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Impact of Natural Disasters on the Income Distribution**

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March 2020

Abstract

During the last decades, the United States experienced an increase in the number of natural disasters as well as their destructive capability. Several studies suggest a damaging effect of natural disasters on income. In this paper, I estimate the effects of natural disasters on the entire income distribution using county-level data in the United States. In particular, I determine the income fractions that are affected by natural disasters. The results suggest that natural disasters primarily affect middle incomes, thereby leaving income inequality levels mostly unchanged. In addition, the paper examines potential channels that intensify or mitigate the effects, such as social security or the severity of natural disasters. The findings show that social security, assistance programs and migration are important adaptation tools that reduce the effects of natural disasters. In contrast, the occurrence of multiple and severe disasters aggravate the effects.

Keywords: Disaster, Income Distribution, United States, Migration, Panel Data

JEL classification: D63, O51, Q54, R23

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1 Introduction

Recent decades experienced more frequent and more destructive occurrences of natural disasters all over the world. In fact, some of the most devastating disasters materialized in the last 15 years, such as the 2004 earthquake and tsunami in Southeast Asia, Hurricane Katrina in the United States in 2005, the 2010 earthquake in Haiti, and the 2011 earthquake, tsunami and nuclear disaster in Japan. In 2019, the Bahamas were ravaged by Hurricane Dorian, the most devastating cyclone on the country's record. The death toll, the destruction of property and the displacement of people is presumed to have a long-lasting effect on people's lives as well as the economy as a whole, by slowing economic growth and raising unemployment rates (Coffman and Noy, 2012).

The aim of this paper is to estimate the effects of natural disasters on the income distribution in the United States using county-level data. Unlike the previous literature, this paper provides a comprehensive analysis of the effects in the entire United States using all types of natural disasters. Previous papers focus either on one type of natural disasters or on regional effects. In addition, I differentiate between two income measures, namely measures based on either individual- or household incomes. In the inequality or income distribution literature, households are commonly used as the main unit of analysis. However, household-based income disregards important intra-household dynamics, because it explicitly assume perfect equality within the household. Another contribution is the detailed depiction of the underlying mechanisms of the effects of natural disasters on the income distribution. One relevant feature is the distinction between capital and labor income. Finally, I empirically evaluate potential channels that might either intensify or dampen the effects of natural disasters. Examples include the severity of disasters and migration.

In general, the topic is relevant from a policy perspective as well as a societal point of view. Increasing income inequality is a contributing factor to social unrest and the rise of populism. In the United States, where income inequality is reaching high levels compared to other OECD countries, these effects are especially important. In particular, this paper determines the income groups mostly affected by natural disasters. Regardless of whether they lead to rising or declining inequality levels, the growing occurrence of natural disasters in the United States poses additional stress on the income distribution and, thus, on politics and society.[1] Therefore, policies are necessary to tackle the additional stress by introducing affordable insurance as well as offering financial assistance to citizens in need. These measures cannot prevent disasters, but they help mitigating the consequences. The analysis of the entire income distribution identifies the affected population in a more precise way. Previous studies on the effects of natural disasters on income focus on average effects. However, this paper will show that average effects often underestimate the true effect of a disaster.

The direction of the effects on the income distribution is ex ante ambiguous. The vulnerability argument encompasses the notion of varying susceptibility of individuals and households at different positions of the income distribution. In particular, it states that poor households are more vulnerable as they are more likely to be employed in the primary sector and consequently more exposed to weather-related disasters, such as floods and droughts. This line of argument is mainly applicable to developing countries. The United States has highly developed insurance markets and social security provisions. In addition, disaster-related assistance programs are provided for affected individuals and households. In contrast, the risk argument claims that rich individuals or households are more affected due to their business and capital

[1] Climate-related events act as "threat multipliers", namely that they amplify the likelihood of social instability or even violent conflict by exacerbating pre-existing problems, such as poor economic conditions, political and economic inequality, or deficient governance.

income[2] that are subject to economic volatility. Further, most low- and middle-income households are working for a risk-free salary that is to a large part substituted by unemployment insurance in case of unemployment, which smooths out large income losses.

The United States is particularly suitable for such an analysis due to high data availability and coverage, as data are available on the county level for both incomes and disasters. A common challenge in estimating the effects of disasters is the heterogeneity of initial disaster-prevention measures. Developed countries have on average more preventive measures, e.g. in the form of construction laws, warning systems and disaster management during a disaster. These adaptation measures as well as functioning institutions are mainly responsible for the considerably lower death toll in developed countries (Kahn, 2005). Furthermore, they have the financial means and the necessary institutions to deal with the damages after the disaster. This heterogeneity poses a challenge on the comparability of the effects across countries. However, by focusing on the United States, the heterogeneity is reduced since the disaster-related measures and institutions are comparable across counties and states. Also, the variation in economic development is less pronounced across counties than across countries of the world.

Using the United States for the study has also practical reasons. Disasters in the US occur frequently, with a variety of types (e.g. flood, hurricane, drought) and with geographic variation. Previous studies mainly focus on hurricanes because they are the most destructive disasters. But this paper includes all natural disasters of the United States and shows that there is a substantial hetereogeneity in the effects on incomes. To the best of my knowledge, there is no other paper that provides the effects of all natural disasters in the United States.

[2] Note that capital income is defined as income derived from capital, such as interest and dividend payments. The measure does not include wealth.

The main finding shows that natural disasters have a damaging effect on middle incomes. This effect is driven by labor earnings and capital income. In addition, the effects are generally higher for individual-based measures, because potential income losses of one household member is absorbed by the other. The results on potential adaptation channels suggest that social security, assistance programs and migration are important mitigation tools. Whereas the occurrence of multiple and severe disasters magnify the effects of natural disasters on incomes.

The next section presents the most related literature on the topics of natural disasters and incomes. In Section 3, I present the theoretical background, including the mechanism model and the derived hypotheses. The data is presented in Section 4, followed by the main methodology in Section 5. In Section 6, I present a number of results, including the effects on total, capital and labor income as well as the channels that influence the initial results. The paper concludes in Section 7.

2 Related Literature

There are numerous contributions that estimate the effect of natural disasters on average income. In the United States, Deryugina (2017) finds no effects on average county earnings in the decade after a hurricane hits due to large government transfers, such as unemployment insurance, into affected counties. In fact, the author argues that total fiscal costs exceed the costs of specific disaster aid. However, counties experiencing more severe hurricanes receive only marginally higher transfers, thereby leading to larger negative earning effects. In contrast, Groen et al. (2019) show that the 2005 hurricanes led to short-term decline in earnings, but long-term increases in affected areas in the US. Also, the decline in earnings is mainly due to shifts from employment to unemployment. The long-term increases can be attributed to increased labor demand, particularly in construction-related sectors. Similarly, Belasen and Polachek (2008) suggest decreases in employment, but increases in earnings in the aftermath of a hurricane in Florida. On Hawaii, Coffman and Noy (2012) show that even 18 years after hurricane Iniki the population counts, incomes and number of private sector jobs are lower in the affected regions. Lynham et al. (2017) analyze the effect of the 1960 Tsunami in the city of Hilo on Hawaii. Using non-affected islands as the control group, the findings indicate that even 15 years later unemployment is still at 32% and population down by 9% due to people moving away from the affected areas, whereas wages did not decline in that period.

Other studies focus on aggregate growth and development, such as Nordhaus (2010), Felbermayr and Gröschl (2014), Klomp (2016) and Loayza et al. (2012). They find that, on average, natural disasters have damaging effects on economic growth and development. Nordhaus (2010) shows that economic losses, measured by GDP, increase with storm severity in the US. Using a panel of countries, Loayza et al. (2012) suggest that these effects differ by type of the disaster and the affected economic sector. Noy (2009) suggests that countries with a higher literacy rate, better institutions, higher per capita income, higher degree of openness to trade, developed financial markets and higher levels of government spending are more resilient to natural disasters. The described studies analyze the effect of natural disasters on income, but not the resulting inequality.

Another important consequence of natural disasters is migration. Even though the United States experienced a decline in general interstate migration in the last decades (Kaplan and Schulhofer-Wohl, 2017), some of the migration patterns can be attributed to climate change according to various authors. For instance, Feng et al. (2012) find a link between agricultural productivity and net migration in the US. In particular, they show that climate has a long-lasting effect on productivity that leads to mobility in rural areas. These results are mainly driven by young adults who seek improved economic opportunity. Similar results are suggested by Bohra-Mishra et al. (2017) in the Philippines, where young educated males migrate out of rural areas in response to increased typhoon activity. Boustan et al. (2017) suggest that counties hit by severe disasters experienced larger out-migration, lower home prices and higher poverty rates. The results are particularly strong in high disaster risk areas.

In addition, Boustan et al. (2012) show that men between 30 and 40 were more likely to migrate from disaster-prone areas in the 1920s and 1930s. However, migration became less likely after the introduction of post-disaster government aid. Hence, government transfers serve as an adaptation tool for the long-run effects of climate change that countervail the effects on migration. Other mitigating factors are land allocation, agricultural adjustments as well as limited geographic mobility of labor and capital, which lead to considerable differences in migration patterns as well as short- and long-run costs of natural disasters (Hornbeck, 2012). Analyzing the short- and long-run effects of the Dust Bowl in the 1930s, Hornbeck (2012) suggests that the most prominent adaptation channel during this disaster was migration. Counties strongly affected by the Dust Bowl experienced large population declines. In contrast, Long and Siu (2016) claim that the population decline during the Dust Bowl was driven by the drop in migration inflow. Also, farmers, even though the most affected, were the least likely to move away. The role of migration for this analysis is twofold. First, it is an important adaptation tool, as suggested by Hornbeck (2012). Second, it constitutes a source of endogeneity because selective in- and out-migration affects the income distribution. Therefore, I will include migration into the analysis.

