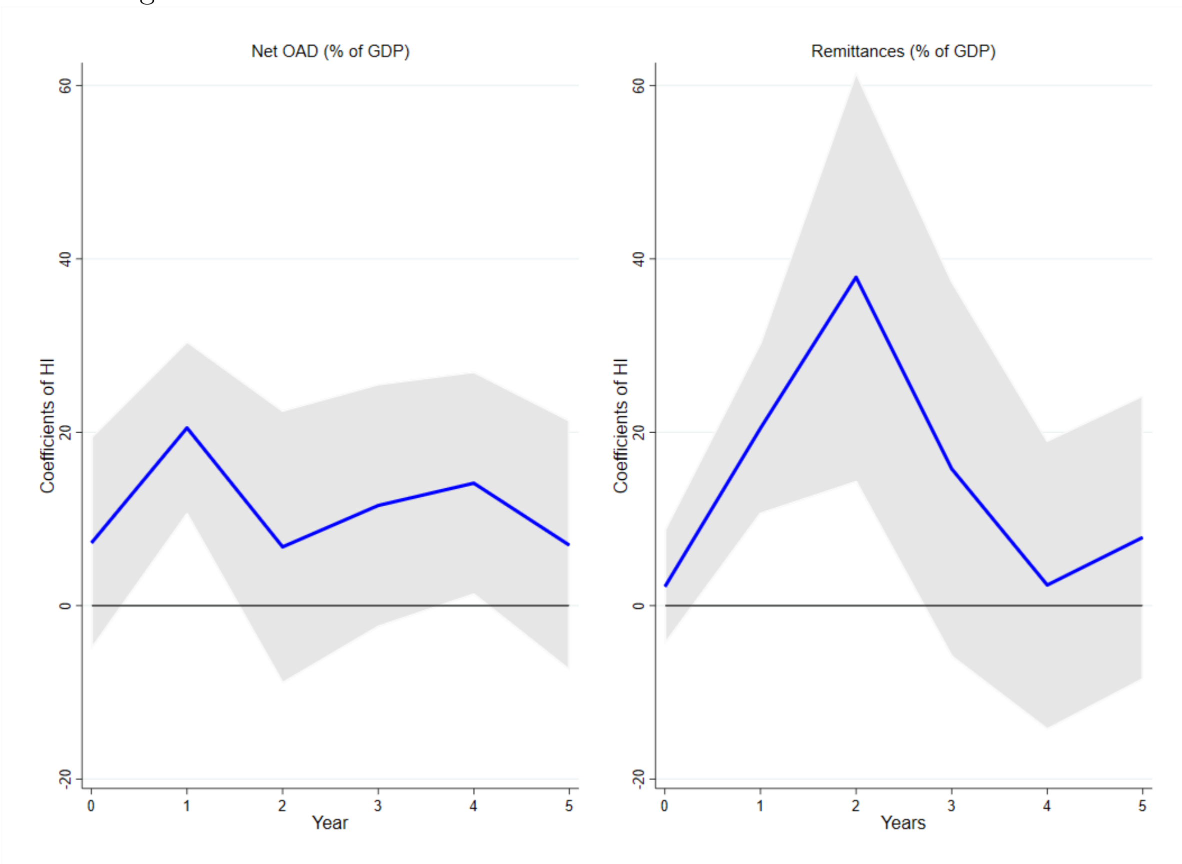


Point Estimators and 90%-Confidence Intervals (Country Sub samples, Twoway FE Panel Regression with Controls)

7.2 OAD and remittances channel

In order to explain the decline in disposable inequality in low-income countries, we will first analyze the effect of ODA. The left-hand side of Figure 7 presents the impact of the hurricanes on ODA. We see that in the year following the shock, ODA increases in the affected country. This international solidarity smoothes out the shock and targets mainly the poorest part of the population. Looking at the right-hand side of Figure 6, we see that cyclones increase remittances for the two years following the shock. This countercyclical effect can also explain the drop in the Gini disposable. Indeed, for developing countries, remittances represent a significant part of access to finance. Migrants have often maintained a link with the families left behind. In a context where government transfers are highly complicated, migrants play this role. Thus, this double influx of international financing could increase the income of individuals in these countries in a sustainable way, leading to a decrease in post-transfer inequalities.

Figure 7: Cumulative Effect of Hurricane Index on OAD remittances



Point Estimators and 90%-Confidence Intervals (Low income countries, Twoway FE Panel Regression with Controls)

8 Conclusion

Although the economic effects of natural disasters have been subject to increasing interest throughout the last decade, little knowledge on the medium-run effects on inequalities has yet been available. This paper helps fill this gap by delivering a systematic analysis of the effects of tropical storms. Using a genuinely exogenous hurricane index derived from a meteorological database, we find strong empirical evidence in favor of the hypothesis that hurricanes exert conditional effects on the afflicted countries depending their level of GDP.

