Introduction

Within-country income inequality has been rising over several decades in many countries. The Covid-19 pandemic has only exacerbated these long-term trends by hitting individuals employed in more contact-intensive sectors, the lower-skilled, women, and other vulnerable groups particularly hard (Chapter 3, 2021 April WEO). Other major epidemics in this century have also had adverse macroeconomic effects (World Bank, 2020) and lead to a significant and persistent increase in income inequality (Furceri et. al., 2021). In Sub-Saharan Africa, major disasters seem to have had heterogeneous macroeconomic effects in the short-run but an unambiguously negative effect on long-run growth and social development (SSA REO, 2019).

Inequality and natural disasters have the potential to create a vicious cycle (IMF, 2021). Pre-existing social and economic vulnerabilities tend to amplify the immediate effects of shocks as poor households tend to be more exposed to natural disasters and often have little means to prepare for or react to them (Masozera, Bailey and Kerchner, 2007). Being at the intersection of low socioeconomic status and low income raises the ex-ante probability of disaster incidence and lowers the ex-post ability to absorb economic losses and to make the needed investments to bounce back—a double hit. At the macro level, financial vulnerabilities, stemming from high public debt burdens and low fiscal buffers, can limit the ability to respond to severe disasters in many emerging markets and developing economies (EMDEs) (Otker and Loyola, 2016). Poor health care, high informality—70 percent of the labor force in many EMDEs (World Bank, 2020)—widespread poverty and food insecurity are important shock amplifiers in these countries.

When and how do natural disasters worsen within-country income inequality and how persistent are these effects? We answer this question in several steps. First, we develop a conceptual framework outlining the main channels—both macroeconomic and socioeconomic—through which natural disasters may have distributional effects and survey the pertinent literature. Next, we empirically analyze when natural disasters affect within-country income inequality in advanced economies (AEs) and in emerging and developing economies (EMDEs), respectively. To do so, we build a comprehensive dataset of natural disasters from the past four decades for 180 AEs and EMDEs, expanding the existing EM-DAT database with those of major pandemic/epidemic events from Furceri et al. (2021). Next, we empirically assess their effect on income inequality by running a systematic search for plausible associations using local projections with different disaster definitions and severity cutoffs. Finally, we complement our macro analysis with a descriptive event analysis, illustrating heterogeneous labor market effects of major natural disasters over the last four decades in affected versus non-affected U.S. states, using data from the U.S. Current Population Survey and EMDAT for the United States. This allows us to focus on more granular distributional effects of major natural disasters along socioeconomic strata.

Our main findings from the local projections are as follows. First, within-country income inequality, as proxied by the market Gini, tends to increase significantly following severe and repeated severe natural disasters. While the effects in AEs are detectable for severe disasters alone, EMDEs only experience an increase in income inequality if the severe disaster coincides with a growth slowdown or is repeated at least twice within the year. Moreover, we find suggestive evidence for heterogeneous effects across types of natural disasters. Severe epidemics, droughts, and floods tend to increase income inequality in EMDEs while severe earthquakes are relevant in AEs. In short, the effect of natural disasters on income inequality varies based on their severity, whether they co-occur with growth slowdowns, their frequency of occurrence within the same year, the type of disaster, and the country's income status. Moreover, the results are sensitive to what we define to constitute a severe disaster. The estimated size of the increase in inequality is substantive and larger than the increase in the Gini that was

observed before and after the GFC on average for AEs, and before and after the "taper tantrum" for EMDCs.[1] Another feature of the data is that the estimated natural disaster effects on inequality are consistently larger in AEs than in EMs. One reason could be that a general lack of disaster insurance in EMDEs implies that everybody is vulnerable to disasters in EMDEs but this hypothesis is not explored in this paper. Moreover, we likely pick up disasters with a much higher destructive potential in AEs than in EMDEs because our severity metrics are based on realized destruction indicators.

Results from an US states event analysis corroborate the notion that natural disasters likely disproportionately affect members of disadvantaged groups. Specifically, we find that employment of less educated individuals, women, racial minorities and young individuals tends to suffer in the aftermath of disasters. These findings resonate with the evidence for significant gender and racial inequality in the labor market impact of the COVID-19 pandemic (IMF, 2020) as well as the evidence of distributional effects of major disasters on marginalized groups (Ibarraran et al., 2009).

Several caveats are in order. First, the results are likely affected by measurement errors due to well-known data quality issues in the Gini coefficients from the SWIID database (Jenkins, 2015, UN, 2018), with issues such as data imputations likely more widespread for EMDEs. We accept this drawback against the background of the comprehensive country coverage of SWIID, which is key for our international dataset. Second, the results for AEs and EMDEs are not directly comparable as they are likely based on shocks with different intensities in the sense of objective destructive potential (our severity metrics are based on realized destruction indicators as EMDAT lacks a measure of destructive potential of natural disasters). Third, proxying inequality via Gini coefficients may obscure other important heterogeneities along the distribution of income. Strata such as gender, race and socioeconomic status might be more meaningful and/or offer additional insights into the root causes of these inequalities. We address this via our U.S. states analysis. Finally, while our empirical approach allows for a flexible and easy exploration of the relationship under study, it is important to stress that it is not a tool for causal inference. Improvements upon these caveats would be fruitful avenues for future work.

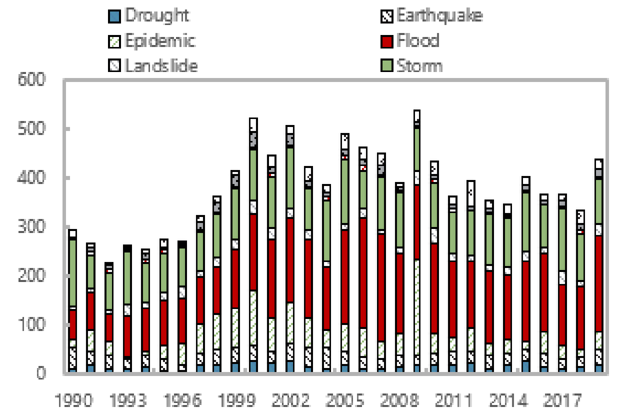
The rest of the paper is structured as follows: Section II highlights some key stylized facts about major natural disasters to motivate the discussion. Section III discusses the conceptual framework and surveys the pertinent literature. Section IV explains our empirical strategy for the local projections, discusses the main results and reports some descriptive evidence on socioeconomic vulnerabilities in the U.S. The final section concludes.

[1] The average percent increase in the market Gini across AEs before and after GFC (2007-2009) was around 0.9 percent, while that across EMDCs before and after the "taper tantrum" episode (2013-2015) was 0.6 percent. The peak inequality effects of severe disasters co-occurring with growth-slowdowns are estimated at around 4 percent for AEs and at slightly above 1 percent for EMDEs three years after the shock, respectively (Figure 10, pp. 24).

Stylized Facts of Natural Disasters and Inequality

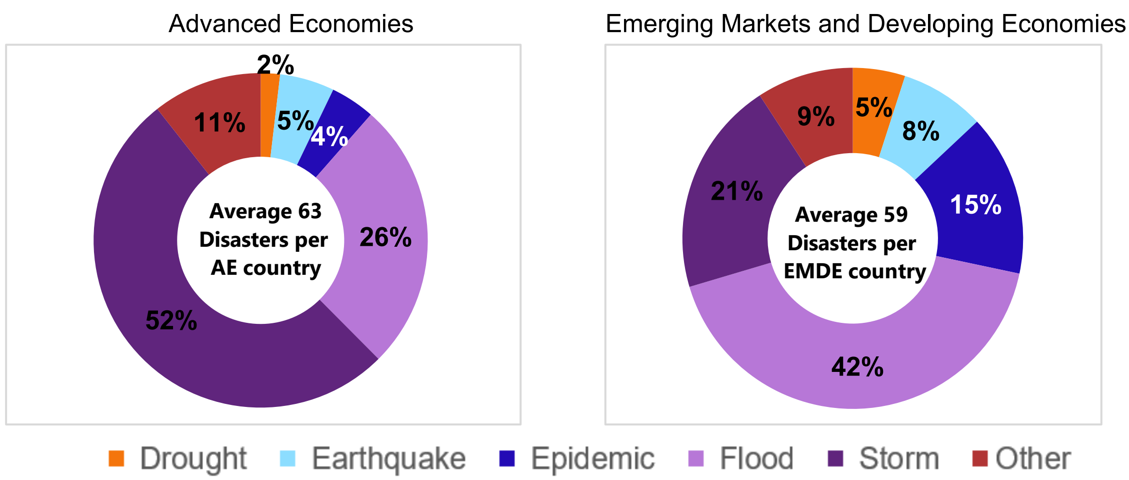
This section illustrates natural disasters globally from 1990-2019, focusing on their type, frequency, location, and severity, based on the share of affected population as well as the direct economic costs to affected countries' GDP. Natural disasters, defined as natural events leading to damage, dislocation or loss of life, are grouped in 8 major categories in the EM-DAT database: droughts, earthquakes, epidemics, floods, landslides, storms, volcanos, and wildfires.[2] The EM-DAT database records 11,739 natural disasters between 1990 and 2019 globally. The number of disasters ranges between 300-400 per year except for 2009, when the number of disasters was around 500, while in the early 1990s, natural disasters ranged slightly below 300 per year (Figure 1). The EM-DAT database includes multiple major natural disasters and epidemics, such as Hurricane Katrina in 2005 and Storm Jonas in 2016.

Figure 1. Natural Disasters Over Time and Across Countries (1990−2019)



Sources: EMDAT and IMF Staff Calculation.
Note: The number of natural disasters for a given year is calculated as the sum of disaster incidences across all countries.

Figure 2. Incidence of Natural Disasters by Types and Country Groups (1990−2019)



Sources: EMDAT and IMF Staff Calculation.

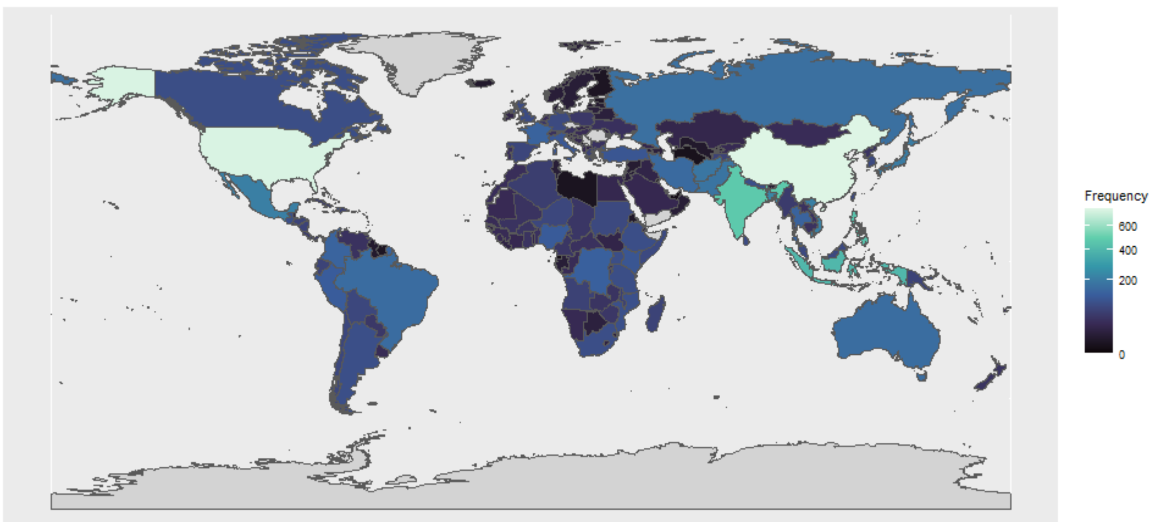
The incidence of natural disasters varies by frequency and type. Over 1990-2019, emerging and developing economies (EMDEs) suffered many more natural disasters (8707) compared to advanced countries (AEs)

[2] The paper relies on the EM-DAT disaster database (http://www.emdat.be/), including, the definition of events and categorization. Please refer to Appendix I for more information on EM-DAT database and additional data sources for the paper.

(2251), though AEs were hit on average by 63 disasters per country compared to 59 disasters per country in EMDEs. Overall, storms and floods have historically been the most frequent disasters globally. Figure 2 also shows a higher proportion of epidemics, floods, droughts, and earthquakes in EMDEs.

In terms of geographical regions, natural disasters are more frequent in East Asia and Pacific, Sub-Saharan Africa, and Latin America and Caribbean, where the average incidence of natural disasters is well above the global average, ranging between 837 and 3833 disasters per country (Figure 3). At the country level, the United States and China exhibit the highest incidence of disasters (above 750) over the 1990-2019 period, followed by countries from Southeast Asia, Sub-Saharan Africa, and Caribbean countries (India experienced 473 disasters, Mexico 208, and the Democratic Republic of Congo 129).

Figure 3. Geographical Distribution of Natural Disasters (1990–2019)

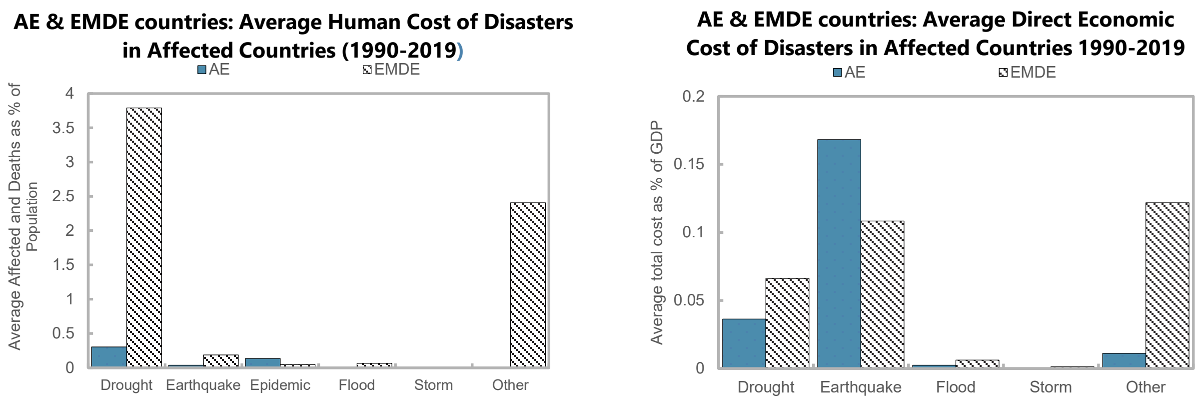


Source: EM-DAT and IMF Staff Calculations.
Note: The disasters include the number of disasters per country across 1990-2019.

Natural disasters also vary by the severity of their social and direct economic costs. We proxy disasters severity by the number of affected population (including death toll) as well as the current US$ value of the direct economic damages of disasters from the EM-DAT database. Figure 4 shows the average social and direct economic costs of disasters as a share of affected population (including death toll) in affected countries' population and the share of direct economic damages in affected countries' GDP by disaster types and by affected countries' income status. For some disasters, e.g., epidemics, the social costs of disasters is far more relevant, while for others, e.g., floods and storms, direct economic costs (damages to physical assets) seem more important. In line with the literature, Figure 4 documents variations in social and direct economic costs of natural disasters across affected countries' income status: AEs tend to record higher physical damages than EMDEs, likely reflecting the higher value of the coastal real estate that suffers flood and storm-induced destruction, while EMDEs tend to register higher social costs of natural disasters, likely reflecting the higher share of vulnerable populations due to high informality and poverty, and relatively low investment in disaster-proof infrastructure (Khan, 2005).