In this paper, I want to analyze the effect of natural disasters on the income distribution, which is related to the income inequality literature. The evidence on the effect of disasters on income inequality is still fairly unexplored (Karim and Noy, 2016). Most available studies are conducted in Asia, such as Abdullah et al. (2016) in Bangladesh, Bui et al. (2014) in Vietnam, Keerthiratne and Tol (2018) in Sri Lanka, and Sawada and Shimizutani (2008) in Japan. Abdullah et al. (2016) and Keerthiratne and Tol (2018) detect inequality-decreasing effects due to the higher income groups bearing a considerably larger fraction of the economic damages. In contrast, Bui et al. (2014) find an overall decline in incomes and expenditures but increased income and expenditure inequality as well as poverty. A cross-country analysis of the effects of natural disasters on income inequality is conducted by Yamamura (2015). The study suggests short-run increases in inequality levels, but no effects in the long-run. Studies in the United States usually focus on hurricanes and regional effects. For instance, Shaughnessy et al. (2010) shows inequality-decreasing effects of hurricane Katrina in New Orleans. Another study presents inequality-increasing effects of hurricanes on the state-level (Miljkovic and Miljkovic, 2014).

However, to the best of my knowledge, no other study analyzes the effects of different natural disasters on the entire income distribution in the United States. This paper attempts to close this gap in the literature and obtain an improved understanding of the underlying mechanisms in the income dynamics across different fractions of the income distribution.

3 Theoretical Background

3.1 Mechanism Model

The main mechanism of the effects of natural disasters on the income distribution is passing through total income. Several papers, such as Groen et al. (2019) and Coffman and Noy (2012), suggest income-reducing effects of hurricanes in the United States. In contrast, Deryugina (2017) suggests no effect on county earnings. Thus, there seems to be different effects depending on the income measure as well as the time frame used in the analysis. In the simple model, I partition total income into labor and capital income.

$$\begin{aligned} Y_{i,t}^{Total} &= Y_{i,t}^{Capital} + Y_{i,t}^{Labor} \\ &= Y_{i,t}^{Capital} + Y_{i,t}^{Earnings} + Y_{i,t}^{Transfer} \end{aligned}$$

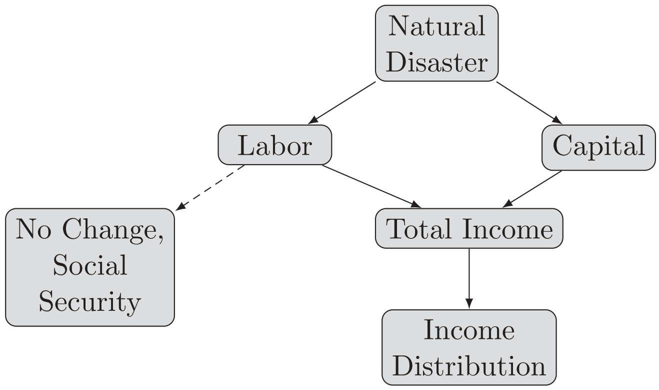
Labor income $Y_{i,t}^{Labor}$ comprises of earnings, $Y_{i,t}^{Earnings}$, and transfer income, $Y_{i,t}^{Transfer}$. Earnings include wages, salaries and income from self-employment (e.g. farm income, business income) for individual i in year t. Capital income, $Y_{i,t}^{Capital}$, denotes any income derived from capital, such as interest payments, rents and dividends. $Y_{i,t}^{Transfer}$ includes among others unemployment benefits, retirement, social security and educational assistance.[3] The share of capital income of total income is on average at about 5%. The average capital income share of the top 5% is 7%. Hence, capital income shares are rather low and further decreasing for lower income groups. As a consequence, labor income shares are increasing at lower incomes. Within labor income, earnings are decreasing with decreasing total income and welfare benefits are increasing.

The distinction between capital and labor income is relevant due to their difference in the amount of risk that each of the income components bear. The introduction of risk is particularly relevant in this context because the United States has advanced social security and insurance markets, which reduce the risk factor in labor income. In contrast, capital income is risky and, thus, susceptible to potential economic shocks. Figure 1 gives an overview of the mechanisms at work.

In general, total labor income is less risky than capital income and, thus, less affected by natural disasters. If (negative) changes in employment or earnings occur, they are to a substantial part substituted by unemployment insurance, thereby reducing the effects on

[3]A complete list of all types of incomes is provided in Table A2 in the appendix.

Figure 1: Mechanism Model



total labor income. There are occupations, particularly in the low- and middle-income sector that experience an economic boom after a natural disaster. The most prominent example is the construction sector that experiences increases in working hours as well as wages after a disaster.[4] However, the majority of the sectors are likely to be negatively affected by natural disasters leading to declines in earnings. The most prominent example being the hospitality sector.

In contrast, capital income is often not protected by insurance, thereby generating risky income. A natural disaster leads to the destruction of capital, which decreases income derived from capital, e.g. capital income. In sum, natural disasters affect the income distribution through capital income and to some degree through labor income, as denoted in Figure 1.

The distinction between risky and non-risky income is crucial to understand the effects on the income distribution. In particular, individuals in the low income group are likely to be employed as wage-receiving labor with low levels of income risks and no capital income. Hence, this income group is only affected if labor income moves due to employment-unemployment shifts or large income losses. Groen et al. (2019) suggest sustained higher earnings in affected areas even years after the 2005 hurricanes. One potential explanation are the after-disaster

[4]See Groen et al. (2019).

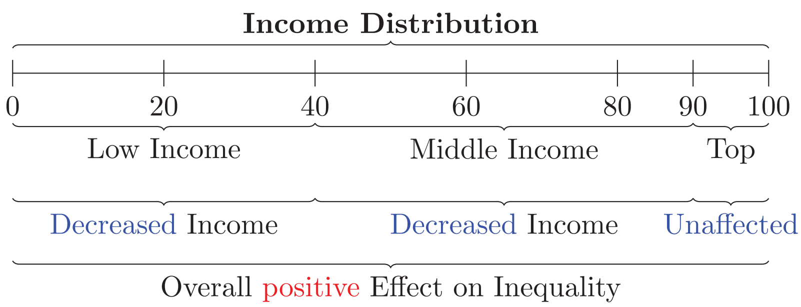
booms in infrastructure-related sectors. However, these hurricanes were particularly destructive. The effects are likely to be less strong for other natural disasters.

In contrast, the top 10% group are more likely to invest in financial assets and earn capital income, which makes them exposed to economic volatility. Therefore, they are likely to experience losses in capital income in the short-term. Once capital is replaced by more productive technologies, capital income is reinstated and potentially increasing in the long-term due to the creative destruction argument. Thus, capital income might overshoot compared to pre-disaster levels. But the effects on total income of the top 10% group is likely to be negligible since even the high-income group's total income contains mainly labor income.

The middle income group combines characteristics of the top and low income group. Similar to the low income group, middle income members are likely to be employed in form of paid labor, which makes them less vulnerable to large income losses due to social security compensations. But this group also includes business owners that might experience some income losses due to their capital income and ownership.

Due to the described income characteristics, I hypothesize negative effects of natural disasters on low and medium incomes. The effects on the low income group are expected to be less severe as it benefits from the after-disaster boom and has no capital income. In contrast, the effect on the middle income group is likely to be stronger since this group includes small to medium sized business owners with capital income. Unemployment insurance, agricultural subsidies for farmers and disaster assistance programs are expected to remedy the full effects, but they occur with a time lag and often do not cover the full costs. The top income group is only affected by capital income which constitutes only a small part of total income. As a consequence, overall income inequality is increasing in the short term. In the analysis, I will use Gini-coefficients and Palma ratios based on total incomes as proxies for income inequality. Related to the Lorenz curve, the Gini-coefficient is defined as half of the relative mean absolute difference, which is the average absolute difference of all observations divided by the average. The Palma ratio denotes the ratio between the top 10% income share to the bottom 40% income share. Hence, it is a measure that relates the two tails to each other. The graphical representation of the short-term effects is provided in Figure 2.

Figure 2: Short-term Effects on Income Distribution



Notes: Figure shows the short-term effects of natural disasters on the income distribution of a county. The numbers denote the percentiles in the distribution. The top income group has incomes between the 90th and 100th percentile. I chose to analyze the top 10% due to the attention this income group gets in society as well as the literature. In addition, most of the capital income is concentrated within this group. The low income group encompasses incomes between 0 and the 40th-percentile. Using this threshold gives enough variation for the analysis. Lower thresholds include too many zero incomes. The middle income group is defined between the two described thresholds.

3.2 Relationship of individual- and household-based Income Inequality

The previous literature on income inequality generally relies on household-based incomes. However, household-based measures smooth out some of the variation in individual incomes, as it completely disregards the role of intra-household income inequality. Using household-level data explicitly assumes complete income equality within the household. As a consequence, household-based inequality underestimates the true inequality. In contrast, individual-based income inequality incorporates both, household and intra-household inequality. However, individual-based measures do not account for household sharing as potential income losses by one member might be absorbed by other member(s). Hence, individual-based measures overestimate the true inequality. Using both, household- and individual-based, measures provides upper and lower bounds of the effects.

By construction, individual income inequality is larger than household inequality as intra-household inequality cannot be negative. Intra-household inequality might increase as one member looses his or her job or experiences a wage increase after a disaster, which has ramifications for individual-based income inequality. The second option might occur if individuals are employed in the construction sector, which booms after disasters due to massive infrastructure restorations, experience a wage increase, either as a result of more working hours or shortage of labor. After a couple of years, the restorations are usually completed and working times return to their previous levels. However, wages have a strong nominal downward rigidity that do not allow them to return to their initial levels (Banerjee, 2007). Thus, overall intra-household inequality decreases but by less than the initial increase. With household-based income inequality returning to its former value, e.g. higher level of inequality, there might be an overall, though small, positive effect on individual-based income inequality in the long-run. However, the effect is absent if the initial wage increase is not sufficiently large.

Optimal mitigation policies should take household- as well as individual-level effects into account. By using household-level data, it is impossible to disentangle the detailed mechanisms at work. For instance, since natural disasters have heterogeneous effects on specific industry sectors (Groen et al. (2019)) using household-based measures underestimates the effects as any household with individuals having jobs in different sectors offset the actual magnitudes of the effects.