We highlight the role of redistribution policies in smoothing the impact of storms. Then, pre-redistribution inequalities tend to increase the year following the strike and decrease four years after. Conversely, hurricanes tend only to higher disposable inequalities up to three years after. These results are robust to the exclusion of the most touched countries.

However, the significant contribution of the paper is to show that the inequality effects of tropical storms differ substantially between countries on different levels of development. For low-income countries, we find that disposable Gini tends to decrease while the market one remains insignificant, which could be explained by a surge in remittances and OAD the year after the strike.

For the high-income group, market and disposable inequality tend to decrease the year after the shock. We find an increase in market Gini four years later, which points to a Schumpeterian effect of creative destruction. We show that subsidies and transfers increase, which supports the hypothesis that redistributive policy is central to smoothing natural disasters.

Nevertheless, in some cases, there is poor redistribution: the impact of the hurricane would be less intense in the absence of redistribution. This mechanism may result from the capture of resources by groups, but this could not be demonstrated here.

Thus, these results are hopeful in an uncertain climate context and underline the significant role of redistribution.

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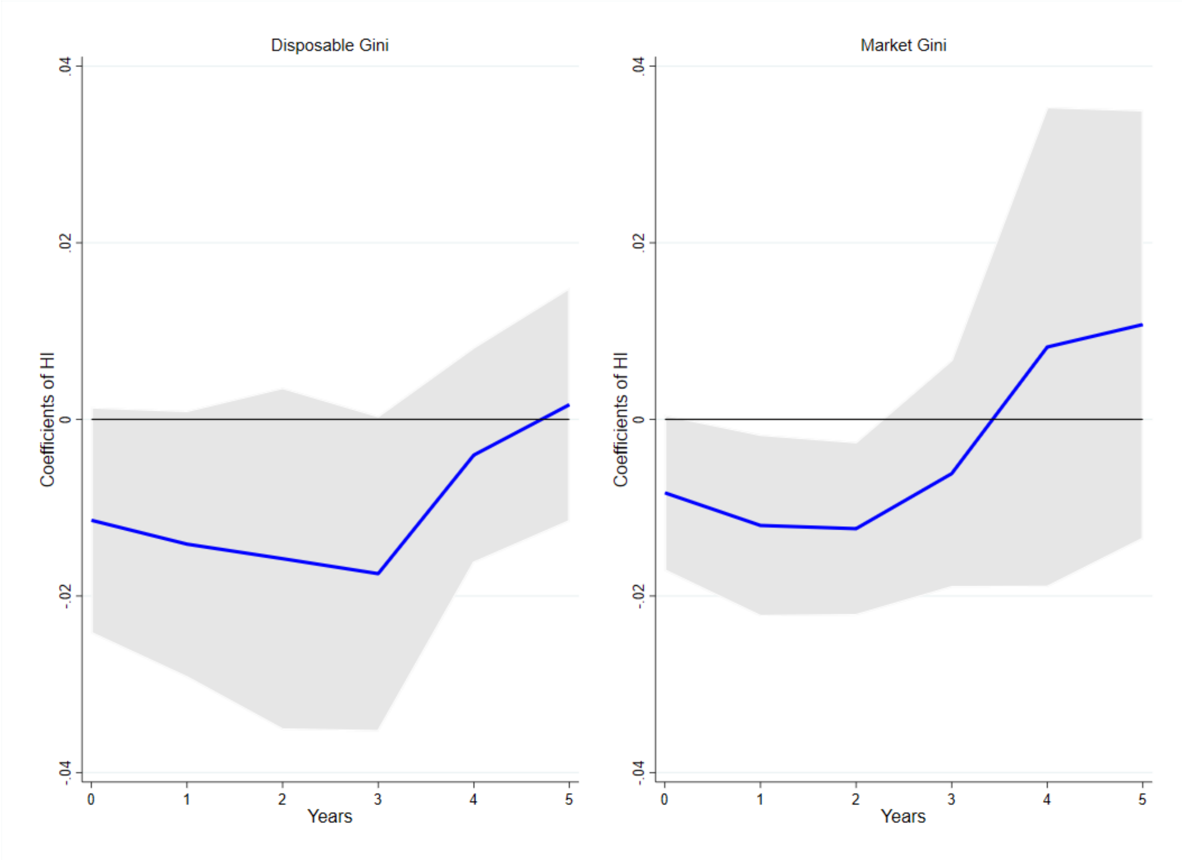
9 Appendix

Figure I.1: Cumulative Effect of Hurricane Index on disposable and market Gini



Point Estimators and 90%-Confidence Intervals (Country all sample, Twoway FE Panel Regression without interactive term.)