Figure 4. Average Social and Direct Economic Cost of Disasters

People affected in percent of population | Economic Damages in percent of GDP



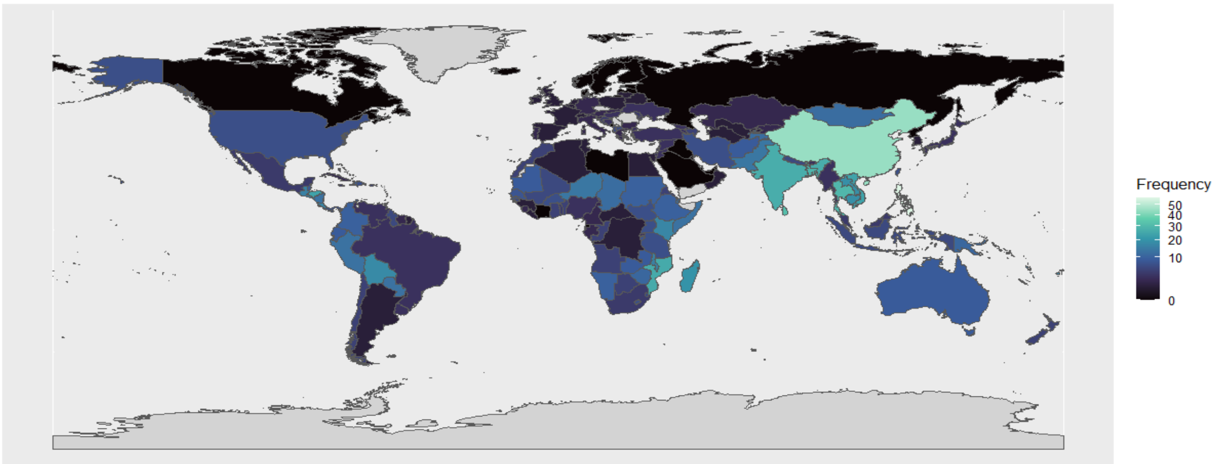
Source: EM-DAT and Furceri and others, 2021, and IMF staff calculations.

Figure 5 illustrates the top 10 percent most severe disasters in our dataset. These are defined as disasters with social costs (normalized by national population) or economic damages (normalized by GDP) in the top 10 percentile of natural disasters across all countries and years over the 1990−2019 period.[3] By definition, the top 10 percent most severe disasters have significantly higher social costs and economic damages as compared to the sample average. Specifically, disasters among the top 10 percent in terms of severity exhibit an average affected or dead population of 8.7 percent of a country's total population, counting 5.9 million people on average or average economic damages of 2.3 percent of a country's GDP, approximately 2.1 billion USD in damages. In contrast, for all disasters taken together, the average social cost is 1.8 percent of a country's population, counting 1.7 million people on average, and the average economic damages are 0.2 percent of a country's GDP on average, approximately 0.9 billion USD in damages.

The frequency of severe disasters among the top 10 percent fluctuated between 30 and 40 per year over the 1990-2019 period, except for the peak in 2009, which included more than 60 severe disasters, such as the H1N1 epidemic, the Red river flood, and several destructive earthquakes. Severe disasters included many storms, floods, and epidemics as well as other disasters. Many countries experienced one severe disaster per year, on average, even though some EMDEs (e.g., China, the Philippines, and several Caribbean economies) were hit more frequently, on average by several severe disasters per year, reflecting the concentration of *repeated* severe disasters in this area. The frequency of severe disasters is expected to increase with climate change (IMF, SSA REO, 2016).

[3] Note that in section IV we vary the severity threshold to identify the percentile cutoff above which natural disasters can have statistically significant distributional effects.

Figure 5. Geographical Distribution of Severe Natural Disasters

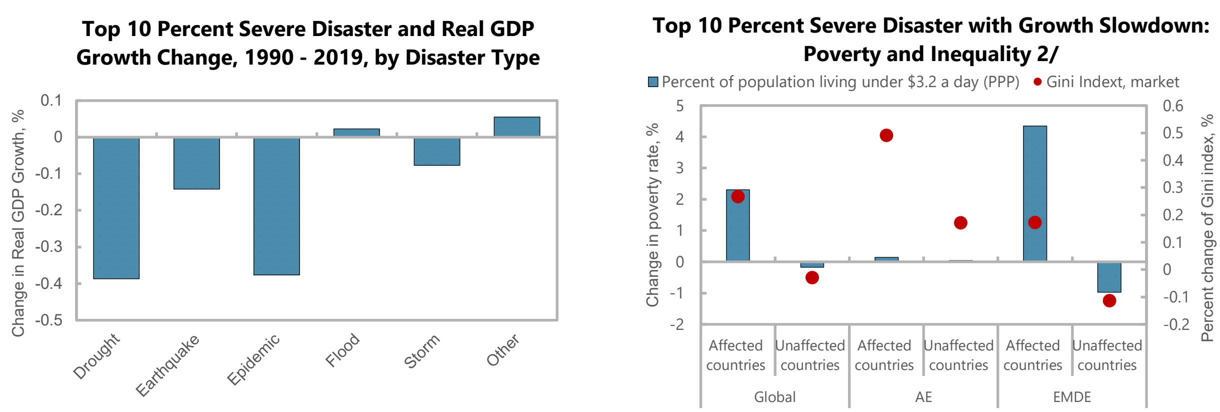


Source: EMDAT, Furceri and others (2021) and IMF staff calculations.

Note: The severe disasters group includes the number of top 10 percent of most severe disasters per country across 1990-2019.

Near-term macroeconomic effects of natural disasters are often mixed, reflecting differences in their severity, frequency, and type, as well as potentially obscuring third factors or offsetting policy responses (Ibarraran and Ruth, 2009). For instance, in Sub-Saharan Africa, evidence on the impact of natural disasters on short-term growth is mixed, except for the clear adverse effect of droughts on growth in small states (IMF, 2016). In our sample, some severe disasters, e.g., draughts, earthquakes, and epidemics were accompanied on average with a growth slowdown, compared to a pre-disaster year, while others, e.g., floods were not.

Figure 6. Severe Disasters, Economic Growth, Poverty, and Inequality1/



Source: EM-DAT and Furceri et.al., July 2021, WEO, SWIID 8.3 data, and IMF staff calculations.

Notes: 1/ Data on natural disasters is from the EM-DAT database, expanded with the data on major epidemics from Furceri et al. (2021). Data on market Gini coefficients is from the Standardized World Income Inequality Database (SWIID 8.3) (Solt, 2009). Data on poverty headcount is from the World Bank, Poverty and Inequality Platform.

2/ The average changes in poverty and inequality in treatment groups control for real GDP growth slowdown.

Inequality and poverty tend to worsen following severe natural disasters, particularly in EMDCs. Comparing the change in poverty and inequality as measured by the poverty headcount and the market Gini coefficient, respectively, suggests that both poverty and income inequality increased relatively more in countries experiencing severe natural disasters than in unaffected countries (Figure 6). The increase is more pronounced in emerging market and in low-income countries than in advanced economies.[4] Given that the focus of this paper is to assess the direct impact on income inequality, before public transfers and other policy interventions in response to disasters, the empirical analysis in this paper uses the market Gini coefficient.

Channels of Distributional Effects: Literature Review

In this section, we discuss the channels through which severe natural disasters may affect within-country income inequality (Figure 7), taking the existing literature as a starting point. Studies have looked at two main channels, the macroeconomic environment, and socioeconomic factors such as the stratum of the affected in terms of socioeconomic status, gender, race, and age, as well as interactions between the macro- and socioeconomic channels. The effect of natural disasters could be mitigated via prevention or adaptation channels, e.g., by implementing timely and effective policy responses, or be magnified via intensification channels (Pleninger, 2020). The extent to which their impact is visible at the macro level therefore depends on disasters severity and frequency as well as other potentially offsetting factors such as the government's policy response (Ibarraran and Ruth, 2009).

A. Macroeconomic Channels

Disasters, especially severe disasters, can induce negative supply shocks by damaging physical and human capital and cause production and labor supply disruptions with an immediate negative effect on growth. First, a severe disaster induces a negative shock to the productive capital stock, which could disrupt supply, causing a temporary fall in production (e.g., in agriculture, tourism-related services or manufacturing due to transport or supply disruptions). Disasters may also lead to physical capital misallocation (Hallegatte and Vogt-Schilb 2019), damage global value chains and cause supply disruptions (Rodrik,1999). Disaster-induced transport disruptions can reduce labor supply and lead to productivity losses (Cerra and Saxena 2008; Sawada 2007). Severe disasters can also induce negative demand shocks. By damaging the housing stock, natural disasters induce a negative shock to household wealth, which can reduce discretionary household spending (e.g., on hospitality, entertainment, retail), lowering consumer demand in turn. Reduced consumer demand together with increased business uncertainty lowers firm investment (Baker, Bloom, and Terry 2019), particularly when disasters are severe (Ludvigson, Ma, and Ng 2020). At the same time, job losses and lower household income, increased debt servicing costs and an elevated fear factor (e.g., due to a perceived risk of infection) can further exacerbate the impact on domestic demand.

External balances may worsen due to reduced exports and increased import demand, reflecting potential production shortfalls and reconstruction needs following severe disasters (Rasmussen, 2004, IMF, 2016). The fiscal position may also deteriorate due to lower tax revenues amid increased spending needs for

[4] Note however that data on poverty headcount is not used in the empirical analysis that follows, due to the limited data for AEs.

reconstruction. Significant enterprise and household losses from the destruction of productive capital and residential homes as well as employment losses can worsen financial sector health (e.g., NPLs) and household balance sheets. When disaster-induced recessions trigger financial crises, these effects could be even stronger. The increased demand for liquidity and the associated credit crunch affects productive, innovating firms (De Ridder, 2016; Fatás, 2000), curtailing their access to bank lending (World Bank, 2020). This constrains private sector investment and its recovery, leading to higher long-term unemployment and lower labor productivity (Oulton and Sebastian-Barriel, 2017).

The effects of natural disasters vary based on their severity and frequency, with generally stronger effects of severe disasters (Ludvigson, Ma, and Ng 2020, World Bank, 2020, IMF, 2016, Raddatz 2007; Acevedo 2014, Cabezon and others, 2015, Loayza and others, 2012). This is especially the case in developing countries given their relatively lower disaster resilience (Kahn, 2005). Correspondingly, some studies find that disasters cause immediate economic contractions, worsen fiscal and external balances and increase poverty and inequality (Rasmussen, 2004), especially in small states in the Caribbean (Otker and others, 2017, and IMF, 2016). In Latin America and the Caribbean, severe disasters tend to be accompanied by a growth slowdown in the year of the disaster, followed by a rebound in the following year (Charveriat, 2000). Major epidemics tend to exacerbate inequality in both advanced and emerging economies (Furceri et. al., 2021). Other studies found that in Sub-Saharan Africa, major disasters have mixed effects on short-term growth, but with clear adverse effect on long-term growth, poverty, and inequality (IMF, 2016). Moreover, the impact of disasters is found to depend on the economic size, the degree of integration of the affected sector/area with the rest of the economy, and the adaptation mechanisms to varying production conditions (Benson and Clay, 2004). The effects also vary by disaster type, with adverse effects of droughts, particularly in low-income countries (Raddatz, 2009, Loayaza et. Al., 2009) and in small states in Sub-Saharan Africa (IMF, 2016), and of hurricanes on small island states (Raddatz, 2009).

B. Policy Responses as Adaptation Channels

The disruptions resulting from natural disasters could be short-lived if emergency responses are timely and effective, e.g., quickly restoring the damaged infrastructure such as transport roads, electricity, etc., and ensuring proper support to affected and vulnerable populations. Even if disasters have important local effects, prompt and effective federal emergency assistance in an affected area may fully offset the impact of the disaster, making their effect insignificant at the national level. Rapid reconstruction efforts and aid flows, for instance, often lead to a quick rebound, potentially offsetting the effects in the more resilient (insured) Caribbean countries (Otker and others, 2017). The net effect of disasters on the near-term growth could even be positive as emergency reconstruction efforts may increase the demand for less-skilled labor, income, and consumption above pre-disaster levels via multiplier effects (Moretti, 2010). Investment, construction, and employment levels could increase even further during the transition period, as the capital stock reverts to its steady state level (Weinstein, 2002). Moreover, ex-ante risk mitigation policies of accumulating fiscal buffers (self-insurance), arranging for disaster insurance (risk-transfer) and/or securing contingency financing can help build disaster resilience (Alleyne and others, 2017, and Cebotari and Youssef, 2020).

C. Macroeconomic Vulnerabilities as Intensification Channels

Pre-existing macroeconomic vulnerabilities can intensify the effects of natural disasters on income inequality. For instance, limited fiscal space and high public debt risks can constrain countries' capacity to conduct countercyclical policy and respond to natural disasters (Alleyne and others, 2017); meanwhile the disasters can have severe adverse effects on the fiscal accounts and public debts, and in some cases putting fiscal sustainability in question, exacerbating in turn the macroeconomic effects of disasters (Laframboise and Loko, 2012). Worsening fiscal positions and debt sustainability concerns could trigger a sudden large increase in government borrowing costs, further worsening the health of the banking system, if banks' balance sheets are intertwined with those of the government in a "sovereign-bank nexus", which can further intensify the effects of natural disasters (IMF, 2016 and World Bank 2020). Structural weaknesses, such as lack of economic diversification, poor medical care, high informality—70 percent of the labor force in EMDEs (World Bank, 2020) —widespread poverty, and food insecurity can further intensify the distributional effects of disasters and limit the ability to develop resilience and respond effectively to major disasters (IMF, 2016).