3.3 Hypotheses

Following the theoretical arguments above, I want to test the following hypotheses in the subsequent empirical analysis:

Hypothesis 1 *Natural disasters have a positive effect on overall income inequality.*

Hypothesis 2 *The low and middle income groups' incomes decrease.*

Hypothesis 3 *The top income group is unaffected.*

Hypothesis 4 *The effects are larger for individual-based measures.*

3.4 Potential Channels

Dell et al. (2014) indicate that the magnitude of the disaster effects depends on two major channels, namely the adaption and intensification channel. The adaptation channel denotes the potential of disaster-resilient measures, e.g. dams, to mitigate the consequences of natural disasters. In contrast, the intensification channel strengthens the adverse consequences by generating additional stress to the environment.

Applied to the income distribution case, the adaptation channel includes migration away from disaster-prone areas (Feng et al., 2012; Bohra-Mishra et al., 2017; Boustan et al., 2012; Hornbeck, 2012), social security and disaster mitigation policies. Whereas the intensification channel encompasses the occurrence of multiple disasters within a short time period as well as the increase in the severity of disasters.

The adaptation channel is likely to dampen the effects of natural disasters on incomes. For instance, the existence of unemployment insurance decreases the devastating effects that disasters might have on incomes, assets and labor market outcomes. Migration is an important adaptation tool due to its reallocation of incomes and capital from disaster-prone to safer areas, as suggested in the literature (e.g. Boustan et al. (2012); Bohra-Mishra et al. (2017)).[5] Consequentially, the effects of natural disasters will decrease over time. For this reason, I will devote a section in the results to the analysis of migration.

In contrast, the intensification channel is likely to increase the effects of natural disaster on incomes. In the result section, I provide an analysis of the effects of frequent and severe disasters on the income distribution.

4 Data Description

4.1 Incomes and Income Inequality

I construct county-level Gini-coefficients, Palma ratios and average incomes based on individual and household incomes, respectively. The data is provided by the Current Population Survey (CPS) from 1996 to 2017 (Flood et al., 2019).[6] The CPS is a monthly survey on employment-related statistics conducted by the United States Census Bureau for the Bureau of Labor Statistics (BLS).[7] In addition, the CPS include an Annual Social and Economic Supplement (ASEC) on incomes and other individual and household characteristics. The ASEC uses a multi-stage sample stratification in which the geographic areas and then the households are sampled. The included counties in the survey are depicted in A2. In addition,

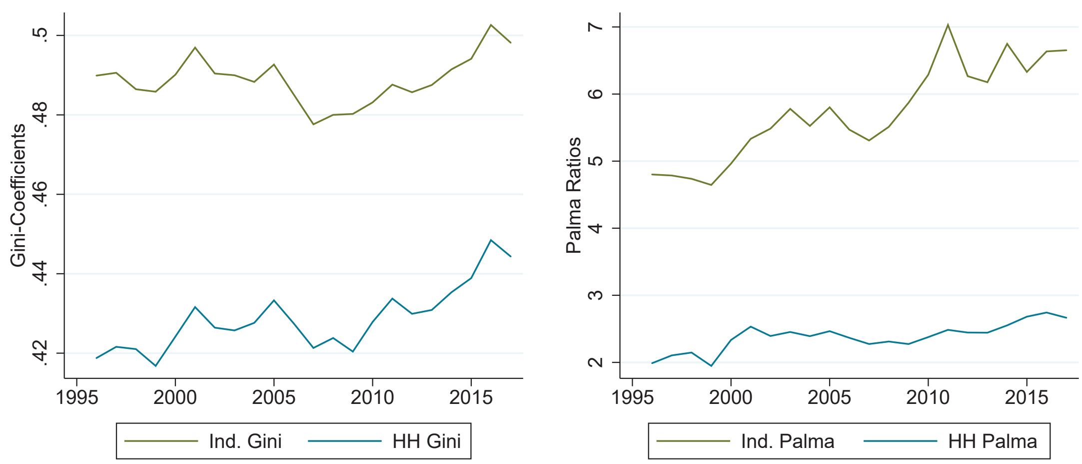
[5]Basically, migration serves as an insurance again income risks and, hence, is used as an adaptation channel (Bohra-Mishra et al. (2017)).

[6]Information on individual and household incomes are available from 1962 but without county information. Therefore, I restrict my analysis to 1996 to 2017.

[7]Note that top incomes are modified to preserve the privacy of individuals reporting high incomes. From 1996-2010, a replacement value threshold was introduced. The replacement values are equal to the mean income of other individuals with the same characteristics as the high-income individual. As a consequence, income inequality and top income shares are likely to have a small downward bias as outliers are averaged out. But this method leads to considerably less bias than traditional censoring where all incomes above a threshold are recoded to values equal to that threshold. From 2011-2017, the Census Bureau shifted to a rank proximity swapping procedure. This technique ranks all incomes above a specified thresholds and systematically swaps incomes within a bounded interval. Hence, this method preserves the distribution of values above the threshold.

the survey provides individual and household weights to correct for oversampling. Note that the survey is a repeated cross-section, namely individuals and households are not followed over the years. By constructing aggregate measures, I generate a panel of average incomes and income inequality on the county-level.

Figure 3: Gini-Coefficients and Palma Ratios



Notes: Graph shows Gini-coefficients and Palma ratios based on individual and household incomes in the United States for 1996-2017. The levels of household-based measures are considerably lower throughout the sample period.
Source: Current Population Survey (CPS).

The Gini coefficients ranges from 0 to 1, where 1 denotes perfect inequality. In the CPS data, the average individual Gini is 0.49, whereas the average household Gini-coefficient is considerably lower at 0.43. The individual-based Gini-coefficient is higher because it also includes intra-household inequality, see Section 3. The Palma ratio is the share of all incomes received by the top 10% divided by the share of all incomes received by the bottom 40%. It is an alternative inequality measure to the Gini-coefficient. In contrast to the Gini-coefficient, the Palma ratio incorporates only the tails of the income distribution into its measure. Changes in the middle incomes usually leave inequality measures unchanged, thereby attenuating the relevance to include middle incomes into inequality measures. Figure 3 suggests that income inequality was increasing over the last decades in the United States.

This paper focuses on the analysis of the effects on the entire income distribution. In particular, I calculate average total, capital and labor incomes for each quintile of the income distribution. The findings suggest that is in fact important to analyze the income distribution in more detail as aggregate inequality as well as income measures often do not capture the effects. The summary statistics of all measures are provided in Table A3 in the appendix.

4.2 Natural Disasters

For natural disasters, I use the OpenFEMA Dataset by the Federal Emergency Management Agency (FEMA) of the Department of Homeland Security.[8] OpenFEMA provides data on disaster declarations for different types of disasters on the regional, state and county level. Next to the obvious advantage of data availability, using declarations has the advantage of analyzing counties that are actually affected and struggle to deal with the consequences of a disaster. For instance, a natural disaster might occur in a remote area where damages are very limited. Including this disaster might bias the results towards zero as county incomes are likely to be unaffected. The different types of disaster include among others severe storms, earthquakes and hurricanes. The focus of this paper is on natural disasters, thus, men-made or technical disasters are excluded from the analysis. A complete list of relevant disasters are provided in Table 1.

Thus, I have 33,391 declared disasters in counties all over the United States from 1996 to 2017.[9] The United States is an interesting case as it has a variety of disasters from common

[8]https://www.fema.gov/media-library/assets/documents/28318, accessed June 19, 2019. Disclaimer: FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and/or Data.gov.

[9]Note that one disaster can affect multiple counties or even states. On average, between 0 and 2.1 natural disasters occur in a county per year (maximum is 6 disasters in one year).

Table 1: Disaster Types

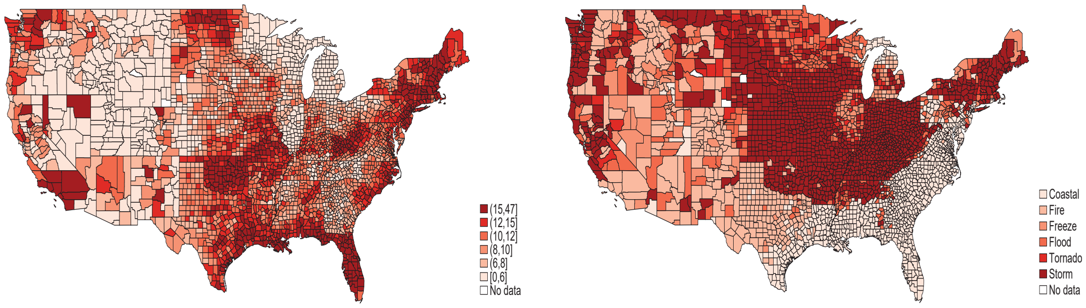
Type	Freq.	Percent	Cum.
Coastal Storm	382	1.13	1.13
Earthquake	63	0.19	1.31
Fire	2,959	8.72	10.03
Flood	3,333	9.82	19.85
Freezing	85	0.25	20.11
Hurricane	9,090	26.79	46.90
Mud/Landslide	29	0.09	46.98
Severe Ice Storm	1,840	5.42	52.40
Severe Storm(s)	13,712	40.41	92.81
Snow	2,099	6.19	99.00
Tornado	328	0.97	99.97
Tsunami	9	0.03	99.99
Volcano	2	0.01	100.00
Total	33,931	100.00	

Notes: Table shows the disaster types of all declared natural disasters in the United States between 1996 and 2017.
Source: OpenFEMA Dataset by the Federal Emergency Management Agency (FEMA).

storms to hurricanes, floods and even earthquakes and tornadoes. In addition, there is some spatial distribution of these disasters, namely that some disasters are more common in some regions but not in others. Figure 4 shows the spatial distribution of natural disasters in the United States. The left graph depicts the total number of disasters in the sample period by county. In general, the coasts and the Midwest have a higher number of declared disasters. The graph on the right shows the spatial distribution of different types of disasters. For each county, I calculated the most frequent natural disaster. Coastal storms, such as hurricanes, occur on the east and golf coast. Fires occur more in the West, such as Arizona, Nevada, New Mexico and California. Freezing and snow storms occur frequently in North Dakota and Minnesota. Also, most disasters occur in a number of counties, so that the effect on incomes can be estimated with enough variation.

Using this data, I construct a dummy on whether at least one disaster was declared in a county within a year, which is the main variable of interest in the subsequent analysis.

Figure 4: Natural Disaster Count (left) and Type (right)



Notes: Left graph shows the total number of disasters for each county in 1996-2017. Darker red indicates a higher number of disasters. Right graph shows the spatial distribution of the most frequent natural disasters, calculated on the county level. Each type of disaster is denoted in a different color. Alaska and Hawaii are excluded.

I deviate from the disaster dummy variable in two sections of the paper. First, I introduce a variable on the severity of a disaster in Section 6.3.2. The EM-DAT-database[10] by the Centre for Research on the Epidemiology of Disasters (CRED) provides the number of deaths for each natural disaster.[11] Using the data, I construct a variable on the severity of a disaster. Basically, the variable is equal to 1 if at least 10 deaths occurred. One important caveat is in order, namely that the number of deaths refers to the severity of a disaster in general and not the severity of a disaster in a particular county. Thus, the subsequent results are likely to underestimate the true effects. The second deviation from the main disaster dummy variable is in Section 6.4. In order to construct a variable on disaster types, I made use of the types depicted in Table 1 provided by the FEMA data. I assign all FEMA disaster types

[10] https://www.emdat.be/, accessed July 22, 2019.

[11] I also tried to test severity using two different FEMA disaster declaration types, namely emergency and major disaster declarations. An emergency declaration allow for federal assistance with an upper limit of $5 million. In contrast, a major disaster declaration provides a number of federal assistance programs for individuals, households and the public. Using major declarations as a proxy for severity led to smaller or even positive effect on incomes due to the large number of assistance programs. Thus, in order to test the severity hypothesis, I relied on an alternative dataset.

to seven major types for the estimation: hurricane, storm, flood, fire, winter storm, tornado and geophysical activity.[12] Similar to the main variable of interest, the disaster type variable is a dummy equal to 1 if the respective type occurs in a given year.

5 Methodology

The identification strategy denotes the estimation of the following econometric model:

$$Inequality_{i,t} = \beta_1 Disaster_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{1}$$

$$Incomes_{i,t} = \beta_1 Disaster_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{2}$$

where i denotes the county, α_i county fixed effects and γ_t time fixed effects.[13] In the basic model, $Disaster_{i,t}$ is a dummy on whether at least one disaster occurred in a county. Extensions of the model will include variables on the frequency as well as severity of natural disasters. $Inequality_{i,t}$ denotes Gini-coefficients and Palma ratios. $Incomes_{i,t}$ are average incomes of different income groups, namely low-, middle- and high-income group, or income quintiles based on either individual or household incomes, respectively.[14] The equation is estimated using population-weighted fixed-effect regression clustered by county.[15]

One potential challenge for the identification strategy is the impact of migration on inequality and average income measures. I need to control for the possibility that migration,

[12]The exact partition is provided in Table A1 in the appendix.

[13]I also estimated the effects using regional fixed effects. A county belongs to a specific disaster region if the respective disaster is the most frequent one in the county. The assumption is that a county has specific unobserved characteristics that determine which type of natural disaster is more likely to hit. The disaster region fixed effect is related to the right map in Figure 4. The results did not differ qualitatively.

[14]The low-income group includes incomes up to the 40th percentile, denoted as "0-40" in the results tables. The middle-income group has incomes between the 40th and 90th percentile ("40-90") and the high-income group comprises of the top 10% incomes ("90-100").

[15]Using a dynamic model with a lagged disaster dummy yields no statistically significant effects on average incomes or income inequality.

in particular selective out- or in-migration, is driving the effects. Fortunately, the CPS data includes information on migration patterns, namely where survey participants moved in the previous year and why.

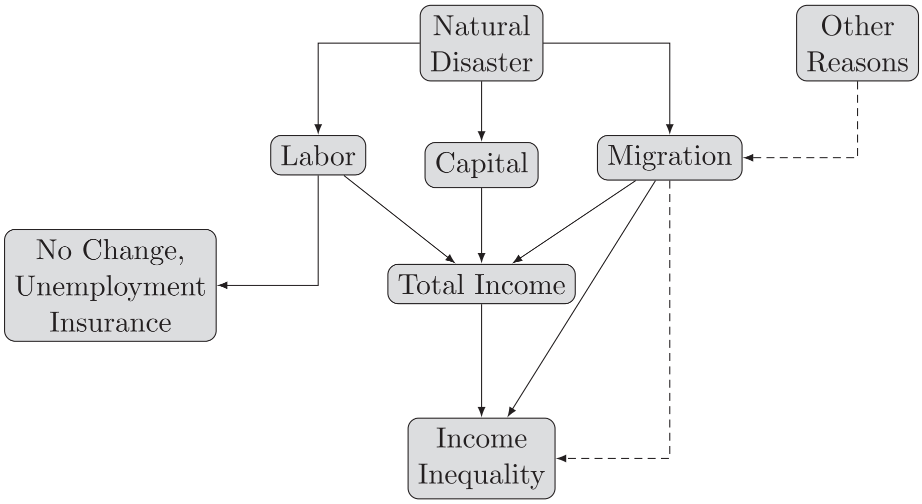
Table 2: Migration in the United States 1996-2017

Type	Frequency	Percent
Same house	1,531,738	88.47
Moved within county	128,350	7.41
Moved within state, different county	30,108	1.74
Moved between states	32,601	1.88
Abroad	8,627	0.50
Total	1,731,424	100.00
Total Moved	199,686	11.53
Total Moved out of County	71,336	4.12

Notes: Table shows the migration responses of the estimation sample from 1996-2017.
Source: Current Population Survey (CPS).

Table 2 depicts the type of migration in the CPS data. The table suggests that about 12% of the sample moved during the analyzed time period, where only around 4% changed the county. Less than 1% of all movers give natural disasters as the primary reason for their move (see Table A7 in the Appendix). These movers do not pose a threat to the identification, because migration caused by natural disasters is just an intervening effect on income, see Figure 5. Note that the effects of migration can directly affect income inequality or indirectly through effects on average incomes, see both non-dashed lines from migration to total income and income inequality in Figure 5. Any migration caused by other reasons, such as job or retirement, might cause income inequality and average incomes to change if they are selective, namely when migration leads to changes in income percentiles. For example, massive net out-migration of top incomes reduces the 90th percentile, thereby decreasing average top 10% income. This change is unrelated to natural disasters and has the potential to distort the effects of natural disasters on income inequality and incomes, depicted in dashed lines in Figure 5.

Figure 5: Extended Mechanism Model



The CPS only provides data on individuals that moved to a county last year and their previous state, as opposed to county, of residence. Also, there is no data on individuals that moved away, e.g. out-migrants. Hence, I cannot construct exact synthetic measures in which I reassign individuals to the previous county of residence to estimate the effects in absence of migration.

Therefore, I will construct upper and lower bounds where I assume that all out-migrants have incomes in the top 10% (or the bottom 40%) of the income distribution.[16] Generally, a move of a top income individual or household is likely to have a larger effect on percentiles and average incomes compared to an individual or household in the low-income group. But I still check the effects when the bottom 40% is reassigned, because the mean income of migrants is lower than the one for the entire population, suggesting that on average more low-income individuals or households are moving. Note that I have data on incomes of incoming migrants. Thus, I will construct alternative income measures where I remove the incomers but assign top 10% incomes to out-migrants. In particular, I will reassign all movers to their previous

[16]See Manski (1990) for a theoretical approach to selectivity and bound estimation.

state of residence by adding them to each county and then remove all migrants that earn less than the top 10% (or more than the bottom 40%) in the respective county.[17] Hence, I build worst-case scenarios by assuming that all top 10% (bottom 40%) income-movers moved away from one county. This reassignment allows me to test whether migration affects the results.

6 Results

The section presents the results on the effects of natural disasters on individual- as well as household-based Gini-coefficients, Palma ratios and average incomes. Gini-coefficients and Palma ratios provide a first insight into the effects of natural disasters on the income distribution. As discussed above, these aggregate measures often neglect the effects on middle incomes. For this reason, an important contribution of this paper is to show the effects of natural disasters on the entire income distribution. Furthermore, this section provides results for capital and labor income separately. Given the nature of theses two components of total income, the results as well as the affected income groups are expected to be different. In subsequent parts, the baseline model results are extended. In Section 6.2, I discuss the role of social security, assistance programs and migration on the baseline results. The subsequent section presents the results for the occurrence of multiple as well as severe natural disasters (Section 6.3). The results will show that multiple as well as severe disasters yield stronger effects on incomes. In the last section, I explore the heterogeneous effects of different types of disasters.

[17] Note that I exclude migrants from abroad.

6.1 Baseline Model Results

The results section begins with the inequality effects. In Table 3, I provide the results of the effects of natural disasters on different measures of income inequality. As described above, the variable on natural disasters is a dummy on whether at least one disaster occurred in a county in a given year. The first two columns in Table 3 suggest that natural disasters do no have a statistically significant effect on both Gini-coefficients. Similarly, there is no effect on the individual-based Palma ratio. Hence, the ratio between the top and bottom income shares is not changing significantly. Only the household-based Palma ratio is positive and statistically significant on the 10%-level, which indicates that the share of top incomes increases compared to the share of low incomes. In contrast to the stated hypotheses, the effects of natural disasters on income inequality is stronger for household-based measures. It is still valid to assume that household income is more able to absorb idiosyncratic shocks to income. However, the result suggests that natural disasters are more systemic than idiosyncratic in nature. As a systemic shock, natural disasters are likely to affect all incomes within a household, thereby exacerbating the effects on household income.