D. Socioeconomic Vulnerabilities as Intensification Channels

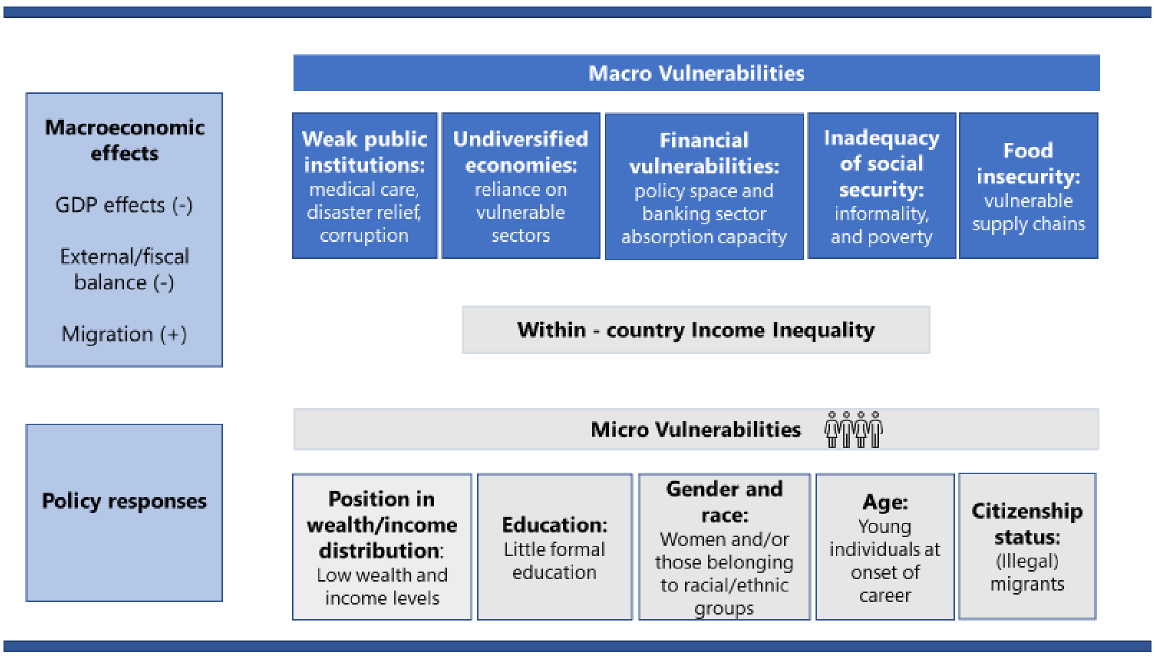
Pre-existing social and economic vulnerabilities can also intensify the immediate effects of disasters at the individual level (Masozera, Bailey and Kerchner, 2007), particularly on population groups at the intersection of low-incomes, non-male, non-white, non-prime age and less educated. For instance, women are significantly more likely to be poor and therefore less able to evacuate (Morrow, B.H., Enarson, E., 1996), especially women of color. Black populations also tend to live in high-hazard areas (Masozera, Bailey and Kerchner, 2007). Women are also more likely to die from natural disasters (Neumayer and Plümper, 2007). Taken together, individuals with a low socioeconomic status are likely to be poor, raising the ex-ante probability of disaster incidence due to less access to early-warning signals and fewer resources to evacuate and lowering the ex-post capacity to absorb economic losses by making the necessary follow-up investments to bounce back—a double hit. Vulnerable groups also often face higher volatility of employment due to precarious low-wage employment e.g., in the informal sector or in sectors more susceptible to shocks such as the service sector, making them more likely to be laid-off during economic downturns. The literature has also documented significant gender and racial inequality effects of the current COVID-19 pandemic shock (IMF, 2020).

E. Complexities

When macroeconomic and socioeconomic vulnerabilities interact, there is a potential for lasting effects of natural disasters on vulnerable population groups. For instance, if low-income households lack access to credit markets, they cannot insure against a catastrophe, which reduces their resilience and ability to bounce back (Ibarran et al., 2007). Their human capital could also depreciate in prolonged spells of unemployment, particularly as low-skilled workers face higher risk of unemployment during recessions, altogether leading to worsening income distribution. Psychological repercussions can worsen a state of (intensifying) economic

precarity. Vulnerable individuals pushed (further) into a state of economic scarcity and unpredictability can also experience psychological distress, further limiting their ability to participate in the labor market.[5]

Figure 7. Severe Natural Disasters: Channels for Distributional Effects



With these complexities in mind, we next present an empirical study to gauge some of the potential effects of natural disasters.

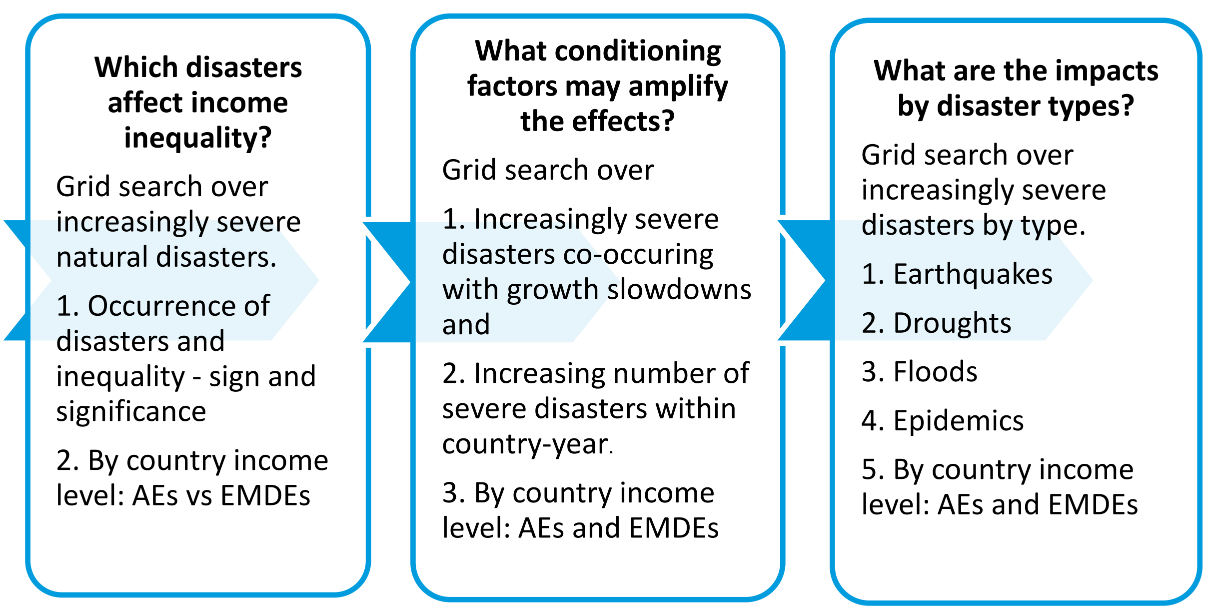
The Distributional Impact of Natural Disasters

In this section, we empirically investigate the effect of natural disasters on within-country income inequality as measured by the Gini coefficient in a sample of 180 advanced, emerging and developing economies. The main hypothesis is that the occurrence of severe disasters bears a positive empirical association with income inequality. To test this, we run a grid search exercise, iterating over different percentile-based cutoffs of disaster severity, which is based on the distributions of social costs and economic damages, normalized by national population and GDP, respectively, to account for differences in countries' size (Figure 8). In each iteration, the disaster indicator contains a collection of increasingly severe disasters. This approach allows us to capture the potentially non-linear nature of the effects of disasters on inequality without having to impose our priors on what constitutes a sufficiently severe disaster to be economically relevant (as cost in population, cost in GDP). It also speaks to the caveat that measuring disaster severity is a noisy undertaking so that looking at a variety of metrics based on different plausible ideas of what may constitute severity seems prudent. We also

[1] Some equations could not be estimated reliably for AEs because much fewer severe disasters happened there and choosing a more restrictive treatment and/or control group cutoff lowers the number of observations based on which the interaction term was estimated further—sometimes to the extent that no estimate was obtained.

investigate factors likely to intensify the inequality impact of disasters (socioeconomic vulnerabilities), such as a co-occurrence with growth slowdowns (macroeconomic channels) and whether disasters occur repeatedly in the same country and year (disaster intensity). While we do not directly control for the channels discussed previously here, we expect both macro-and socioeconomic vulnerabilities as well as their interactions to intensify when countries are hit amid a concurrent economic malaise and/or do not get a break to recover from shocks, which we aim to capture here. Finally, we check for heterogenous effects by disaster type as the impact on inequality may vary and/or follow a different timing structure.

Figure 8. Grid Search Exercises: Summary and Main Questions



A. Empirical Strategy: Local Projections

We assess the impact of severe natural disasters, as defined in Section II, on inequality using local projections, following Jorda (2005) and Furceri et al. (2021), and estimating impulse response functions over four years ahead. Specifically, the model is shown in eq. 1 and the main variable of interest is $\beta_0^{(k)}$ for k=1,…,4:

$$y_{i,t+k} = \alpha_{1,i}{}^{(k)} + \alpha_{2,t+k}{}^{(k)} + \beta_0^{(k)} D_{i,t} + \theta^{(k)} X_{i,t} + \varepsilon_{i,t+k},\ k=1,\dots,4 \qquad (1)$$

where

$$X_{i,t} = \sum_{j=1}^{2} \beta_j^{(k)} D_{i,t-j} + \sum_{l=1}^{2} \gamma_l^{(k)} y_{i,t-l} + \sum_{l=0}^{k-1} D_{i,t+k-l}$$

where $y_{i,t}$ is the natural logarithm of the market Gini for country i in year t, α_i are country fixed effects, controlling for constant country-specific factors influencing inequality as well as other factors affecting the

incidence of severe natural disasters such as the quality of the social safety nets, social norms and the proximity to the equator. ${\alpha_{2,t+k}}^{(k)}$ are year fixed effects, controlling for global shocks, $D_{i,t}$ is the treatment dummy, indicating the occurrence of a severe natural disaster in country i in year t when equal to one, no disaster or a minor disaster when equal to zero, and a disaster which was neither minor nor sufficiently severe when missing. If a severe disaster was longer than one year, the dummy is equal to one during the period it took place (more on this below). The vector, $X_{i,t}$, includes two lags of the dependent variable and the natural disaster treatment dummy, following Furceri et al. (2021), also controlling for shocks within the forecast horizon, following Teulings and Zubanov (2014). Finally, $\varepsilon_{i,t+k}$ represents robust standard errors clustered at the country level to account for serial correlation. Equation (1) is estimated for an annual panel of 180 countries over 1990-2019, for each horizon k=0,…,4.

While the severe disaster treatment variable, $D_{i,t}$, is expected to be exogenous, we recognize that advanced economies are generally more resilient to natural disasters than less developed economies. Therefore, the probability of a natural disaster with a given level of destructive potential to turn into a severe disaster as measured by its realized destruction (i.e., in terms of economic damages and humans affected, relative to countries' GDP and national population, respectively, to account for differences in countries' size) arguably depends on country income level, which we control for by means of country fixed effects. Advanced economies generally have better early warning signals and better information structures that prevent the loss of human life (Kahn, 2005). They also have deeper pockets to aid in a rapid rebuilding process. Such differences may result in selecting fewer and more severe disasters in AEs than in EMDEs, which is considered when interpreting the findings below. Moreover, if more unequal places were more prone to severe natural disasters, there might be concerns about the validity of the parallel trends' assumption. To alleviate such concerns, the model includes lags of the Gini as well as lags of the treatment dummy in addition to country fixed effects to control for countries' differences in income inequality levels and for differences in their history of disasters. To further mitigate these concerns, the analysis also includes separate regressions for AEs and EMDEs.

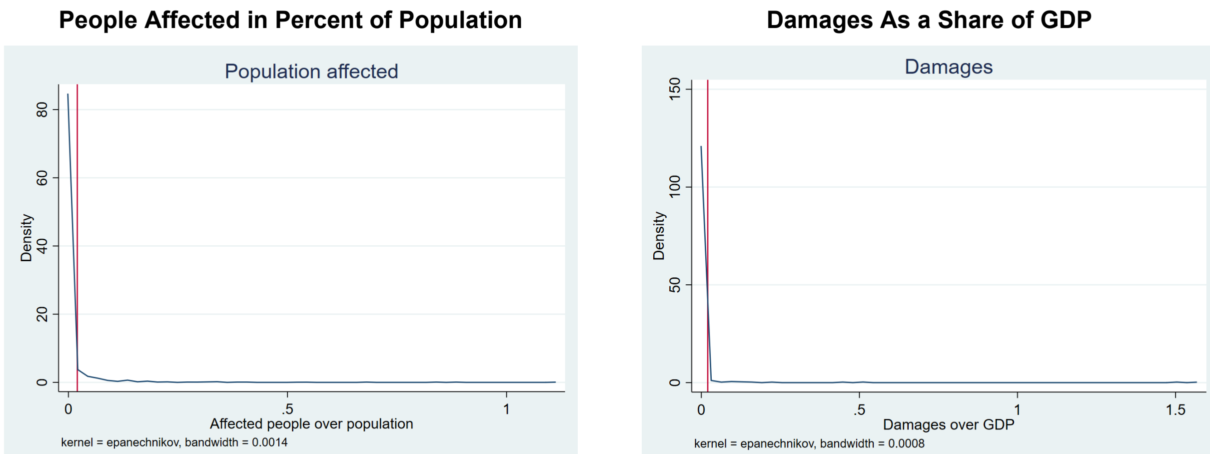
B. Constructing the Severe Disaster Dummy

This section explains the method for constructing appropriate treatment and control variables that measure the occurrence of severe disasters.

Measuring the Severity of Natural Disasters

Figure 9 plots the distributions of the two measures used to determine the severity of natural disasters: social costs, defined as affected population (including deaths), and economic damages (normalized by national population and GDP, respectively). The distribution of both severity measures is highly skewed to the left - while the average social and economic costs are 0.7 percent of the population and 0.2 percent of GDP, respectively, the corresponding averages for the top 10 percent most severe disasters are far greater at 2.1 percent of population and 12.7 percent of GDP. The skewed distribution of the two severity measures suggests that only a few very severe natural disasters are likely to have significant macroeconomic and aggregate inequality effects, while recognizing that some less severe disasters could have still significant local effects, affecting specific regions, local communities, or vulnerable groups (see the event-study in section D).

Figure 9. Skewed Social Costs and Economic Damages of Disasters



Source: EM-DAT and Furceri and others, 2021, and IMF staff calculations.

The next section explains two selection approaches used to identify the most severe and frequent disasters and develops the appropriate treatment and control variables that are in turn used in the estimations.

Appropriate Treatment and Control Variables using Two Approaches

The analysis uses two complementary approaches to select severe natural disasters, given that the country-year panel data structure requires aggregating EM-DAT natural disasters that took place in the same country and in the same year. The **aggregate approach** recognizes that a country repeatedly hit by disasters in the same year may suffer large cumulative losses scaled by its GDP and population as a proxy for its size, which can worsen within-country inequality. This approach implies summing up all losses from natural disasters incurred by any country in any given year and is used by a number of existing papers in the literature (e.g., Furceri et al. 2021, Boustan et al., 2021). Second, the **event-based approach** recognizes that it may only be individually severe disasters whose losses relative to its size (proxied by country's GDP and population) cumulatively affect income inequality as less severe disasters may only have local effects. This approach implies summing up the losses of only sufficiently severe disasters within the same country and year. To illustrate the difference, think of a series of medium-severe storms that occur in the same year. In the aggregate approach, the sum of cost of all storms would be calculated and if the sum exceeded a threshold (e.g., top 10 percent), it would constitute a severe disaster. In contrast, in the event-based approach, each individual disaster in a country is valued separately, and only the individual ones that exceed a certain threshold would be considered severe. The losses of these individually severe disasters would then be summed up and constitute a severe disaster at the country-year level. In other words, a wave of less damaging disasters would likely not be captured as a severe event in the latter event-based approach – but it would in the former aggregate approach. We will let the data inform us which approach is empirically associated with inequality.

Table 1 shows the severity cutoffs for disasters in the top and bottom percentiles of the severity distribution according to the aggregate and event-based approaches as explained above. The aggregate approach considers the aggregate severity of all events at the country-year level, whereas the event-level approach considers the aggregate severity of events with individual social costs or economic damages above a certain threshold only. Therefore, the cutoffs are smaller in the latter approach. We also include control group cutoffs–

the bottom percentile of minor disasters included in the control group. For instance, the inclusion of the bottom 50 percent of natural disasters in terms of severity into our control group under the aggregate approach allows us to increase the number of observations used for our estimation without introducing too much noise as we now mix country-years with minor disasters and without disasters in our control group. As shown below, the average damages/GDP ratio and the average share of people affected for the bottom half of the disasters is practically zero.

Table 1. LHS: Aggregate Cutoffs; RHS: Event-level Cutoffs

	Aggregate		**Event-level**	
Top x Percent Disasters	**AVG Affected Population (In percent)**	**AVG Damages/GDP (In percent)**	**AVG Affected Population (In percent)**	**AVG Damages/GDP (In Percent)**
>= 25	1.0	0.5	0.1	0.1
>= 20	1.8	0.8	0.2	0.2
>= 15	3.3	1.1	0.5	
>= 10	6.0	2.0	1.0	0.7
>= 5	13.6	4.7	3.3	1.9
>= 1	39.1	25.3	22.8	12.1
Bottom y Percent Disasters				
< 75	0.01	0.52	0.1	0.1
< 50	0.001	0.001	0.01	0.02
< 25	0.0001	0.0002	0.000004	0.00003

Box 1 uses an example to illustrate differences in the selected severe disasters across the two selection approaches used to identify the most severe and frequent disasters. The main take-away from these illustrations is that one can look at disaster severity from different perspectives, each assigning a different set of country-years in our treatment group and each plausibly representing a set of truly severe disasters. Ex ante, we cannot judge which one is more or less likely to affect income inequality. This is what we set out to investigate next. The analysis uses the treatment and control groups, selected based on the aggregate as well as the event-based approach, as discussed above for various severity cutoffs (see Table 1) to analyze the severity threshold above which natural disasters are likely to affect inequality.

Box 1. Differences Across the Two Approaches: An Illustrative Example

The assumptions about the aggregation technique of losses from natural disasters in the same country and year matter for the selection of severe events. We illustrate this in the below example using the two approaches to select the top 10 countries based on the following criteria: (i) countries that are hit most often by severe disasters and (ii) country-years that account for the highest number of severe disasters. The first criterion helps understanding the composition of the treatment group on the extensive margin, whereas the second one offers a view on its intensive margin, that is, countries in the treatment group with the heaviest concentration of natural disasters within the year.

The top-10 countries selected based on the first criterion, namely countries that are hit most often by severe disasters, varies across the two approaches (Table 1.1). There is an overlap of only about ½ of the top-10 countries with the highest incidence of severe disasters in the treatment group across the two approaches (marked in gray). Cambodia, China, Djibouti, Mongolia and Niger are severely affected countries regardless of whether the selection is based on the aggregate or event-based approach. Tajikistan, Bangladesh, Namibia, El Salvador and Haiti are among the top 10 countries based on the aggregate approach, whereas Laos, Malawi, Thailand, Ethiopia, and Fiji are among the top 10 based on the event-level approach. The differences in the lists based on the aggregate and event-level approach reflect different disaster experiences. Some countries have a series of medium-size disasters which when aggregated make it into the top 10 (e.g., Bangladesh); other countries have experienced only large individual disasters such as a cyclone (e.g., Fiji), so they feature in the second list based on the event-level approach; and there are also countries such as Cambodia which experience both types of disasters and hence make it to both lists individually.

Table 1.1. Top-10 Countries Selected into the Treatment Group

A. Aggregate Approach		B. Event-level Approach	
Country	**Number of years**	**Country**	**Number of years**
Cambodia	8	Cambodia	13
China	7	Lao P.D.R.	12
Djibouti	7	China	10
Tajikistan	7	Djibouti	9
Bangladesh	6	Malawi	9
Mongolia	6	Thailand	9
Namibia	6	Ethiopia	8
Niger	6	Mongolia	8
El Salvador	5	Niger	8
Haiti	5	Fiji	7

Source: EM-DAT and IMF Staff calculations.
Notes: Countries with the highest incidence of severe disasters (top 25 percent), according to the two approaches.
The coloring shows overlap of countries in both lists based on the two different approaches.

Table 1.3 shows the top countries selected based on the second criterion, namely country-years accounting for the highest number of severe disasters. Two countries in (South-)East Asia, namely China and the Philippines, account for the top five country-years most intensively hit by disasters in any given year regardless of the chosen approach. When considering the incidence of disasters based on the aggregate country-year approach, China stands out as the country with the largest number of disasters, which is less surprising due to its combination of size and geographical location. But the Philippines is ahead of China when the event-based approach is used, as it is hit most frequently by the most severe disasters.

Box 1. Differences Across the Two Approaches: An Illustrative Example (Concluded)

Table 1.2. Aggregate Approach: Country-years with the Highest Frequency of Disasters

Country	Year	Severe Disasters	Disasters	Severe Droughts	Severe Earth-quakes	Severe Floods	Severe Storms	Damages (Percent of GDP)	Affected (Percent of population)
China	2013	6	42	1	1	1	3	0.4	2.0
China	2014	5	41	1	0	2	2	0.3	4.8
China	2006	12	36	1	0	5	6	0.5	6.8
China	2015	2	36	0	1	0	1	0.2	0.3
Philippines	2011	14	36	0	0	5	9	0.4	12.6

Table 1.3. Event-based Approach: Country-years with the Highest Frequency of Severe Disasters

Country	Year	Severe Disasters	Disasters	Severe Droughts	Severe Earth-quakes	Severe Floods	Severe Storms	Damages (Percent of GDP)	Affected (Percent of population)
Philippines	2011	14	36	0	0	5	9	0.4	12.6
Philippines	2009	13	26	0	0	2	11	0.5	14.8
China	2006	12	36	1	0	5	6	0.5	6.8
Philippines	2006	11	20	0	0	2	9	0.3	10.1
Philippines	2013	10	14	0	1	4	5	4.7	26.7

Source: EM-DAT and IMF Staff calculations.

Note: Country-years with the highest number of severe disasters (top 25 percent) across the two approaches. Less than half of the country-years are present in both lists. It is worth noting that while the Philippines is repeatedly selected among the top 5 country-years in terms of disaster frequency, it is not among the top 10 countries in terms of disaster frequency at the year level. This is because the Philippines has experienced just a few years of repeated severe disasters, while other countries have experienced fewer and yet severe disasters during a larger number of years.

C. Econometric Results

This section describes the results of our empirical analysis. In line with our schematic of the empirical strategy, we first assess the impact of severe disasters on within-country income inequality as proxied by the market Gini. Next, we move on to zooming into severe disasters accompanied by growth slowdowns and those which are repeated within the same country-year. This allows us to focus on the instances where shocks were most likely to be economically relevant due to dire concurrent macroeconomic conditions and/or a lack of time to recover from other shocks. Finally, we dive into potential heterogeneities of the impact of natural disasters by disaster type as different disasters may conceivably act as different fundamental shocks. Think of a drought, which likely has large effects on harvests and households compared to a wildfire or storm, which likely has a stronger bearing on physical capital in addition to households in the affected regions.

In line with the conceptual framework, we find that severe natural disasters are more likely to affect within-country income inequality when accompanied by growth slowdowns or when they repeatedly hit affected countries, thereby complicating the recovery. In the empirical analysis, we iterate over several percentile-based severity cutoffs such that, in each iteration, the disaster indicator contains a collection of increasingly severe disasters, to identify the threshold beyond which natural disasters are sufficiently severe to affect income inequality. We assess the inequality effects of: (i) severe disasters only, (ii) severe disasters which co-occur with a growth slowdown, (iii) severe disasters which repeatedly hit a country (>= twice within the same year), and (iv) severe disasters by disaster type. We also check the robustness of our results across the two disaster

selection approaches (the event-based and the aggregate approach) discussed in the previous section (Appendix 2).

Several caveats apply. First, while the grid search exercise allows for a comprehensive exploration of the relationship between natural disasters and income inequality, it is not a tool for causal analysis. Second, the treatment dummy which measures the severity of natural disasters is subject to measurement error as the EM-DAT database does not contain measures for the destructive *potential* of disasters (e.g., the strength of earthquakes on the Richter scale) but only of their *realized* destruction (e.g., the number of people dead or affected as a consequence of the disaster), which may in part be endogenous to countries' institutions, policies and income status. We alleviate this concern by running separate regressions for advanced economies and emerging and developing economies, and including country fixed effects, to account for differences in countries' resilience to disasters. Kahn, 2005, finds that this tends to vary based on countries' development/income level. Still, the underlying disasters in the top severity percentiles affecting the AEs sample are likely more severe in terms of their destructive *potential* than those in the top severity percentiles of the EMDEs sample. The next sub-section discusses the main results.

Severe Disasters

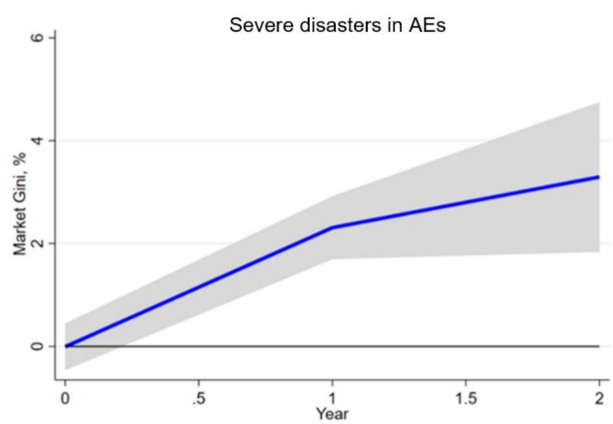
This section summarizes the effect of severe natural disasters on inequality as proxied by the market Gini.

Severe disasters above the 85th percentile according to the aggregate approach (i.e., damages > 1.1 percent of GDP or population affected > 3.3 percent)—with massive realized destruction—lead to an increase in the market Gini of about 2.3 percent one year after the disaster and 3.3 percent two years after the disaster in AEs (Figure 10).

Moreover, severe disasters above the 75th percentile according to the event-based approach (i.e., damages > 0.1 percent of GDP or a population affected > 0.1 percent) lead to a significant and persistent increase in the market Gini by about 1 percent two years after the shock, with increases of 1.4 percent, 1.3 percent and 2 percent in the following three years in AEs. This effect is qualitatively robust to varying the control group cutoff.

Figure 10. Local Projections Estimates of Inequality Effects of Severe Disasters in Advanced Economies

Increase in Market Gini in Percent, AEs



Source: EM-DAT and IMF Staff Calculations.
Note: Severe disasters defined as the top 15 percent most severe disasters in terms of human cost or direct damages in percent of GDP and population, selected based on the aggregate method.

Taken together, these results suggest that it is both, individually severe events whose realized destruction compounds and disasters whose aggregate damages are extremely large that affect income inequality in AEs. We do not find a significant increase in the Gini following severe disasters in EMDEs for any of the two approaches. One possible explanation for this surprising result could be that disasters in EMDEs affect everyone as disaster insurance is scarce, meaning that even the well-off have a lot to lose in EMDEs, at least when it comes to income. However, these results do not control for second- round effects (growth-slowdowns) which are explored in the next section. It should be also noted that these results mask a substantial heterogeneity in the effects of different types of disasters, which are discussed below.

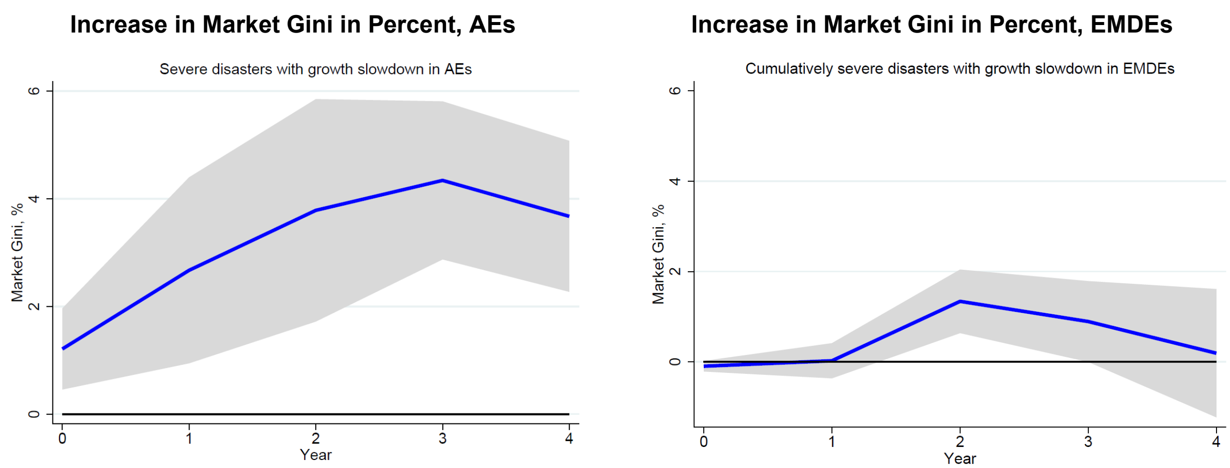
Severe Disasters Accompanied by Growth Slowdowns

This section assesses the inequality effects of severe disasters when accompanied by a domestic growth slowdown, i.e., a year where the change in the growth rate of per capita GDP is less or equal to 0. As set out in the conceptual framework, disasters are likely to have a greater bearing on inequality when they have macroeconomic repercussions that go beyond their direct destructive impact. However, in practice, we cannot distinguish between a natural disaster that *led to* and one that merely *co-occurred* with a growth slowdown. There may certainly be cases, in which a severe but localized natural disaster spuriously co-occurred, in that it did not lead to, a domestic growth slowdown. Therefore, the results may overestimate the true impact of severe natural disasters that lead to growth slowdowns (what we want to measure) because it may falsely attribute some of the rise in inequality due to growth slowdowns to the occurrence of a severe disaster (noise). The results of the following exercise are therefore to be interpreted with caution.

As before, the results are obtained by running separate regressions for AEs and EMDEs. To investigate the effect of severe disasters which coincide with domestic growth slowdowns, the disaster treatment variable is adjusted accordingly. Specifically, it is equal to one whenever a severe disaster coincided with a non-positive change in the GDP per capita growth rate and zero otherwise. In both cases, there is evidence for stronger effects when controlling for co-occurring growth slowdowns than for severe disasters alone.

We find that for both AEs and EMDEs, there is evidence for stronger effects when controlling for co-occurring growth slowdowns than for severe disasters alone. More specifically, severe disasters that co-occur with a growth slowdown above the 75th percentile according to the event-based approach in AEs lead to a stronger and more persistent increase in the Gini than in the case of severe disasters alone, with a rise of 1.2 percent on impact and a rise of 2.7 percent, 3.8 percent, 4.3 percent and 3.7 percent in the four years thereafter, as shown in Figure 11. This result is qualitatively robust to varying the control group cutoff.

Figure 11. Local Projections Estimates: Severe Disasters with Growth Slowdown



Source: EM-DAT and Furceri and others, 2021, and IMF staff calculations.