Table 3: Effects on Income Inequality

	Gini		Palma	
	Individual	Household	Individual	Household
Disaster	.000	.001	-.108	.041*
	(.001)	(.001)	(.136)	(.024)
Observations	5169	5169	5169	5168
Number of Counties	385	385	385	385
Number of years	22	22	22	22

Notes: Table shows the effects of natural disasters on individual- as well as household-based Gini-coeffficients and Palma ratios (see column header). The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

In Table 4, the results of the effects of natural disasters on total incomes are shown. In general, there is no statistically significant effect of natural disasters on the total average income (0-100), though the effect is negative for both, individual- and household-based, measures. In the next three columns, I provide the results on incomes for each income group. Interestingly, only the middle incomes are affected, see column (40-90) and last three columns of Table 4. The effects are statistically significant up to the 5%-level. Natural disasters lead to an average decrease in income of $373, which is about 1% of annual total income. The results for household-based incomes are very similar, though slightly weaker.

Table 4: Effects on Average Total Incomes

	Total	Income Groups			Middle Incomes (40-90)		
	0-100	0-40	40-90	90-100	40-60	60-80	80-90
Disaster (on Ind)	-255.13	-28.64	-373.48^{**}	-773.62	-241.02^{*}	-427.32^{**}	-457.94^{*}
	(159.55)	(54.07)	(161.06)	(978.72)	(126.24)	(177.60)	(266.58)
Observations	5169	5169	5169	5169	5169	5169	5169
Disaster (on HH)	-386.22	-174.05	-641.09^{*}	-659.80	-424.33	-638.53^{*}	-1076.47^{*}
	(365.52)	(144.79)	(348.23)	(2056.64)	(278.61)	(374.52)	(562.77)
Observations	5169	5169	5169	5169	5169	5169	5168

Notes: Table shows the effects of natural disasters on total individual- as well as household-based incomes by income groups and for middle incomes (see column header). For instance, ”40-90” denotes the average of incomes between the 40th and 90th percentile. The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 385 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

In sum, natural disaster mainly affect middle incomes, which explains why the inequality measures are mostly unaffected. Middle income changes usually do not affect inequality measures. Another important result is that all incomes are negatively affected by natural disasters. Thus, natural disasters have a damaging effect on incomes in the year of the occurrence. The result is remarkable given that natural disasters almost only occur in the second half of the year and still affect average annual incomes.

Capital income is more risky compared to labor income. Hence, it is more susceptible to economic volatility. In addition, capital income is mainly held by high income groups. In fact, the top 5% has the highest capital income share of about 7%. In contrast, the top 10% has about 5%. The capital share of total income is steadily decreasing with income. In Table 5, the results suggest a strong negative effect on capital income. In particular, total individual and household capital income decreases by around $45 or $88, respectively. The decrease is driven by the high capital income group, which implies that individuals that have more capital income are also losing more income.[18] Natural disasters destroy capital and wealth and, thereby, reduce income from capital. On average, the top 10%'s income decreases by $428, which denotes about 2.6% of average top 10% capital income but only 0.3% of top total income.

Table 5: Effects on Capital Income

	Total	Top Capital Income Groups					
		Capital Income Percentiles			Total Income Percentiles		
	0-100	80-90	90-100	95-100	80-90	90-100	95-100
Disaster (on Ind.)	-44.89*	-49.85	-427.88**	-641.70*	-83.39	-298.80*	62.99
	(23.13)	(32.57)	(212.26)	(363.83)	(91.45)	(159.00)	(284.30)
Observations	5169	5132	5169	5162	5169	5169	5168
Disaster (on HH)	-88.21*	-173.41*	-632.03	-667.34	-490.60**	-191.07	1204.17**
	(50.21)	(95.14)	(429.70)	(715.23)	(205.20)	(349.51)	(567.00)
Observations	5169	5149	5168	5104	5169	5168	5121

Notes: Table shows the effects of natural disasters on high individual- as well as household-based mean capital incomes based on capital income percentiles ("Capital Income Percentiles") and on total income percentiles ("Total Income Percentiles"). The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 385 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

It is crucial to note that the top capital income group is not necessarily equal to the top income group of total income. In order to relate the results to the ones on total income, the

[18] Other quintiles are statistically insignificant.

last three columns provide the results where total income percentiles are used as brackets for the average top incomes. The results for individual-based income are similar because the top 10% group's income decreases. However, the top 5% exhibits a small but insignificant increase. All in all, the income ranking between capital and total income earners is not significantly different. Individuals with a high total income are also more likely to have more capital income. Since capital income is only a small part of total income, the significant decreases in capital income do not appear in total income.

The results differ for household-level incomes. Only the average capital income between the 80th and 90th percentiles is negatively affected by natural disasters.[19] Interestingly, the capital income of the top 5% group when measured by total income is large and strongly positive. One explanation is that individuals or households in the top 5% group are likely to diversify their financial assets, thereby being unaffected by natural disasters happening in one place. In summation, capital income resembles the decrease in household-based middle incomes found in Table 4.

Many studies, such as Deryugina (2017) and Groen et al. (2019), show the effects of natural disasters on earnings. Deryugina (2017) suggests no long-term effects on average earnings, where as Groen et al. (2019) find short-term declines but long-term increases in earnings. The main argument for the short-term decline is job separation, namely employment to unemployment patterns rather than earning changes. This argument is in line with the general notion of nominal wage rigidity, implying that wages are particularly rigid downwards. Employees are reluctant to accept wage decreases, thereby often forcing employers to let employees go and hire new ones with lower wages. Both mentioned studies focus on average wages. In contrast, the following table provides results of the effects on the entire income distribution. In particular, Table 6 shows the effect on total average earnings (first column),

[19]Results for all quintiles are available upon request.

on income groups (next three columns) and the components of earnings, namely wages, business income from self-employment and farm incomes (last four columns).

Table 6: Effects on Total Earnings and Components

	Total Earnings				Components of Earnings			
	Total	Income Groups			Wages	Business	Farm Income	
	0-100	0-40	40-90	90-100	40-90	40-90	40-90	95-100
Disaster (on Ind.)	-174.03	27.79	-296.31*	-1001.27	-353.82**	59.64**	-2.13	-253.78*
	(157.35)	(29.02)	(162.64)	(922.69)	(26.71)	(28.57)	(3.58)	(147.57)
Observations	5169	5169	5169	5169	5169	5169	5169	5158
Disaster (on HH)	-254.00	-121.82	-411.25	-781.06				
	(358.07)	(150.47)	(341.13)	(2103.69)				
Observations	5169	5169	5169	5168				

Notes: Table shows the effects of natural disasters on individual- as well as household-based average earnings (first four columns) and their components (last four columns), namely wages, business income from self-employment and farm income. The respective income groups are depicted in the header. For instance, ”40-90” denotes the average earnings between the 40th and 90th percentile. The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 385 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

Similarly to the results on total income, the middle income group is affected, whereas there is no statistically significant effects on overall earnings (first column) or other fractions of the income distribution. The negative effect on mid-level earnings is mainly attributed to wage decreases, see column ”Wages”. The occurrence of at least one natural disaster leads, on average, to a wage decrease of $354, which is about 1% of wage income. The results are in line with Groen et al. (2019) to some degree, namely that earnings are decreasing in the short-term. But my results are weaker because only the middle income earnings experience decreases. There are no effects on total earnings. The difference in overall earnings is likely to stem from the included disaster types. Groen et al. (2019) uses the most destructive disasters of 2005 that have, by construction, stronger effects. In contrast, the analysis in this paper incorporates different types with different severity of disasters into the analysis.[20] Interestingly, business income from self-employment experiences a small but positive effect of natural disasters. There is no effect on mid-level farm income. However, the results for top 5% farm incomes show negative effects suggesting that only large farms with high yields are affected by natural disasters. There are no effects of natural disasters on household-based earnings or their components.

In sum, income inequality exhibits small increases. All income groups experience decreases in incomes, but only the middle income group's income decreases are statistically significant. These results imply that it is very crucial to analyze the entire income distribution rather than just aggregate measures of income inequality and average incomes. In addition, individual-based income decreases are stronger compared to the household-based measures. Thus, households are an important income-smoothing tool. Another important tool is social security. Note that I did not provide the results for total labor income, namely earnings plus transfer benefits, yet. The next section will introduce the role of social security and other transfer measures for incomes. In order to not overload the following extensions of the main analysis with additional results, I will focus on individual based measures from this point on.[21]

6.2 Adaptation Channel

This section explores potential adaptation channels that mitigate or dampen the effects of natural disasters on incomes. In the first part, I analyze the role of social security and disaster-related assistance programs for the effects of natural disasters. In general, social security and assistance programs provide means to deal with potential hardship associated

[20] The following sections will provide a more detailed analysis of different types and severities of natural disasters.

[21] Household-based measures yield similar patterns but are generally weaker in magnitude.

not only with natural disasters but also other systemic and idiosyncratic shocks. The second part will accommodate two main goals. The more obvious one is the role of migration as an adaptation tool. Strongly affected individuals and households decide to move to another county or state to avoid future impacts of natural disasters (see Boustan et al. (2012) and Bohra-Mishra et al. (2017)). At the same time, this highly relevant adaptation tool poses a potential endogeneity problem, which constitutes the second goal. The initial identification strategy might be flawed because migration rather than natural disasters is driving the results. In particular, changes in incomes might not have been a causal effect of natural disasters but rather of people moving away, see Figure 5 and discussion in Section 5.

6.2.1 Social Security and Assistance Programs

Social security and disaster-related assistance programs are important adaptation tools in the case of a natural disaster. The previous section presented the results for the effects of disasters on earnings. The main finding is that middle income earnings are negatively affected by disasters. In this section, I show the results for total labor income, namely the sum of earnings and all forms of transfer payments. A complete list of of transfer payment types is provided in Table A2. Since the majority of natural disasters occur in the second half of the year, benefits are likely to arrive only in the following year. For this reason, I provide the effects of contemporaneous as well as lagged values of disasters. The results in Table 7 suggest no statistically significant effects of contemporaneous disasters on total labor incomes. This is a very important result, because it shows that social security and other form of benefits absorb potential shocks to earnings. The effect on middle incomes is still negative, but not statistically significant. As for the lagged value of natural disasters, the effects are positive for the low and middle income group, but negative for the top income group. However, only the effect on the low income group is statistically significant. The positive effect might stem from two sources. First, the low income group is the main recipient of transfer payments. If transfer payments increase after a natural disaster, this group is the largest benefactor from the increase. Second, individuals or households in the low-income group are likely to benefit from higher wages and higher employment rates due to reconstruction efforts after a natural disaster.