In EMDEs, we find significant effects above the 95th percentile according to the aggregate approach (i.e., damages > 4.7 percent or humans affected > 13.6 percent). Specifically, we find peak effects in the range of 0.4 percent - 1.3 percent three years after the shock, depending on the severity of the event under consideration. These results are robust to different specifications of the disaster severity and control group

cutoff. Again, we see that the effects are smaller in EMDEs than in AEs, possibly for the same reason given in the previous section. However, when accounting for growth slowdown we find significant effects for EMDEs whereas we did not when looking at severe disasters alone. One possible explanation for this is that once we consider the second-round effects of severe disasters (growth slowdowns), the results also hold for EMDEs, meaning that vulnerable households are hit harder during economic downturns, and inequality deteriorates.

Repeated Severe Disasters

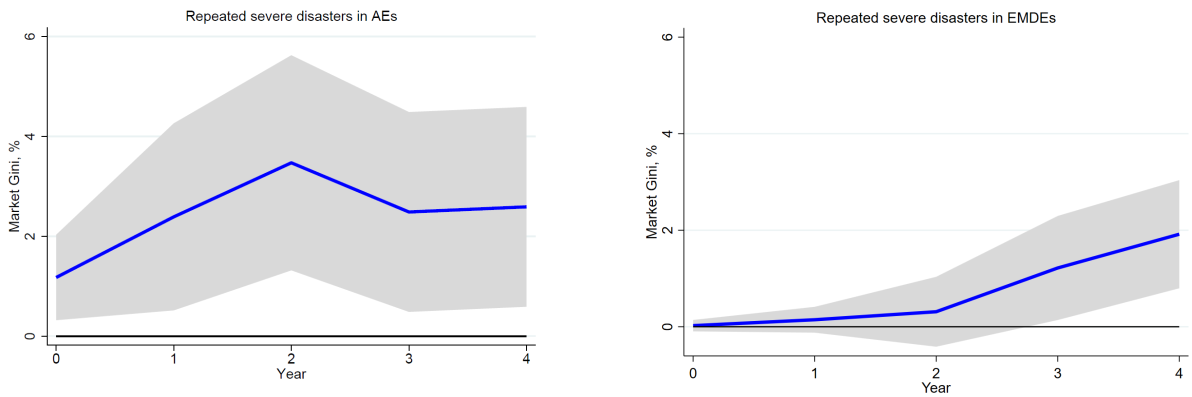
This section looks at the impact of repeated severe disasters on inequality, again running separate regressions for AEs and EMDEs. As natural disasters are likely to become more frequent with climate change, an important question is whether the *frequency* of severe disasters plays a role in exacerbating income inequality. Losses and hardship may compound if severe disasters hit the same country more frequently, not allowing enough time to recover, exacerbating differences in recovery speed along socioeconomic lines or worsening public finances to the extent that room to respond to disasters and support the recovery is limited.

To investigate the effect of disaster frequency on income inequality, we construct a discrete disaster count variable containing the number of severe disasters in any given country-year according to the aggregate and event-based approach, respectively. For the aggregate approach, the disaster frequency variable counts the number of disasters in any country-year, in which their aggregate direct costs (social and economic damages) were above the 75th percentile of the distribution. For the event-based approach, the disaster frequency variable counts the number of individually severe disasters with direct costs above the 75th percentile of the distribution that took place in the same country-year. The main difference here is that the aggregate approach counts all the disasters, including the minor ones, as long as the aggregate direct costs of all the disasters in that country-year are above the 75th percentile, while the event-level approach only counts the individually severe disasters (with direct costs above the 75th percentile) that took place in a given country-year. While the exact severity cutoff is an empirical question, the analysis here uses the 75th percentile to balance the need to select sufficiently severe disasters and drop events with very small direct costs (recall the skewness of the distribution discussed in section B), while ensuring sufficient variation in the disaster frequency variable at country-year level to meaningfully investigate the impact of frequency.

Turning to the results, repeated severe disasters based on the event-level approach significantly affect inequality, as proxied by the market Gini coefficient. In AEs, a severe disaster (above the 75th percentile severity cut-off), repeated at least twice in the same country-year leads to a contemporaneous increase in the Gini of 1.2 percent and a rise of 2.4, 3.5, 2.5, 2.6 percent in the four consecutive years (Figure 12). In EMDEs, a severe disaster repeated at least twice in the same country-year leads to an increase of the Gini of 1.4 percent three years and 1.9 percent four years after the shock, although the results are not robust to varying the control group cutoff.

Figure 12. Local Projections Estimates: Repeated Severe Disasters

Increase in Market Gini in Percent, AEs **Increase in Market Gini in Percent, EMDEs**



Source: EM-DAT and Furceri and others, 2021, and IMF staff calculations.

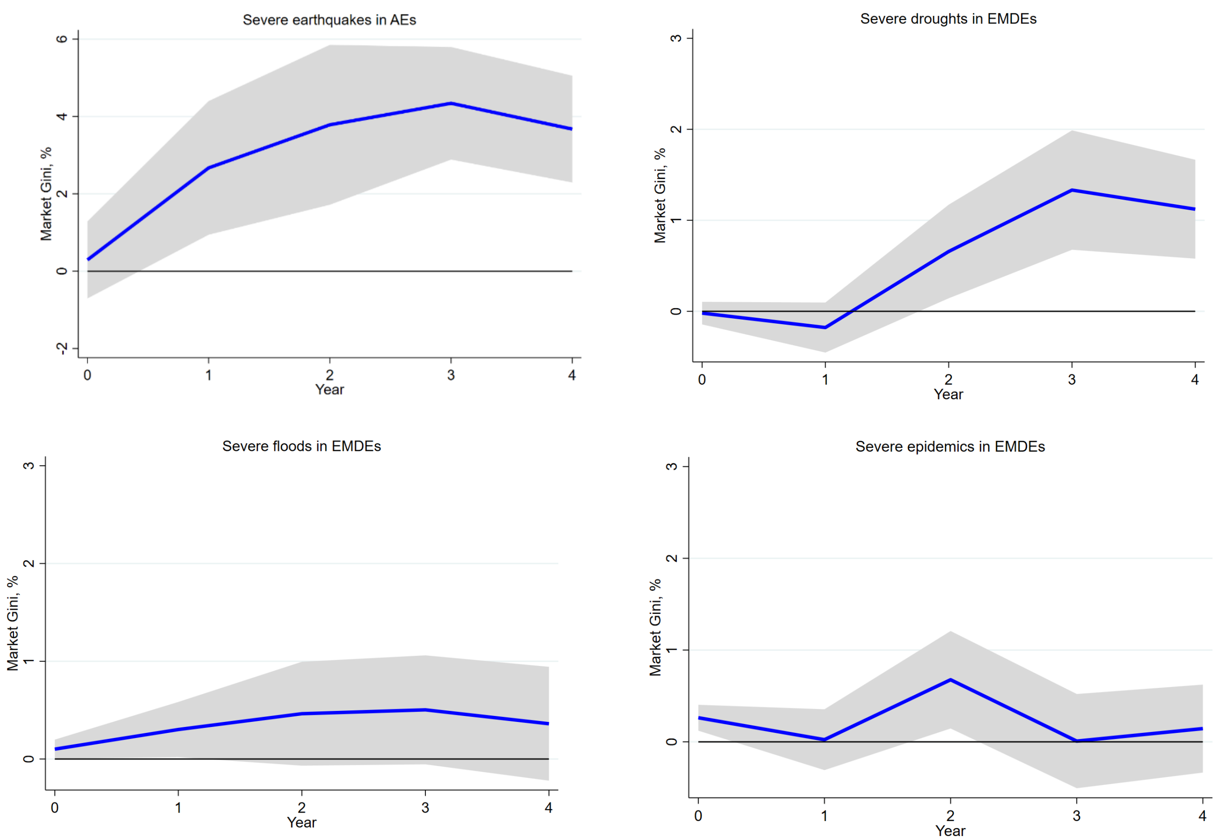
Heterogeneity by Disaster Types

Given the significant heterogeneity of natural disasters, and the evidence for heterogeneous effects across different disaster types in Section III, this section assesses the impact of specific types of natural disasters on inequality across AEs and EMDEs (Figure 13). The results suggest that AEs are especially prone to rises in income inequality following severe earthquakes above the 75th percentile according to the event-based approach (i.e., with damages > 0.1 percent of GDP or affected 0.1 percent of population), with a projected rise in the Gini of 2.7 percent after one year, 3.8 percent after two years, 4.3 percent after three years and 3.7 percent after four years.

In contrast, EMDEs experience a significant increase in the Gini following severe droughts (1.3 percent after three years), severe epidemics (0.6 percent after three years) and severe floods (0.3 **percent** after one year), all with severity cutoffs of the 90^{th} percentile of the respective distributions of direct costs, based on the event-based approach (i.e., with damages > 0.7 percent of GDP or affected > 1 percent of the population).

Figure 13. Local Projections Estimates: By Disaster Types

Increase in Market Gini
(In percent)



Source: EM-DAT and Furceri and others, 2021, and IMF staff calculations.

Robustness

The results presented in the previous section comprise a small fraction, selected out of all the results coming out of our grid search exercise. Given that the severity cutoff beyond which disasters can affect inequality is an empirical question, the objective was to empirically test, which types of disasters would be associated with a rise in income inequality. Although some of the results discussed in the previous section support the hypothesis that severe disasters have significant effects on inequality, these results are often not sufficiently robust. As

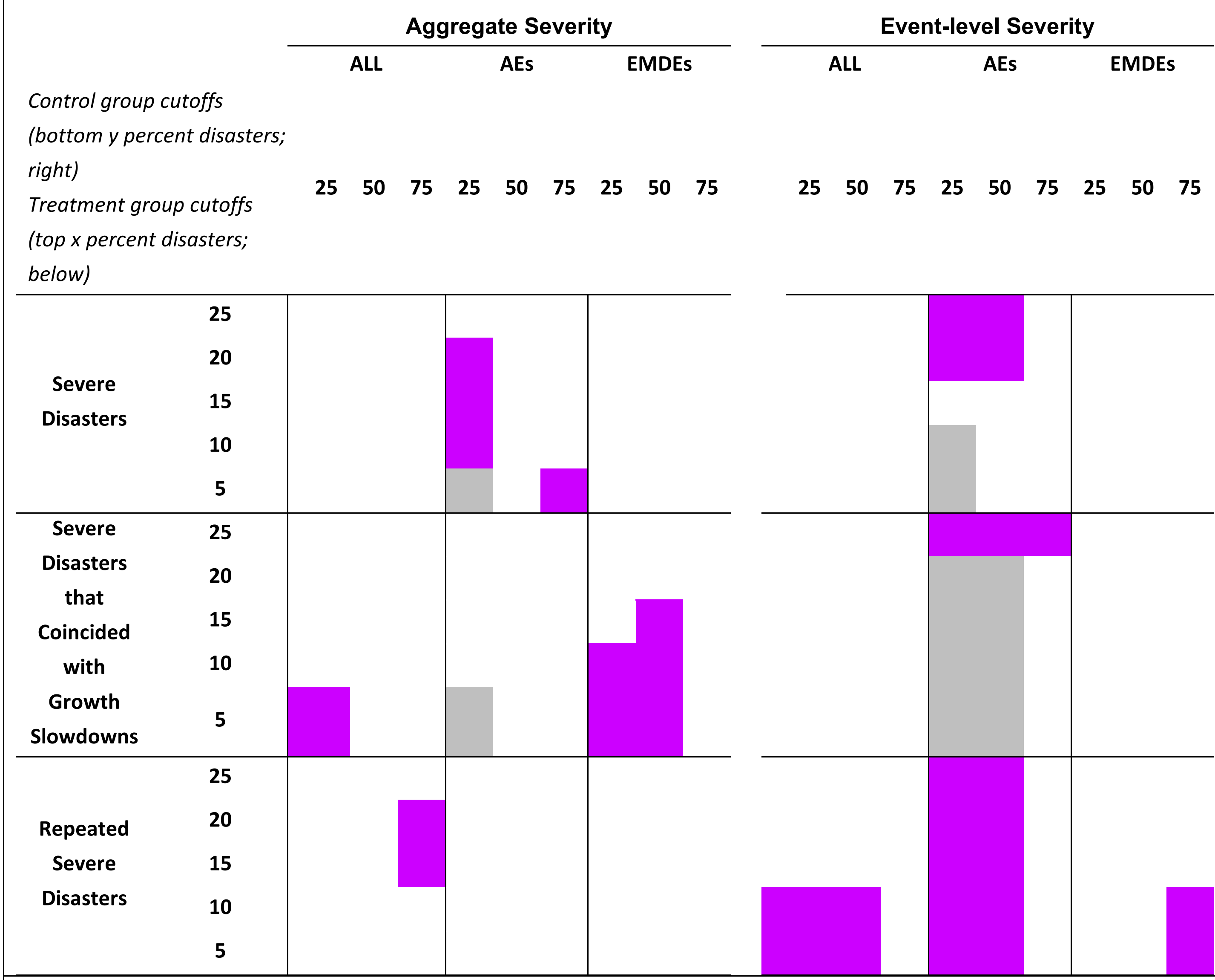
discussed throughout this section, the results are sensitive to the definition of treatment and control group, likely reflecting measurement error and potentially offsetting policy responses, for which our analysis cannot control explicitly.

The sensitivity of the grid search results across various specifications is illustrated in the overview Figure 14 and Figure 15, based on detailed tables in Appendix 2. The results about the impact of severe disasters on inequality are summarized using a color-coded scheme across different severity treatment group cutoffs (rows) and control group cutoffs (columns). The results are also available for all the regressions run on the pooled sample, as well as separately for the AEs and EMDEs samples. Furthermore, the figure also shows results based on different specifications of severe events—e.g., the disaster treatment dummy alone (the first block), when severe disasters coincide with growth slowdowns in the same country (the second block), when severe disasters are repeated at least twice in the same country-year (the third block), and finally, the baseline regression for severe disasters is also run separately by disaster type. In the Figures 14 and 15, fields colored in purple mean there is significant evidence for positive association between the natural disasters and income inequality within our forecast horizon of four years, those in white mean there is no evidence, while gray-colored fields mean that these specifications were not estimated. Regressions for severe disasters by disaster type are run only using the event-based approach to only capture individually severe disasters within each disaster type sample.

Overall, these results show that the results are sensitive to small changes to the treatment cutoff group used by the treatment dummy for the severe disasters (columns) as well as to the control group cutoff (rows).[1] The most robust evidence we find is for severe disasters that coincided with growth slowdowns and for droughts, specifically, both in EMDEs, and for repeated severe disasters and earthquakes, both in AEs.

[1] Some equations could not be estimated reliably for AEs because much fewer severe disasters happened there and choosing a more restrictive treatment and/or control group cutoff lowers the number of observations based on which the interaction term was estimated further—sometimes to the extent that no estimate was obtained.

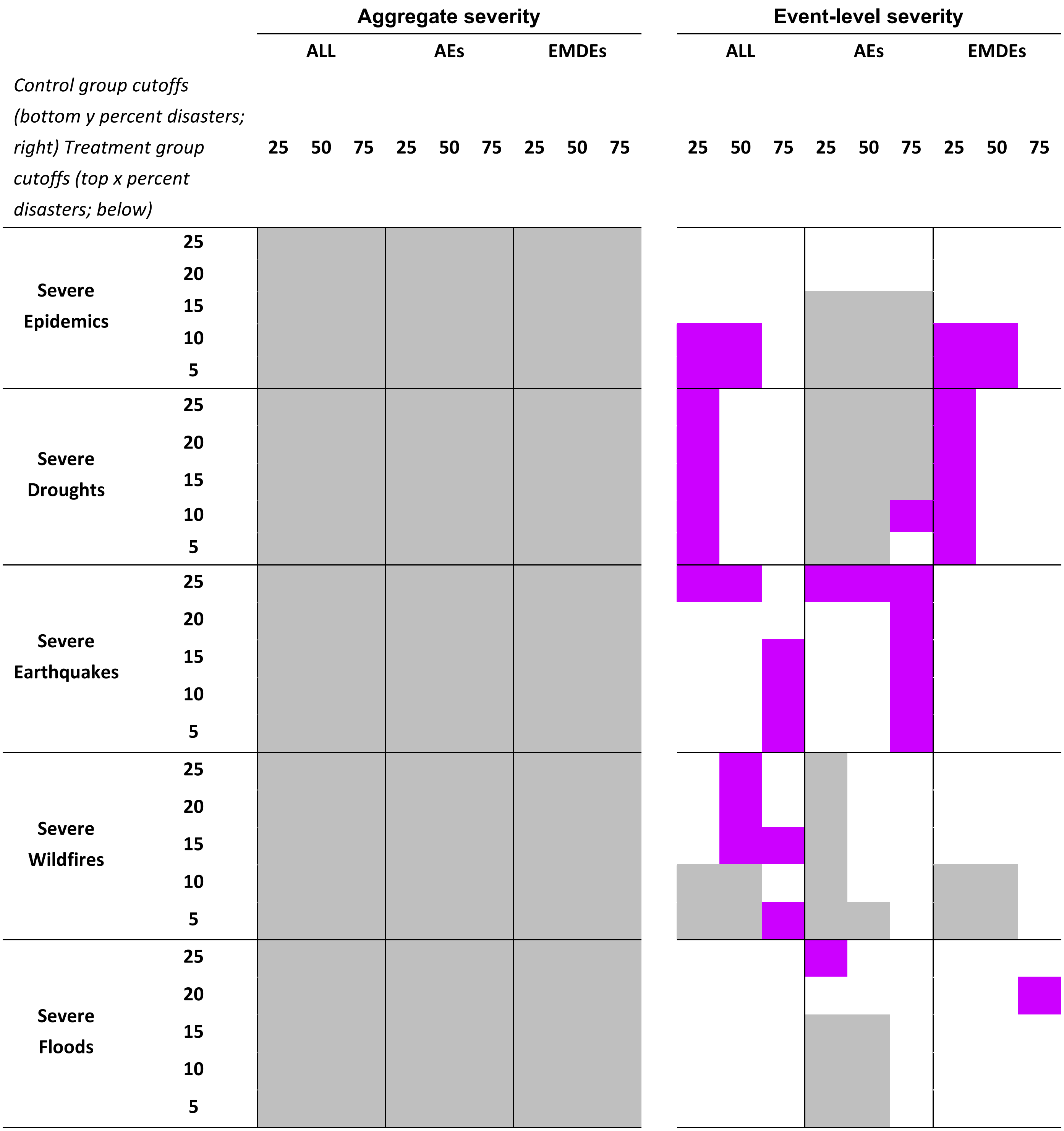
Figure 14. Local Projections Estimates: Grid Search by Severe Disaster Definition, Severity (Treatment Group) Cutoff, and Control Group Cutoff



Source: EM-DAT and Furceri and others, 2021, and IMF staff calculations.

Note: Purple colored filed indicates significant evidence for positive association between natural disasters and income inequality within the forecast horizon, white colored fields indicate no evidence, while gray-colored fields indicate that these specifications were not estimated.

Figure 15. Local Projections Estimates: Grid Search, by Disaster Type, Severe Disaster Definition, Severity (Treatment Group) Cutoff, and Control Group Cutoff.



Source: EM-DAT and Furceri and others, 2021, and IMF staff calculations.

Note: Purple colored filed indicates significant evidence for positive association between natural disasters and income inequality within the forecast horizon, white colored fields indicate no evidence, while gray-colored fields indicate that these specifications were not estimated.

Other caveats to robustness may apply in this setting. First, the literature has documented data quality issues with the SWIID database, which could lead to measurement error in the Gini coefficients (Jenkins, 2015). Specifically, while the SWIID dataset is the most complete dataset, this comes at the cost of some data issues, including cross-country comparability of estimates, as in many cases they are produced using different variables (e.g. income versus consumption), and questions remain about the assumptions behind extensive data imputations (UN, 2018). Proxying inequality by the Gini coefficients also offers a crude view on the distributional effects of natural disasters on vulnerable populations as effects could be felt more in the affected regions and cities, or impact specific population groups relatively more (e.g., across gender, race, or the relative position in income distribution). Since checking for more refined effects across specific groups require more granular data, the local projections are also complemented with a descriptive event study, illustrating the heterogeneous labor market effects of major natural disasters on the U.S. states since 1990, using the U.S. Current Population Survey data (see the next sub-section). Further, the treatment dummy for severe disasters is subject to measurement error, as the EM-DAT database does not include measures for the destructive *potential* of disasters (e.g., the strength of earthquakes) but only about their *realized* destruction. The latter may in part be endogenous to countries' institutions, policies, and income status and results in selecting objectively more severe events in AEs than in EMDEs.

Summary

Taking stock, we found some evidence for a relationship between severe natural disasters and within-country income inequality. Specifically, our findings can be summarized as follows: (i) severe natural disasters affect income inequality in AEs, while there are important heterogeneities across different type of disasters and their impact on income inequality in EMDEs, (ii) co-occurrence with a growth slowdown as well as being repeatedly hit by severe disasters seem to amplify the effects of severe disasters on inequality, (iii) severe earthquakes seem to have significant adverse effects on inequality in AEs, while the inequality effects of severe droughts, floods and epidemics seem more important in EMDEs.

Generally, the event-based approach, which aggregates individually severe disasters at the country-year level and discards non-individually severe disasters, seem to select severe disasters shocks that are more likely to have aggregate effects. Highly localized disasters are unlikely to have adverse aggregate macroeconomic and inequality effects, hence seem less useful for this type of analysis.

Finally, as mentioned at the beginning of this section, the results should be appropriately caveated. While the grid search allows for a flexible and easy exploration of the relationship under study – this is not a tool for causal inference. Moreover, the lack of a measure of destructive potential of natural disasters in the EMDAT database implies that the results for AEs and EMDEs are not directly comparable as they are likely based on shocks with different intensities in the sense of objective destructive potential. Improvements upon these caveats would be fruitful avenues for future work.

D. The United States: Local Effects of Major Natural Disasters

Given that proxying income inequality using Gini coefficients may obscure important heterogeneities along the distribution of income, more granular data can uncover important socioeconomic vulnerabilities, potentially intensifying the impact of natural disasters on vulnerable groups along the income distribution. As natural disasters often have local effects on regions and states, annual macroeconomic data may obscure these

effects. To illustrate these socioeconomic vulnerabilities, we supplement our local projections with an event analysis for the U.S. States, using US Current Population Survey Data, focusing on the more granular distributional effects of major natural disasters over the last four decades.

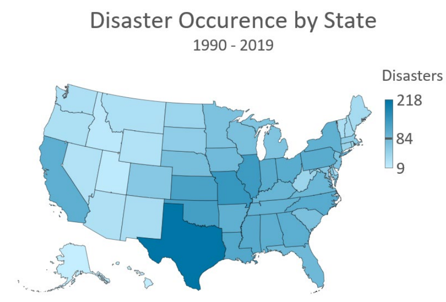
In line with our conceptual framework for distributional effects of disasters (Figure 6), we focus on socioeconomic vulnerabilities stemming from heterogeneous labor market effects across individual characteristics such as education level, race, gender, and age. The results illustrate the disproportional adverse labor market effects of major natural disasters on the less educated, women, racial minorities, and the young in the affected states, compared to the unaffected states (Box 2). These findings are in line with the evidence for significant gender and racial inequality effects of the COVID-19 pandemic (IMF, 2020), and with the evidence of distributional effects of major disasters on marginalized groups (Ibarraran et al., 2009). However, further empirical work is necessary to isolate these effects while better controlling for other contemporaneous factors.

These socioeconomic vulnerabilities are likely to be more pronounced across low-income and developing economies. This is because higher poverty rates in developing countries imply fewer resources to prepare and cope with the effect of natural disasters (Ibarraran et al., 2009). The poor are more likely to have lower human capital and could become reliant on a single source of income, e.g., employed in the informal sector, small businesses, or self-employment, further increasing their vulnerability to natural disasters. The poor often lack access to credit lines, disaster insurance and more generally access to finance, particularly in economies with less developed financial markets, which would make it difficult for them to smooth the impact of the disaster on their consumption and rebuild their housing stock. At the same time, the poor are more likely to live in disasters-prone areas, therefore facing the largest recovery costs in these areas, they often lack social capital and have higher rates of illiteracy, making it hard for them to access information and benefit from government recovery grants (Masozera, 2007). Further research using granular individual data could help identify the strength of these effects in low-income and developing economies.

Box 2. Heterogeneous Labor Market Effects of Natural Disasters in the United States

This Box uses a descriptive event analysis, illustrating socioeconomic vulnerabilities to major natural disasters in the United States, by benchmarking the labor market changes across various population groups across the states affected by major disasters against those in the unaffected states.

Zooming on the occurrence of natural disasters across the U.S. states, we note the relatively higher frequency of natural disasters in the Southeastern, Northwestern, and coastal states compared to other states. Information on natural disasters across the U.S. states over 1990-2020 is based on the EM-DAT database, also compared with the FEMA database and supplemented with aid data from the FEMA database. Examples of the most severe natural disasters by the size of economic damages as a share of affected states' lagged GDP in the United States include the Northridge earthquake (1994), hurricanes "Andrew" (1992) and "Katrina" (2005), while those with the highest human costs as a share of affected states' population include storm Jonas (2016), Riverine flood (2008), and hurricane Frances (2004).

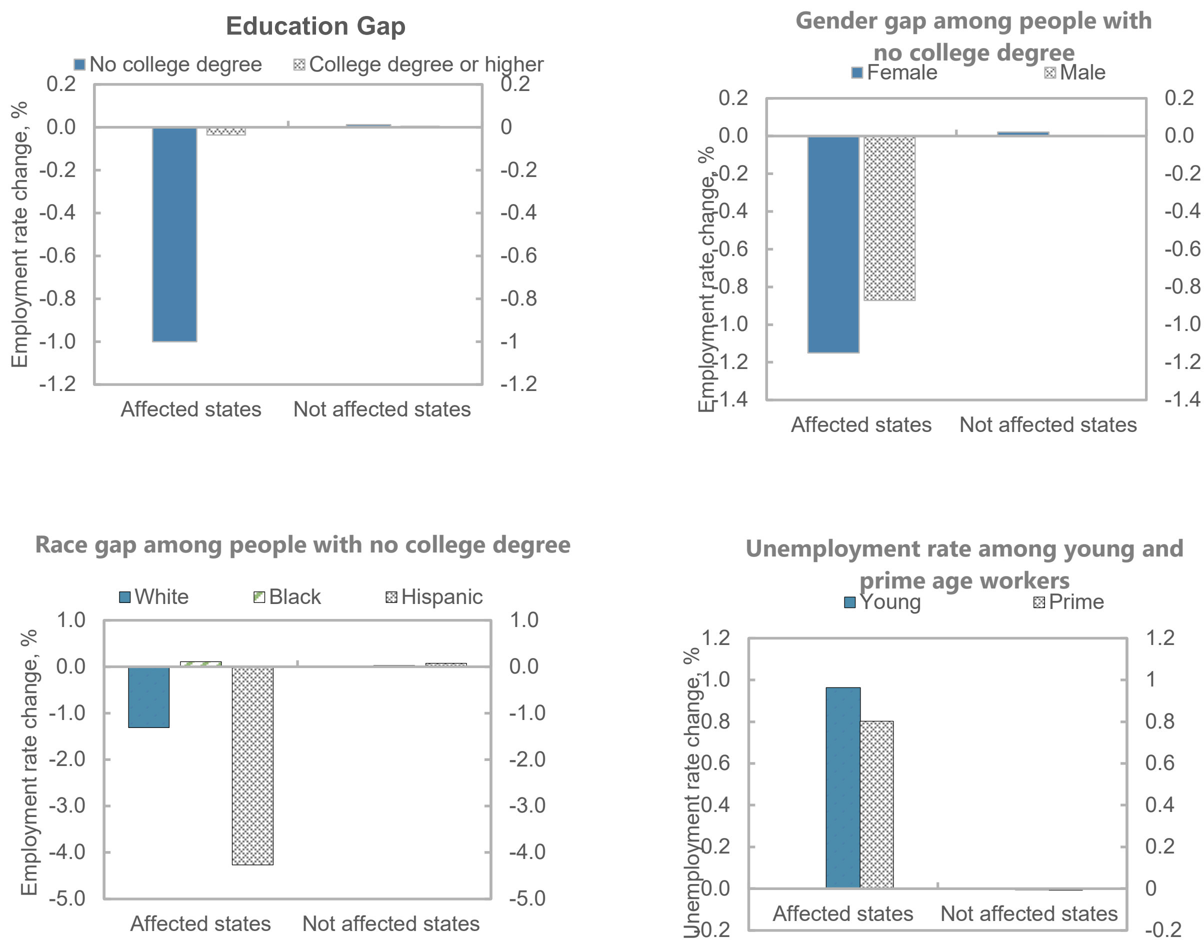


Sources: EM-DAT and IMF staff calculations.

To gauge the distributional effects of the major natural disasters on local labor markets in the affected states, we use the United States Current Population Survey data. The CPS dataset includes rich data on individual earnings, employment status, and occupation, along with other individual characteristics, such as sex, age, race, and education level. The labor data is aggregated at state-month level for each gender-race-age-education characteristic combination and matched with the data on major natural disasters at state-month level. For example, the panel includes the rate of employment, unemployment, and average wage of socio-economic groups that belong to several gender-race-age-education groups, e.g., without college degree, or with college degree and above, which specific race, gender, and of specific age group (young, prime age, older) at a state-month level. The list of major disasters and the procedure to aggregate the individual data across various demographic groups at state-month level is explained in Appendix 3.

Box 2. Heterogeneous Labor Market Effects of Natural Disasters in the United States (Continued)

Figure 2.1. Heterogenous Labor Market Effects of Major Natural Disasters
(Employment effects in affected and unaffected states)



Sources: EMDAT, CPS and IMF Staff calculations.

Note: The figure shows the change in the labor market variables (e.g.the average change in employment rate before and after major disasters) for specific socioeconomic groups (e.g. no college workers/workers with college and above) in affected states, compared to the respective average change in employment rate of the respective socioeconomic groups in unaffected states. For the definition of socioeconomic groups and the list of major disasters, please see Annex III.

Box 2. Heterogeneous Labor Market Effects of Natural Disasters in the United States (Concluded)

The event analysis benchmarks the impact of major disaster shocks on potential heterogeneities in labor market by plotting the average change in labor market variables (before and after major disasters) across socioeconomic groups in the affected states, and comparing them to the respective average changes in employment variables of the same socioeconomic groups in the states unaffected by natural disasters (Figure 2.1.). The results suggest that pre-existing socioeconomic vulnerabilities likely magnify the impact of major natural disasters on specific population groups. Specifically, suggest that major disasters have:

- *Disproportional adverse effects on employment of less-educated workers*. Larger adverse employment effects on less-educated workers (with less than college degree) compared to educated workers (college and above), after controlling for other changes in the employment gap between less-educated and educated workers in unaffected states (top-left chart).