Table 7: Effects on Total Labor Income

	Income Groups					
	0-40		40-90		90-100	
	No Lag	Lag	No Lag	Lag	No Lag	Lag
Disaster	13.50		-110.94		-640.01	
	(47.05)		(149.85)		(1021.87)	
Lag Disaster		78.23*		172.09		-561.71
		(43.49)		(150.06)		(844.46)
Observations	4182	3899	4182	3899	4182	3899

Notes: Table shows the effects of contemporaneous and lagged natural disasters on individual- as well as household-based total labor income for different income groups. The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 385 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

In order to test the first source of the low-income increase, I provide the effects of natural disasters on unemployment benefits and general assistance payments. Note that these assistance payments are not disaster-related. Table 8 displays the results in columns (1), (2), (5) and (6). There is no significant contemporaneous effect of natural disasters on transfer payments. But the effects are positive in the following year. Both, unemployment and assistance benefits, increase in the subsequent year of a disaster. The increase in transfer benefits in the following year can explain the labor income increase of the bottom 40% in Table 7.

In addition, the Federal Management Agency (FEMA) provides additional disaster-related individual- and household assistance programs to mitigate potential effects of natural disasters. These programs mainly aim at compensating for wealth losses but might also include

Table 8: Effects on Transfers

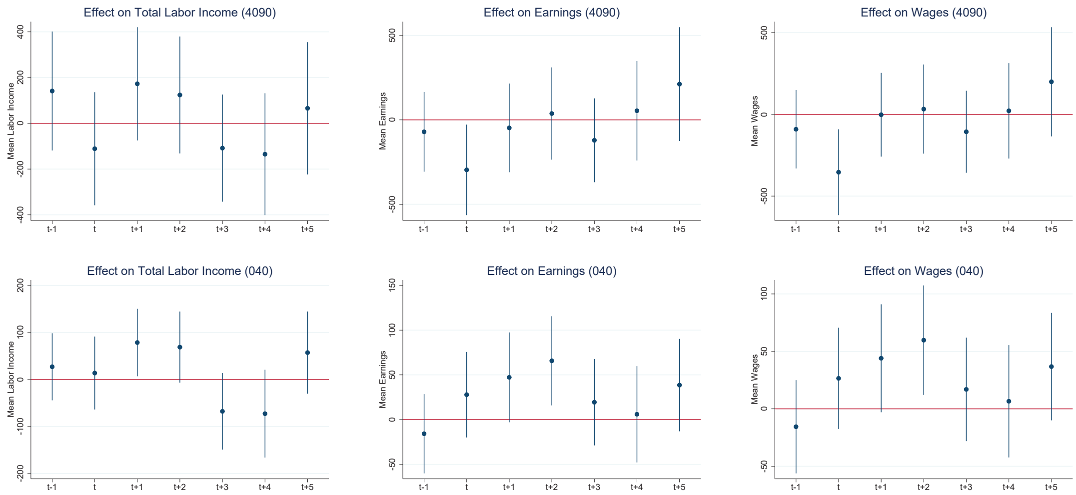
Dependent Variable:	Unemployment				General Assistance			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disaster	-0.71		-4.31		-5.28		-7.86*	
	(4.02)		(4.25)		(4.86)		(4.73)	
Lag Disaster		6.14*		4.85		6.28*		3.51
		(3.63)		(3.62)		(3.34)		(3.89)
Assistance Programs			5.36***				3.85	
			(1.80)				(3.20)	
Lag Assistance Programs				1.66				2.79
				(2.34)				(3.20)
Observations	5169	4818	5169	4818	5169	4674	5169	4674

Notes: Table shows the effects of contemporaneous and lagged natural disasters on unemployment and general assistance benefits. The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The variable on assistance programs denotes the number of individual- or household disaster-related assistance programs. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 385 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

different forms of payments to aid affected individuals and households. Deryugina (2017) suggests that the non-existing effects of disaster on earnings is attributed to larger government transfers into affected areas. These transfers are in the form of disaster-related payments as well as conventional governmental benefits, such as unemployment insurance. In Table 8, I estimate the effects of disasters on unemployment and assistance benefits when controlled for the implementation of assistance programs. The aim is to test whether assistance programs crowd out conventional benefits, such as unemployment insurance. The result in columns (3) and (7) suggest a more negative effect of disasters on unemployment and assistance benefits when controlling for assistance programs. However, the effect is only significant for assistance benefits. In addition, assistance programs increase transfer benefits in general, but only statistically significant in column (3). The results suggest that transfer benefits decrease (or increase by less) if assistance programs are implemented. For instance, the initial positive effect of lagged disaster in column (2) is not statistically significant anymore in column (4).

The same applies for general assistance benefits in column (6) and (8). In addition, benefits for general assistance show signs of crowding out in column (7).

Figure 6: Long-term Effects



Notes: Graph shows the effects of natural disaster on the individual-based middle and low incomes over time. t denotes the year in which at least one disaster occurred. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. Confidence intervals are on the 10%-level.

The main result in this section is that social security and other transfer payments absorb negative effects on earnings and their components. The effects over time are depicted in Figure 6. The top row shows that the initial effects on the middle income group's earnings and wages are mitigated by social security. Another interesting result is the positive, though statistically insignificant, result in the subsequent two years after a disaster. Earnings and wages are increasing. This is particularly visible for the low income group in the bottom row of Figure 6. The effect on total labor income turns positive and statistically significant in the following year after a disaster. This increase seems to be partly due to increases in earnings, but also due to increases in transfer payments. The latter can be deduced from the fact that earnings experience a peak in the second year after a disaster whereas total labor income becomes statistically insignificant in the second year. This suggests that transfer payments constitute a non-negligible part of total labor income of the low income group. In addition, the steady increase of earnings (and wages) in the first two years can be attributed to the after-disaster boom.

6.2.2 Migration

As noted above, migration is an important tool for adapation and a source of endogeneity. Therefore, the goal of this section is to estimate the same effects as in the main analysis in absence of migration. First, I present the results for non-movers, namely for individuals and households that either stayed in the same house or moved within a county (see Table 2 for migration statistics). Then I show the results when only the top 10% or bottom 40% are reassigned to each county of their previous state of residence. The results describe worst-case scenarios since the reassignment investigates whether the results are robust even when all out-migrants of an entire state are coming from one county. As a consequence, the estimation results of the reassignment yield upper and lower bounds of the effects. The effects on total incomes are shown in Table 9.

Generally, the results resemble the results in Table 4, namely that only middle incomes are affected. Only the magnitudes of the effects are different. Note that the magnitudes are to some degree influenced by the type of reassignment. For instance, it is not surprising that the effects are stronger when top 10% incomes are reassigned, because the average middle income is higher by construction. The reassignment automatically shifts percentiles and, thus, levels of incomes. Summary statistics for each reassignment are provided in Tables A4, A5 and A6 in the appendix. When I control for the different levels of income, the effects are similar in magnitude, namely a decrease of about 1% on average. Only the results where the top 10% incomes are reassigned yield slightly larger effects. Thus, the effects are either the same or even larger in absence of migration. This finding implies that migration is a potential

Table 9: Effects on Total Income (Migration)

	Total	Income Groups			Middle Incomes (40-90)		
	0-100	0-40	40-90	90-100	40-60	60-80	80-90
Disaster (on Ind)	-262.65	-14.86	-329.46**	-871.95	-213.09*	-401.90**	-392.10
(Non-Movers)	(160.18)	(54.38)	(161.60)	(1020.87)	(125.97)	(178.34)	(271.47)
Observations	5095	5095	5095	5095	5095	5095	5095
Disaster (on Ind)	-259.53	-57.62	-616.52***	514.46	-389.38***	-656.99***	-918.66***
(Top Reassigned)	(183.44)	(57.99)	(175.63)	(1067.76)	(143.32)	(192.35)	(286.74)
Observations	5162	5162	5162	5162	5162	5162	5162
Disaster (on Ind)	-214.77	-49.02	-274.08*	-712.12	-155.14	-327.24*	-346.63
(Bottom Reassigned)	(136.13)	(41.74)	(148.05)	(876.59)	(111.34)	(168.49)	(247.63)
Observations	5230	5230	5230	5230	5230	5230	5230

Notes: Table shows the effects of natural disasters on total individual- as well as household-based incomes by income groups and for middle incomes (see column header) for different samples. The first sample includes only non-movers. The second and third sample reassigns top 10% and bottom 40%, respectively. The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 381 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

adaptation tool for mainly wealthy individuals. In addition, it implies that migration does not pose a threat to the initial identification strategy.

6.3 Intensification Channels

The previous section showed that social security, assistance programs and migration can mitigate potential adverse consequences of natural disasters. However, the adaptation channels can experience additional pressure when multiple or severe disasters occur within a short time period. This section tests whether the occurrence of multiple disasters and their severity intensify the effects. In light of the current climate change debate that suggests an increase in the occurrence as well as severity of future natural disasters, the analysis of the subsequent impact is highly relevant. The occurrence of a particularly devastating hurricane poses an tremendous burden on social security and assistance programs. Thus, governments are likely to be less able to provide sufficient funds for frequent severe disasters in the future unless adequate policies are implemented. The following sections analyze the effects of multiple disasters and their severity on the income distribution.

6.3.1 Multiple Disasters

Natural disasters are expected to have larger effects when they occur frequently without allowing a county to recover properly. In order to test this hypothesis, I include lags up to five years into the estimation model.

$$Incomes_{it} = \sum_{p=0}^{5} \beta_p Disaster_{i,t-p} + \alpha_i + \gamma_t + \epsilon_{it}, \tag{3}$$

where $\sum_{p=0}^{5} \beta_p Disaster_{i,t-p}$ includes the contemporaneous value of the disaster dummy and its lags up to five years. Hence, I estimate the effect of natural disasters given that disasters occurred in previous years. The results are provided in Table 10. Generally, the effects are considerably stronger as they even spill over to aggregate incomes, such as average total income (first column), earnings (third column) and capital (last column). In contrast, the results in Table 4 show no significant effects on average total income and earnings. Interestingly, the effect on top earnings (second last column) are also statistically significant. The occurrence of at least one natural disasters leads to an average decrease of 2% of top 10% earnings.

Table 10 shows that previous disasters have an intensifying effect on contemporaneous natural disasters. In order to exploit the heterogeneity in the number of previous disasters, I introduce an interaction term on the number of previous disasters into the initial estimation model. The marginally different estimation model has the following form:

$$Incomes_{i,t} = \beta_1 Disaster_{i,t} + \beta_2 Previous_{i,t} + \beta_3 Int_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{4}$$

Table 10: Multiple Disasters over 5 years

	Total Income		Earnings			Capital
	0-100	40-90	0-100	40-90	90-100	0-100
Disaster	-480.03**	-531.93**	-392.87*	-546.46**	-2404.57**	-76.47**
	(217.91)	(212.91)	(218.96)	(213.83)	(1180.69)	(31.94)
Lag Disaster	-33.93	31.87	-93.15	-135.03	-1054.22	40.25
	(201.63)	(191.41)	(179.93)	(191.91)	(1203.67)	(30.52)
2-year lag Disaster	-44.02	-52.75	-50.86	-52.50	-457.42	8.38
	(238.32)	(255.87)	(197.41)	(228.78)	(1271.63)	(36.37)
3-year lag Disaster	-68.30	-42.41	-78.11	-238.79	-620.96	-4.33
	(215.68)	(220.63)	(187.18)	(189.23)	(1318.95)	(35.00)
4-year lag Disaster	127.87	173.17	99.84	48.85	511.51	9.29
	(194.07)	(182.89)	(192.27)	(195.63)	(1315.97)	(32.16)
5-year lag Disaster	341.69	259.06	225.56	106.61	1034.41	38.16
	(214.56)	(197.22)	(205.37)	(215.39)	(1384.05)	(36.90)
Observations	3395	3395	3395	3395	3395	3395

Notes: Table shows the effects of natural disasters on different individual-based incomes, such as total income, earnings and capital income, as well as income groups (see column header). The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 314 counties for 17 years. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

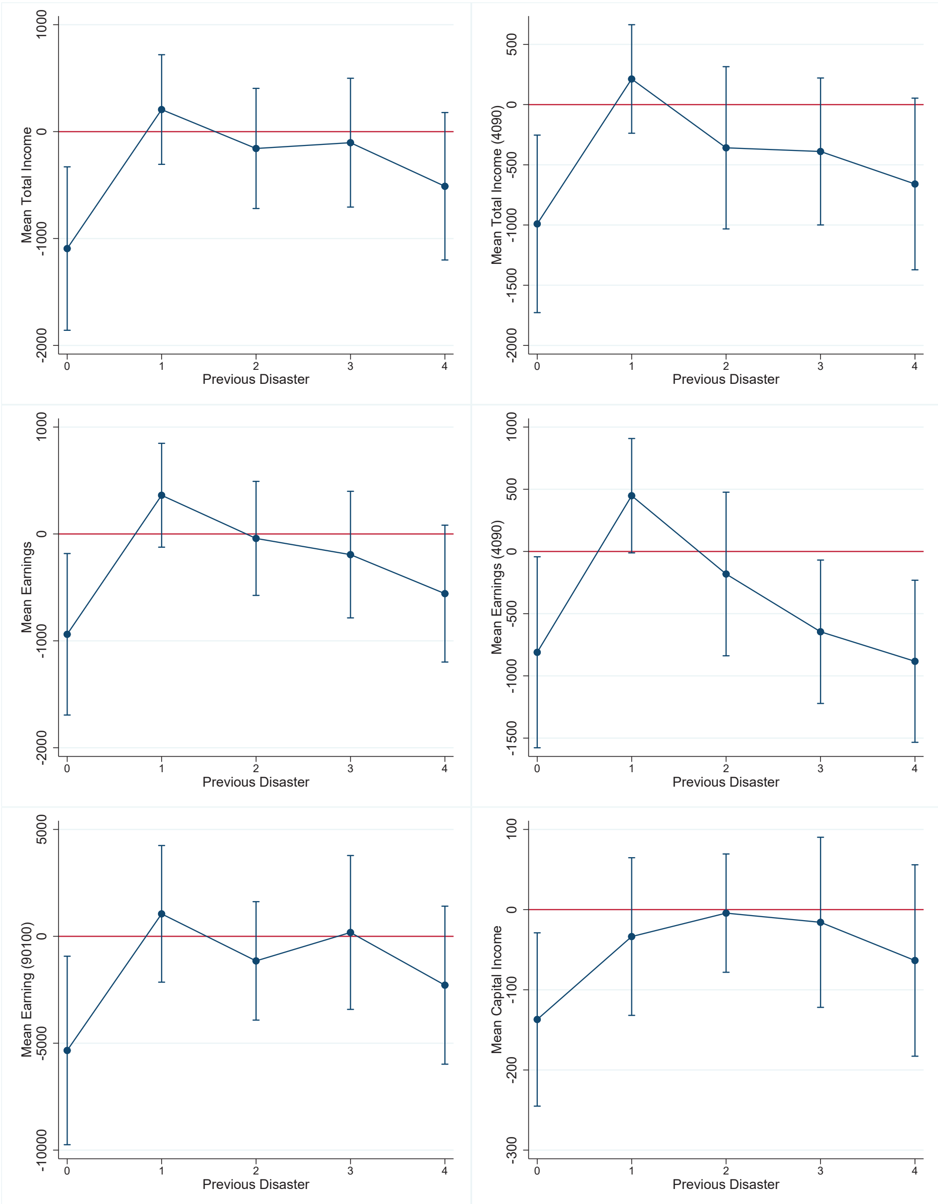
where $Previous_{i,t}$ is equal to the number of previous disasters in the last five years and $Int_{i,t}$ is the interaction between $Disaster_{i,t}$ and $Previous_{i,t}$.[22] In models with interaction terms, a graphical representation is more intuitive than a table. Therefore, graphs depicting the marginal effects of natural disasters on individual-based incomes dependent on the previous number of disasters are displayed in Figure 7.[23] The top row shows the marginal effects on total incomes, where as the second row provides the results for earnings. The last row presents the results for top earnings and capital income.

A common feature in all graphs is the statistically negative effect on incomes when no previous disasters occurred. This is actually related to the notion of adaptation. A county that did not experience a natural disaster in the previous years is likely to be less prepared

[22] A histogram of the frequencies of previous disasters is shown in Figure A1 in the appendix.

[23] The results are provided in Table A8 in the appendix. Figure 7 excludes the dot for five previous disasters because the standard errors are too large to give a meaningful interpretation.

Figure 7: Impact of Previous Disasters



Notes: Graph shows the marginal effects of natural disasters on individual-based income measures (respective y-axis) for different numbers of previous disasters (x-axis). Each dot denotes the total effect of natural disasters on the respective variable on the y-axis. The dot for five previous disasters is excluded because the standard errors are too large to give a meaningful interpretation. Whiskers show 90% confidence intervals.

(adapted) to the circumstance and, thus, experience larger effects. The effects are less strong and close to zero for counties that experienced one or two disasters in the last five years. This result would be in line with the adaptation hypothesis, namely counties having adequate mitigation policies in place. However, as the number of previous disasters increases, the effect becomes more negative, though only statistically significant for middle income earnings, which subsequently decrease with additional natural disasters. Note that the occurrence of five previous disasters is very uncommon and, hence, does not allow to identify the effects, see histogram in Figure A1 in the appendix.

6.3.2 Severity

This section explores another intensification channel. Natural disasters have stronger effects not only due to increased occurrences but also due to increased intensity. Table 11 presents the results where the severity of natural disasters is taking into account. In particular, the table shows the effects of severe disasters on total and capital income as well as earnings by income group.[24] The variable on disaster severity is equal to 1 if at least 10 deaths occurred in a county hit by at least one natural disaster.

Table 11: The Effects of Severe Disasters

	Total Income			Capital Income			Earnings		
	Total	Income Groups		Total	Income Groups		Total	Income Groups	
	0-100	40-90	90-100	0-100	40-90	90-100	0-100	40-90	90-100
Severe Disasters	-476.22**	-468.44**	-2494.68**	-62.89**	-17.54	-591.29**	-463.92**	-457.87**	-2834.28**
	(200.60)	(197.52)	(1261.37)	(31.15)	(12.62)	(289.10)	(186.24)	(187.14)	(1237.86)
Observations	5169	5169	5169	5169	5132	5169	5169	5169	5169

Notes: Table shows the effects of the severity of natural disasters on individual incomes. The variable *Severe Disasters* refers to a dummy on at least one severe disaster in a county within a given year. A natural disaster is considered severe if at least 10 deaths occurred. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

[24] There are no statistically significant effects on incomes of the low income group, thus, the results are not included in the table.

The results suggest overall stronger effects. In contrast to the results in Table 4, natural disaster have a statistically significant and negative effect on overall total income and earnings. The effect on overall capital income is larger for severe disasters. Similarly to the effects of multiple disasters, the earnings of the top 10% are also affected. The losses in earnings and capital income are large enough to show significant results for top total incomes. The results clearly show that the severity of a disaster has an intensifying effect on incomes. In addition, the previous results are confirmed. The middle total incomes and earnings are negatively affected.

6.4 Heterogeneous Effects by Disaster Type

This section detects heterogeneous effects of different types of natural disasters. Table 12 presents the summary statistics for all types of natural disasters. Each type is a dummy variable equal to 1 if the type of natural disaster occurred at least once in a county within a given year. The most common natural disaster is heavy storms closely followed by hurricanes. These disasters account for more than half of total disaster declarations.