- *Disproportional effects on less-educated female employment.* Larger adverse employment effects on less-educated females compared to less-educated males, after controlling for other changes in gender employment gap in unaffected states (top-right chart). This result is in line with the evidence that women find it more difficult to recover because of lower wages and family care responsibilities (Cutter, 2001).

- *Disproportional effects on less-educated Hispanic employment.* Major disasters seem to have a racial component, with larger employment effects on less-educated Hispanic workers, after controlling for other changes in respective employment gaps in unaffected states (bottom-left chart).

- *Disproportional effects on youth unemployment.* Larger adverse unemployment effects on the young, compared to prime age workers, after controlling for changes in the unemployment gaps in unaffected states (bottom-right chart).

These results are in line with the evidence that the intersection of poverty/low-incomes and individual characteristics including gender, race and ethnicity, age, and education status exacerbate socioeconomic vulnerabilities of specific population groups to natural disasters (Cutter, 2001). Masozera et. al. 2007, assessed the effects of the Hurricane Katrina on New Orleans and found that the poor, particularly women and African Americans have been more affected than other groups. Nevertheless, the event study results are purely illustrative and further empirical work is necessary to better control for other factors.

Conclusions

When and how do natural disasters worsen within-country income inequality and how persistent are these effects? We address this question in several steps. First, we develop a conceptual framework presenting the main channels—both macroeconomic and socioeconomic—through which severe natural disasters can affect income inequality. Next, we empirically analyze when natural disasters affect within-country income inequality as proxied by the market Gini for a sample of 180 advanced economies (AEs) and emerging and developing economies (EMDEs) over the last four decades. Finally, we zoom into the socioeconomic factors likely predisposing individuals to adverse labor market effects in the aftermath of disasters at the US state level over the last four decades.

The main part of our empirical analysis is a grid-search exercise, where we iterate over the cutoff beyond which a natural disaster is taken to be severe (and therefore included in the analysis) to identify threshold effects of natural disasters. For each point on the grid, we use local projections, as in Furceri (2021), to assess the effect of severe disasters on inequality, separately for AEs and EMDEs. We compile our database of natural disasters by expanding the existing EM-DAT database with major pandemic/epidemic events from Furceri et al. (2021). The analysis begins with assessing the effect of severe natural disasters, then moves on to severe disasters accompanied by domestic growth slowdown, i.e., a non-positive change in the growth rate of GDP per capita, followed by assessing the inequality effects of repeated severe disasters and an analysis by type of disaster.

Our main findings from the local projections are as follows. Inequality, as proxied by the market Gini, tends to increase significantly after severe disasters in AEs. We also find that inequality increases if severe disasters are associated with growth slowdowns or if there are multiple severe natural disasters in a year in AEs and in EMDEs. Moreover, we find evidence for heterogeneous effects across disaster types. While income inequality in EMDEs seems to be particularly hit by severe epidemics, droughts, and floods, AEs are severely impacted by earthquakes. In short, the effect of natural disasters on income inequality varies based on their severity, whether they are associated with growth slowdowns, their frequency of occurrence within the same year, the type of disaster, and the country's income status. The results are highly sensitive to the precise definition of what we take to be a severe disaster. This may be due to potential data quality issues, including the SWIID data issues of the Gini (Jenkins, 2015), the possibility that results are obscured by other factors, e.g., informality, or offset by policy responses, and that effects of natural disasters are often localized and visible only at a higher frequency.

Severe natural disasters can have disproportional effects on vulnerable populations in the affected regions and cities, stemming from heterogeneous labor market effects across individual characteristics such as education level, race, gender, and age. We therefore complement the local projections with an event study, illustrating the heterogeneous labor market effects of major natural disasters on the U.S. states, affected by major natural disasters since 1990, using the U.S. Current Population Survey data. We use the CPS survey data to construct our labor market variables for different population groups at the state level and combine them with EM-DAT data on natural disasters across US states over the same period. In our event analysis, we compare the differential labor market effects across U.S. states affected by major natural disasters, comparing those in unaffected states. In doing so, we investigate whether socioeconomic vulnerabilities are relevant in explaining the heterogeneous labor market effects of natural disasters.

Our main findings from the US states event analysis point to disproportional employment effects of major disasters on the less-educated, women, ethnic minorities, and the young. These results are purely illustrative and further empirical work is needed to better control for other factors. As socioeconomic vulnerabilities, including higher poverty, informality, lack of robust emergency support and adequate social safety nets, and underdeveloped financial markets are likely to be more pronounced across low-income and developing economies, assessing the granular distributional effects of major disasters in developing countries is an important avenue for future work.

The empirical results give rise to several policy considerations. Efforts to limit the effects of natural disasters on income inequality will need to depend on the type, severity, and duration of natural disasters. As discussed in the conceptual framework, timely and effective policy responses can make a difference on how natural disasters affect within country inequality, and weather second-round effects (a recession) could be averted. The literature suggests actions on three broad areas, though designing specific policies calls for further policy research (Otker and others, 2016):

- Addressing pre-existing macro- and socioeconomic vulnerabilities, including high poverty and inequality, e.g., by deepening insurance and financial markets, enhancing social safety nets, investing in resilient infrastructure, as well as macro policies to build buffers and/or ensure access to external credit lines can enhance the ex-ante resilience and preparedness for natural disasters. To be effective, these policies should be designed with particular attention to their adequacy for disadvantaged population groups, which crucially rely on them.

- Prompt, adequate and effective emergency support in response to major natural disasters, can dampen the inequality effects of the immediate shock, e.g., by using policy space to provide economic relief, while ensuring that disaster relief funds reach out less affluent communities that often have harder time accessing information and resources. For low-income and vulnerable countries with limited space for emergency relief, coordinating disaster relief with donors can help respond to major disasters, as in the Covid-19 pandemic.

- Smart distributional policies should aim to reduce poverty and inequality while supporting the recovery by rebuilding lost capital and confidence. For example, these could include active labor market policies to re-skill workers in affected sectors and regions and support the necessary reallocation of labor, combined with targeted measures to support vulnerable groups that are likely to experience more prolonged effects of natural disasters.

Appendix I. Database for Natural Disasters

The main data source for natural disasters is from EM-DAT, which is a comprehensive database on occurrence and effects of technological and natural hazard-related disasters from 1990 to present. It is an outcome-based database that records number of people affected/killed and estimated economic damages. EM-DAT classifies an event as a disaster when at least one of the four criteria is met: loss of life of at least ten people, at least 100 people are reported affected, a state of emergency is declared, or there is a call for international assistance (EM-DAT). Importantly, if the same disaster hits several different countries, these are counted as individual events.

The EM-DAT database is expanded to include information on the COVID-19 pandemic from Our World in Data. Specifically, the information on the COVID-19 pandemic includes the date for the first case appeared in the given country (considered as the start of COVID), the total number of COVID cases and total number of COVID deaths by July 12, 2021, by country.

Further, the EM-DAT is expanded with information on the following five major epidemics as published by Furceri et al., 2021: SARS during 2003 – 2004, H1N1 during 2009 – 2010, the MERS outbreak during 2013 – 2014, the Ebola outbreak during 2014 – 2015, and ZIKA outbreak during 2015 – 2016. [2]

[2] Davide Furceri, Prakash Loungani, Jonathan D. Ostry and Pietro Pizzuto (2021)—"Will COVID-19 Have Long-Lasting Effects on Inequality? Evidence from Past Pandemics". IMF Working Paper, WP/21/127, April 2021.

Appendix II. Grid Search Exercise

In this section, we present the detailed results of our grid search exercise to estimate the impact of severe natural disasters, severe disasters with growth slowdowns and repeated severe disasters on a country's income inequality as proxied by the market Gini. We run these regressions for the full sample as well as for AEs and EMDEs separately, based on an annual panel of 180 countries over 1990-2019. Specifically, we tabulate below the $\beta_0^{(k)}$from the following equation:

$$y_{i,t+k} = \alpha_{1,i}{}^{(k)} + \alpha_{2,t+k}{}^{(k)} + \beta_0^{(k)} D_{i,t} + \theta^{(k)} X_{i,t} + \varepsilon_{i,t+k}, \text{ k=1,…,4} \quad (1)$$

where

$$X_{i,t} = \sum_{j=1}^{2} \beta_j^{(k)} D_{i,t-j} + \sum_{l=1}^{2} \gamma_l^{(k)} y_{i,t-l} + \sum_{l=0}^{k-1} D_{i,t+k-l}$$

$where\ y_{i,t}$ is the natural logarithm of the market Gini for country i in year t, α_i are country fixed effects, $\alpha_{2,t+k}{}^{(k)}$ are year fixed effects, $D_{i,t}$ is the treatment dummy, indicating the occurrence of a severe natural disaster in country i in year t when equal to one, no disaster or a minor disaster when equal to zero, and a disaster which was neither minor nor sufficiently severe when missing, $X_{i,t}$, is a vector including two lags of the dependent variable and the natural disaster treatment dummy, as well as the treatment dummy within the forecast horizon, and $\varepsilon_{i,t+k}$ are robust standard errors clustered at the country level. Equation (1) is estimated for each horizon k=0,…,4.

In the table below, any coefficient marked with an asterisk is significant at the 10 percent level. Each row corresponds to a different threshold for which disasters are deemed severe. For example, the first row takes the top 25 percent of disasters in terms of damages or people dead or affected as a severe disaster. The super columns, on the other hand, indicate which disasters are included in the control group (in addition to country-years with no disaster at all).[3] The columns indicate the forecast horizon k for any given pair of treatment group cut off (rows) and control group cut off (super columns). All country-years with disasters in between the treatment and control group cut off were discarded from the respective regression. Apart from this, the estimations are carried out as described in Section C.

[3] We experiment with this because the EM-DAT database contains a number of mild disasters which are unlikely to matter at the level of our analysis. As a result, the number of country-years without any disaster in EM-DAT is low, which is problematic for our analysis. Therefore, we chose to experiment with including disasters in the bottom 25, 50 and 75 percent in terms of severity in our control group.

Table 1. Aggregated Approach

All countries: Bottom y% disasters			25					50					75		
All countries: Top x% disasters (below)	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Severe disasters															
25	0.00	-0.04	0.01	0.08	-0.06	-0.04	0.00	0.03	0.00	0.01	-0.01	-0.07	-0.09	-0.08	-0.12
20	-0.01	-0.04	-0.04	0.10	0.00	-0.06*	-0.02	0.04	0.01	-0.10	-0.02	-0.06	-0.03	0.08	0.21
15	0.03	-0.04	0.06	-0.01	-0.23	-0.03	0.00	0.08	0.05	-0.13	-0.02	-0.02	0.05	0.11	0.23
10	-0.02	-0.04	0.01	-0.30	-0.85*	-0.03	-0.04	-0.12	-0.20	-0.22	0.01	0.04	0.05	0.14	0.16
5	0.01	-0.04	-0.44	-1.20*	-1.11*	-0.03	-0.16*	-0.13	-0.42	-0.45	-0.02	-0.08	-0.03	0.06	0.20
Severe disasters with growth slowdown															
25	-0.12*	-0.04	0.01	-0.31	-0.38	-0.07	-0.07	0.08	-0.29	-0.16	-0.01	-0.02	0.04	0.04	-0.08
20	-0.10	-0.04	0.01	-0.31	-0.38	-0.06	-0.08	0.05	-0.30	-0.16	0.01	-0.04	0.01	0.05	-0.13
15	-0.13*	-0.04	-0.16	-0.88	-2.24*	-0.07	-0.14	0.05	-0.23	-0.65	-0.01	-0.04	-0.07	-0.04	-0.30
10	-0.15	-0.04	-0.13	-0.66	-1.76*	-0.10	-0.06	0.16	0.09	-0.05	0.01	0.00	0.08	0.19	-0.14
5	-0.10*	-0.04	0.9*	1.05*	-0.06	-0.08*	0.02	0.41	0.00	-0.47	0.01	-0.01	0.24	0.59	1.19*

AEs: Bottom y% disasters			25					50					75		
AEs: Top x% disasters (below)	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Severe disasters															
25	-0.11	-0.07	0.76	1.02	...	-0.05	0.06	0.12*	0.11*	-0.18*	0.05	-0.02	0.02	0.03	-0.07
20	-0.07	0.25	1.20	2.67*	...	-0.07	0.14	0.08	0.30	-0.10*	0.03	0.02	0.11	0.24	0.36
15	-0.01	2.31*	3.29*	...	...	-0.02	-0.10	0.10	-0.17	-0.62	-0.04	-0.02	0.11	0.22	0.15
10	-0.72	2.11*	3.29*	...	...	-0.22	-0.09	-0.13	-0.85	-2.27	0.05	0.08	-0.01	0.32	0.03
5	...	...	...	...	...	-0.51	-1.05*	-0.82*	-0.65	0.00	0.07	-0.19	0.18	1.33*	1.20
Severe disasters with growth slowdown															
25	-0.48	-0.51	0.46	0.04	-0.53	-0.31	-0.45	0.03	-0.17	-1.00	0.02	0.02	0.09	0.30	-0.18
20	-0.58*	-0.31	0.46	0.04	-0.53	-0.33	-0.41	0.02	-0.19	-1.02	0.05	-0.05	0.07	0.40	-0.33
15	-0.75	-0.57	-0.08	-0.41	-0.53	-0.38	-0.56	-0.27	-0.54	-1.02	-0.08	-0.18	-0.14	-0.02	-0.39
10	-0.59	-0.37	0.25	-0.04	-0.53	-0.45	-0.39	-0.28	-0.53	-1.02	0.10	0.06	-0.04	0.13	-1.16
5	...	...	...	...	...	-0.59	-1.06*	-0.82*	-0.65	...	0.19	-0.04	0.02	1.30	1.18

EMDEs: Bottom y% disasters			25					50					75		
EMDEs: Top x% disasters (below)	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Severe disasters															
25	-0.02	-0.12	-0.30*	-0.25	-0.27	-0.05	-0.03	-0.08	-0.12	0.00	-0.03	-0.09*	-0.10	-0.12	-0.16
20	-0.02	-0.12*	-0.25*	-0.23	-0.27	-0.07*	-0.07	0.00	-0.01	0.08	-0.04*	-0.09	-0.07	0.01	0.05
15	-0.01	-0.06	-0.14	-0.11	-0.02	-0.03	0.02	0.10	-0.03	-0.09	0.00	0.02	0.10	0.14	0.26
10	-0.04	-0.16*	-0.20	-0.32	-0.74*	-0.03	-0.01	0.03	-0.15	-0.22	0.01	0.07	0.14	0.18	0.22
5	-0.02	-0.27*	-0.38*	-0.63*	-1.11*	-0.04	-0.14*	0.04	-0.33	-0.51*	-0.03	-0.04	0.01	-0.09	-0.20
Severe disasters with growth slowdown															
25	-0.06	-0.14	0.00	-0.16	0.05	-0.05	-0.13	0.08	-0.28	-0.04	-0.01	-0.08	0.06	0.00	-0.01
20	-0.07	-0.13	0.00	-0.16	0.05	-0.07	-0.15	0.02	-0.28	-0.04	0.00	-0.06	0.03	-0.02	0.03
15	-0.10	-0.10	0.30	-0.01	0.52*	-0.07	-0.06	0.40*	0.02	0.07	0.04	0.11	0.21	0.13	0.29
10	-0.14*	-0.08	0.59*	0.39	0.64	-0.11*	-0.04	0.95*	0.57	0.22	0.02	0.11	0.33	0.28	0.70
5	-0.12*	-0.13	0.57*	0.00	-0.29*	-0.10	0.02	1.34*	0.89	0.19	0.00	0.10	0.40	0.42	0.81

Table 2. Event-level Approach

All countries: Bottom y% disasters	25					50					75				
All countries: Top x% disasters (below)	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Severe disasters															
25	-0.02	-0.06	-0.07	-0.09	-0.08	-0.01	-0.07	-0.08	-0.15	-0.04	-0.01	-0.04	-0.06	-0.09	-0.12
20	-0.04*	-0.11*	-0.21*	-0.23*	-0.31*	-0.02	-0.09	-0.22	-0.33	-0.31	-0.01	-0.04	-0.06	-0.06	-0.14
15	-0.03	-0.12	-0.19	-0.26	-0.28	-0.02	-0.17	-0.25	-0.36	-0.39	-0.02	-0.05	-0.03	0.02	-0.05
10	-0.02	-0.06	-0.08	-0.04	0.04	-0.01	-0.03	-0.08	-0.20	-0.02	-0.02	-0.05	-0.04	0.05	0.20
5	0.02	0.00	0.08	0.02	0.01	-0.03	-0.04	-0.01	-0.34	-0.25	-0.04	-0.04	0.04	0.10	0.15
Severe disasters with growth slowdown															
25	-0.02	-0.04	0.13	0.05	0.06	-0.04	-0.07	-0.12	-0.11	0.03	0.00	-0.02	0.04	0.02	0.05
20	-0.04	-0.14	0.14	0.13	0.15	-0.05	-0.14	-0.26	-0.33	-0.27	0.00	-0.02	0.02	0.08	0.14
15	-0.05	-0.05	0.04	-0.02	0.18	-0.07	-0.18	-0.46	-0.50	-0.20	-0.02	-0.07	-0.05	-0.12	0.50
10	-0.08	-0.14	0.10	0.12	0.30*	-0.11*	-0.33*	-0.47	-0.55	-0.17	-0.01	-0.12	0.11	0.14	0.75
5	-0.04	0.11	0.23	-0.15	0.01	-0.11	-0.26	-0.39	-0.72*	-0.67	-0.06	-0.14	0.15	0.39	1.66
Repeated severe disasters															
25	-0.03*	-0.05	-0.07	-0.07	-0.09	-0.01	-0.09	-0.11	-0.13	-0.04	-0.01	-0.04	-0.05	-0.10	-0.15
20	-0.03*	-0.05	-0.07	-0.07	-0.09	-0.01	-0.09	-0.11	-0.13	-0.04	-0.01	-0.04	-0.05	-0.10	-0.15
15	-0.03*	-0.05	-0.07	-0.07	-0.09	-0.01	-0.09	-0.11	-0.13	-0.04	-0.01	-0.04	-0.05	-0.10	-0.15
10	0.14	0.94	0.90	0.64	-0.73	0.06	0.28	-0.22	-0.54	-0.59	0.01	0.07	0.06	0.41	1.28
5	0.14	0.94	0.90	0.64	-0.73	0.06	0.28	-0.22	-0.54	-0.59	0.01	0.07	0.06	0.41	1.28

AEs: Bottom y% disasters	25					50					75				
AEs: Top x% disasters (below)	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Severe disasters															
25	*-0.01**	*0.2**	*0.99**	*1.38**	*1.26**	0.10	0.16	0.57	0.48	-0.05	0.10	0.11	0.12	0.11	0.14
20	-0.06	0.15	0.37	0.79	1.21	0.01	0.25	0.46	0.57	1.89	0.10	0.13	0.14	0.19	0.01
15	0.43	0.21	0.26	0.43		0.24	-0.09	-0.58	-0.26	...	0.07	0.07	0.09	0.29	0.11
10	...	...	...	...	...	0.17	0.15	...	...	...	0.01	-0.05	0.07	0.34	0.65
5	...	...	...	...	...	...	...	...	...	...	0.03	-0.05	-0.53	-1.32	-0.71
Severe disasters with growth slowdown															
25	0.01*	0.03*	0.04*	0.04*	0.04*	-0.02	0.02*	2.18	0.04*	0.04*	0.21	0.00*	0.40	0.54	2.15
20	...	...	...	...	...	-0.39	0.03*	...	...	...	0.21	0.35	0.45	0.81	-0.80
15	...	...	...	...	...	-0.02*	0.01*	...	...	...	0.08	-0.11	-0.20	-0.61	0.31
10	...	...	...	...	...	0.09	0.05	...	...	...	-0.05	-0.17	0.07	-0.22	0.39
5	...	...	...	...	...	...	...	...	...	...	-0.08	-0.01*	-0.02*	-0.02*	-0.81
Repeated severe disasters															
25	0.03	0.34	0.60	1.26	0.88	0.14	0.17	0.44	0.59	-0.61	0.11	0.16	0.17	0.15	0.20
20	0.03	0.34	0.60	1.26	0.88	0.14	0.17	0.44	0.59	-0.61	0.11	0.16	0.17	0.15	0.20
15	0.03	0.34	0.60	1.26	0.88	0.14	0.17	0.44	0.59	-0.61	0.11	0.16	0.17	0.15	0.20
10	0.01*	0.02*	0.03*	0.02*	0.03*	0.45	1.53	1.56	0.04*	0.022*	0.09	0.10	-0.05	-0.17	1.03
5	0.01*	0.02*	0.03*	0.02*	0.03*	0.45	1.53	1.56	0.04*	0.022*	0.09	0.10	-0.05	-0.17	1.03

EMDEs: Bottom y% disasters	25					50					75				
EMDEs: Top x% disasters (below)	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Severe disasters															
25	-0.02	-0.05	-0.06	-0.07	-0.04	-0.02	-0.08	-0.09	-0.15	-0.01	-0.02	-0.04	-0.04	-0.06	-0.08
20	-0.03	-0.12	-0.23	-0.23	-0.28	-0.01	-0.12	-0.24	-0.36	-0.28	-0.02	-0.04	-0.04	-0.06	-0.11
15	-0.04	-0.13	-0.20	-0.26	-0.29	-0.03	-0.19	-0.29	-0.40	-0.41*	-0.03	-0.06	-0.03	-0.02	-0.11
10	-0.02	-0.08	-0.13	-0.12	-0.04	-0.02	-0.08	-0.19	-0.27	-0.10	-0.01	-0.02	-0.02	-0.01	-0.03
5	0.01	-0.04	0.00	-0.06	0.01	-0.04	-0.11	-0.27	-0.48	-0.45	-0.04	-0.01	0.03	-0.04	-0.15
Severe disasters with growth slowdown															
25	-0.05	-0.14	0.05	0.21	0.16	-0.04	-0.12	-0.05	0.02	0.12	-0.01	-0.05	0.02	-0.06	-0.20
20	-0.08*	-0.10	0.11	0.19	0.25	-0.04	-0.05	-0.13	-0.01	0.00	-0.02	-0.05	0.01	0.01	0.21
15	-0.07	0.00	0.03	0.17	0.28	-0.06	-0.10	-0.40	-0.18	0.09	-0.02	-0.01	0.04	0.00	0.35
10	-0.10*	-0.08	0.04	0.24	0.72*	-0.11*	-0.31*	-0.40	-0.18	0.02	0.01	0.01	0.20	0.15	0.67
5	-0.09	-0.10	0.16	-0.15	0.14	-0.12*	-0.31*	-0.79*	-0.36	-0.18	-0.03	0.12	0.31	0.26	0.74
Repeated severe disasters															
25	-0.03	-0.05	-0.06	-0.06	-0.07	-0.03	-0.11*	-0.13*	-0.13	-0.02	-0.02	-0.04	-0.03	-0.07	-0.11
20	-0.03	-0.05	-0.06	-0.06	-0.07	-0.03	-0.11*	-0.13*	-0.13	-0.02	-0.02	-0.04	-0.03	-0.07	-0.11
15	-0.03	-0.05	-0.06	-0.06	-0.07	-0.03	-0.11*	-0.13*	-0.13	-0.02	-0.02	-0.04	-0.03	-0.07	-0.11
10	-0.08	-0.13	0.00	0.00	0.00	-0.07	0.15	-1.98	-2.86	-0.86	0.02	0.15	0.31	1.22*	1.92*
5	-0.08	-0.13	0.00	0.00	0.00	-0.07	0.15	-1.98	-2.86	-0.86	0.02	0.15	0.31	1.22*	1.92*

Source: EMDAT database and IMF staff calculation.

Note: The tables summarize the results of local projections for the period of t to t+4, particularly the estimated coefficients of treatment dummy for different treatment and control groups. The star indicates significance at 10 percent level, respectively.

Appendix III. The U.S. States Event Analysis

The data for our event study for the heterogeneous labor market effects of major natural disasters on the U.S. states uses harmonized IPUMS CPS data[4] and EM-DAT for events in the U.S from 1990–2019.

The CPS data is at individual level with monthly frequency, and include rich demographic information, employment data, and program participation data. Specifically, in the CPS survey the outgoing rotation group/earners study include additional labor data on current work and income. The outgoing rotation group are households in the CPS that are interviewed for four months, postponed for eight months, and resumed interviewing for four more months. The basic demographic data from CPS and Merged Outgoing Rotation Group data were main variables used for U.S. event analysis, including gender, race, age, education, hourly wage, and employment status. The data was aggregated into new groups, created based on individual characteristics based on gender, age, race, and education. For example, Age was aggregated to three major groups as youth (under 18), prime working age (18–55), and older; race was aggregated to keep four major race groups, White, Black, Hispanic, and other; education was regrouped to less than high school, high school, no college degree, college, and advanced degree. From table 1, detailed aggregation from CPS data was listed.

Table 1. U.S. Event study Aggregated Variables

	US event study analysis variable categories	CPS variable categories	Variables for Event Analysis
Gender	Female, male	Female, male	Female = 1, Male = 2
Race	White, Black, Hispanic, Other	White, Black, American Indian/Aleut/Eskimo, Asian or Pacific Islander, Asian only, Hawaiian/Pacific Islander only, Other (single) race, n.e.c., Two or more races	White = 1, Black = 2, Hispanic = 3, Other = 4
Education	Less than High school, high school, no college degree, college degree, and advanced degree	NIU or no schooling; Grades 1, 2, 3, or 4; Grades 5 or 6; Grades 7 or 8; Grade 9; Grade 10; Grade 11; 12th grade, no diploma; 12th grade, diploma or unclear; high school diploma or equivalent; Some college but no degree; Associate's degree; 3 years of college; 4 years of college; Bachelor's degree; 5+ years of college; 6+ years of college; Master's degree; Professional school degree; Doctorate degree	Less than high school = 1, high school = 2, no college degree = 3, college degree =4, advanced degree =5
Age 1/	Youth (15-24), Prime age (25-54), Older (55-64)	0-85	Older =1, Prime age = 2, Youth = 3

Sources: CPS, EM-DAT, and IMF Staff Calculations.

[4] Outgoing Rotation Group/Earner Study User Guide, IPUMS CPS, https://cps.ipums.org/cps/outgoing_rotation_notes.shtml

Notes: 1/ The age groups are defined by definitions from OECD and ILO. The lower and upper bounds of working age is from OECD's definition on working age population is ranged between age 15-64 (OECD, 2022). The youth and prime age are defined by ILO's categories on working age groups for youth (15-24) and prime-age persons (25-54). We then define people who are included as working age population but excluded outside youth or prime-age persons as older worker group.

The event analysis is based on a panel dataset, which is created from the aggregated CPS data merged with EMDAT database. The aggregated CPS data includes the following labor market variables: employment number, unemployment number, labor force number, and weekly wage. For a given gender-race-age-education subgroup, the labor market variables are estimated at state-month-year level as the sum, and the weekly wage variable is estimated at state-month-year level as a simple average. That is,

$$Employment_{t,s} = \sum_i wgt_i * E_i$$

$$Unemployment_{t,s} = \sum_i wgt_i * U_i$$

$$Labor\ Force_{t,s} = \sum_i wgt_i * L_i$$

$$\overline{Wage}_{t,s} = \frac{\sum_i earnwgt_i * W_i}{\sum_i i}$$

where,

i denotes individual in the given gender-race-age-education subgroup.
t demotes the state-month-year combinations, where t = 01011990, 01021990, …, T, T is the different combination of 50 states and 1 districts, 12 months, and 29 years (1990-2019), the total number of T is 17748.
s denotes the gender-race-age-education subgroups, where s = 1111, 1112, …, S, S is the combination of 2 gender, 4 races, 3 age group, and 5 education groups, the total number of S is 120.
wgt_i denotes the composited final weight associated with person i (weights have been provided by CPS, and used to compute the total employment, and population statistics based on the CPS sample.
$earnwgt_i$ denotes the composited earn weight for earn study questions associated with person i
E_i is an indicator variable that equals 1 if person i is employed; otherwise, it is 0.
U_i is an indicator variable that equals 1 if person i is unemployed; otherwise, it is 0.
L_i is an indicator variable that equals 1 if person i is in labor force; otherwise, it is 0.
W_i is individual's weekly wage reported.

The aggregated CPS data is in long format shape, to merged with EMDAT data and prepare for panel analysis, the data is converted to panel wide-format shape with state-month-year as the time point, and gender-race-age-education subgroups as entities.

Given the large number of socio-economic groups across the 50 states and the four individual characteristics as specified in Table 1, as well as that most smaller scale disasters have mild effects in terms of human and social costs, we focus on the impact of the top most severe disasters on vulnerable groups (top 5 severe disasters in terms of human costs and top 5 severe disasters in terms of economic costs). The disasters included are listed in detail in table 2.

Table 2. United States: Major Disasters Over 1990–2019
(Top 5 natural disasters in the United States by damages or human costs)

Event Name	Year	States affected	Damages as Percent of GDP	Percent of Affected population
Northridge earthquake	1994	CA	20.58	0.09
Tropical cyclone "Andrew"	1992	FL, LA	10.16	1.40
Tropical cyclone "Katrina"	2005	AL, LA, MS, GA, FL	8.23	1.32
Tornado outbreak	2011	MS	5.39	0.02
Storm Jonas (Snowzilla)	2016	DC, NY, NJ, PA, MD, VA, TN, KY, DL, WV, GA, NC	0.01	94.81
Riverine flood	2008	OK, MN, WI, IA, IL, MS, SD, ND, NE, KS	0.47	23.59
Tropical cyclone "Frances"	2004	FL, NC, SC, OH	0.71	12.30
Parasitic disease	1993	ND, MN	…	8.01
Hurricane Harvey	2017	TX, LA	5.00	8.04

Source: EMDAT database and IMF Staff Calculations.

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