Table 12: Summary statistics of Disaster Types

Variable	Obs	Mean	Std	Min	Max
Hurricane	5169	0.133	0.340	0	1
Storm	5169	0.150	0.357	0	1
Flood	5169	0.035	0.183	0	1
Fire	5169	0.064	0.244	0	1
Freeze	5169	0.064	0.245	0	1
Tornado	5169	0.003	0.057	0	1
Geophysical	5169	0.002	0.048	0	1

Notes: Table shows summary statistics for different disaster types from 1996-2017.

The results for the effects on incomes are provided in Table 13. They suggest that the previously found effect on middle incomes is driven by hurricanes and storms. Both types of natural disasters lead to significant decreases in individual-based middle incomes. In general, hurricanes receive a large amount of media attention as well as federal assistance. The higher media coverage has important implications for expectations and preparedness. Affected regions are able to anticipate a hurricane and prepare accordingly, which reduces the actual impact of the disaster. As a consequence, the overall effects on total incomes (first column) are smaller for hurricanes than for storms. The reason for the overall larger effect of storms is the decrease in top incomes. On average, the top 10% group's income decreases by about 2.5% after a storm.

Table 13: Effects on Total Income by Disaster Type

	Individual Incomes				Household Incomes			
	Total	Income Groups			Total	Income Groups		
	0-100	0-40	40-90	90-100	0-100	0-40	40-90	90-100
Hurricane	-378.51	51.15	-466.19*	-1933.96	-803.32	-167.34	-999.52	-3127.54
	(274.09)	(92.95)	(268.48)	(1775.05)	(570.65)	(273.69)	(631.74)	(3295.34)
Storm	-519.88***	-47.57	-335.78*	-3375.66***	-767.91**	10.50	-569.63	-5309.10**
	(194.20)	(63.70)	(196.41)	(1174.05)	(390.17)	(176.59)	(391.63)	(2192.54)
Flood	545.93	-187.01	324.85	3984.24	1592.47	392.14	1293.62	7373.20
	(630.98)	(124.90)	(534.39)	(3712.10)	(1308.49)	(499.56)	(1217.75)	(6707.97)
Fire	80.47	7.62	-96.49	880.09	496.19	-109.84	310.99	3379.33
	(212.88)	(73.60)	(247.51)	(1166.27)	(418.66)	(180.18)	(408.06)	(2459.70)
Winter Storm	-129.35	-74.32	-333.82	528.31	-88.12	-21.45	-202.67	-26.85
	(264.12)	(86.61)	(295.65)	(1449.92)	(540.28)	(244.52)	(574.86)	(2865.49)
Tornado	-877.44*	-84.97	-71.85	-8583.11***	-2419.15**	-523.72	-1286.27	-16,372.34***
	(501.15)	(345.13)	(662.78)	(3090.45)	(942.60)	(511.34)	(1246.83)	(5740.81)
Geophysical	99.14	425.37	820.26	-4326.16	-249.77	-103.56	1558.79	-10,571.19
	(1000.58)	(315.39)	(1197.06)	(5872.13)	(1705.44)	(880.04)	(2324.37)	(10011.45)
Observations	5169	5169	5169	5169	5169	5169	5169	5168

Notes: Table shows the effects of natural disaster on total individual- as well as household-based incomes by income groups (see column header) for each disaster type. The disaster dummy is equal to 1 if the respective disaster occurred at least once in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 385 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

Interestingly, the top income group experiences the largest income losses after a tornado. The estimates suggest a 6.6% decrease for individual-based incomes and a 7.6% decrease for household-based incomes. Though many counties in the Midwest experience tornadoes regularly, the occurrence of strong tornadoes that are declared as natural disasters is rare. A warning system in form of tornado sirens, at least where installed, is provided. In addition, a tornado emergency can be declared by the National Weather Service during a strong occurrence in highly populated areas where large damages are expected. In contrast to hurricane forecasts, the tornado warning systems are short-term in nature. People are advised to find shelter immediately. Hence, there is no time to prepare for potential damages, which might explain the large losses in the top income group. Other reasons are discussed below.

Floods, fires, winter storms and geophysical activity have no effects on total incomes. Floods have no effect because flood insurance is mandatory in many locations that are susceptible to flooding. In fact, total labor income increases after a flood due to higher social security payments.[25] Fires do not have a strong overall effect on incomes, because income losses in earnings are compensated by capital income gains, as shown in Table A9 in the Appendix. Winter storms are generally not very destructive and, therefore, do not have any effects on income. Strong geophysical activity occurs very infrequently. Smaller and weak activity is not affecting incomes.

Tornadoes and storms are the only disaster types that exhibit large negative effects on total incomes. Both decreases seem to be driven by income losses in the top 10% group. The effects are particularly large for tornadoes. One explanation for the considerably larger losses are the lower number of public assistance programs after this type of disaster. In fact, the correlation between the number of tornadoes and the number of assistance programs is substantially lower than with hurricanes and storms. In addition, the effect might be driven by out-migration of top incomes. In particular, tornadoes occur mainly in rural counties of the Midwest, hence, the effects might be attributed to migration out of rural areas. The migration argument might also apply for storms.

[25] See Table A9 in the Appendix.

Table 14: Effects on individual-based Income Measures

Effect on Income Type	Disaster Type	Total	Income Groups		
		0-100	0-40	40-90	90-100
Capital Income	Storm	-58.58	-.27**	-6.40	-538.72*
		(35.95)	(0.13)	(15.34)	(325.33)
	Tornado	-104.04	1.06	-5.49	-1250.55
		(95.10)	(0.87)	(44.24)	(957.08)
Observations		5169	5169	5132	5169
Earnings	Storm	-442.99**	26.74	-243.36	-3652.56***
		(171.25)	(37.08)	(186.63)	(1039.71)
	Tornado	-342.60	218.56**	1077.49	-8391.16**
		(482.45)	(91.72)	(775.90)	(3259.35)
Observations		5169	5169	5169	5169
Total Labor Income	Storm	-351.00**	-42.72	-274.65*	-2457.43**
		(158.70)	(53.04)	(160.26)	(1129.12)
	Tornado	-526.01	-64.44	353.75	-6278.76*
		(503.50)	(372.07)	(627.81)	(3304.09)
Observations		4182	4182	4182	4182

Notes: Table shows the effects of natural disasters on individual-based income measures (see first column and column header) for storms and tornadoes. The respective disaster type variable is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero (second column). The effects are estimated using fixed effects regression with standard errors clustered by county and disaster region. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County-, region- and year-fixed effects not shown.

In order to improve the interpretation of the effects of storms and tornadoes, Table 14 shows individual-based results for the income components, namely earnings, capital and labor income. Capital income is only affected to a small degree. Note that previous results usually had an effect on the overall mean of capital income, whereas storms and tornadoes do not (see column (0-100) for capital income). The results on earnings show that the top income group is especially affected by both types of natural disasters. Interestingly, the low income group's average income increases after a tornado. This is a further indication that migration might drive the results, because out-migration of top incomes (net) shifts the percentiles downwards, thereby increasing the average incomes of other income groups. The decreases in earnings are not compensated by transfer payments, because the effects of storms and tornadoes on total labor income is also negative for the top income group as well as the middle income group for storms. The decrease is particularly large for tornadoes. Storms and tornados seem to lead to large income losses for top incomes without adequate compensation in the form of transfer payments.

Table 15: Effects by Disaster Type (Migration)

Migration	Disaster Type	Individual Incomes		Household Incomes	
		0-100	90-100	0-100	90-100
Non-Movers	Storm	-623.45***	-3972.73***	-908.54**	-6100.15***
		(196.62)	(1273.62)	(403.37)	(2343.53)
	Tornado	-790.02	-9088.71**	-1654.94	-16,650.98**
		(580.55)	(3617.35)	(1307.85)	(7362.47)
Observations		5095	5095	5095	5094
Top Reassigned	Storm	-784.85***	-5420.77***	-840.81**	-5854.09**
		(200.21)	(1266.16)	(402.82)	(2325.09)
	Tornado	-1252.60**	-10,459.85***	-2310.09**	-17,302.87***
		(547.99)	(3958.61)	(1059.50)	(6269.94)
Observations		5162	5162	5163	5163

Notes: Table shows the effects of storms and tornadoes on individual- and household-based income measures (see column header) for different migration samples (first column). The respective disaster type variable is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using fixed effects regression with standard errors clustered by county and disaster region. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County-, region- and year-fixed effects not shown.

In a next step, I want to control for potential migration effects. In Table 15, the results for non-movers and the sample where top incomes are reassigned to their previous state of residence are provided.[26] The table shows the results for overall average incomes and top incomes for individual- and household-based measures. In general, the effects are larger. Similarly to Section 6.2.2, the effects are larger by construction, because the reassignment only adds high incomes to the sample. Also, since migrants have a lower average income than the total population, the means of non-movers are also slightly larger. But even when considering the shifted average incomes, the effects are still marginally larger when controlled

[26]More details on the reassignment and the samples are provided in Sections 5 and 6.2.2.

for migration. As a consequence, the main results in Table 13 are not affected by migration. In fact, the effects would have been even larger in absence of migration. Thus, storms and especially tornados lead to large negative effects on top incomes. The effects are mainly coming from earnings that are not compensated by social security and other transfer measures.

In sum, the overall disaster effects in Section 6.1 can be attributed to storms and hurricanes. However, most natural disasters show negative, but statistically insignificant effects on middle incomes. Interestingly, there is quite some heterogeneity between the different disaster measures, which explains why the overall effects are only moderate.

7 Concluding Remarks

Populism, social unrest and even violence have various roots. However, a common source seems to be income inequality. In particular, parts of the population feel excluded from politics, economic opportunities or society as a whole. These parts of the population are especially susceptible to populism or, in extreme cases, even to violence. Extreme events, such as natural disasters, pose additional challenges for the governments. At the same time, people require more government assistance and, thus, are more likely to be susceptible to social unrest if theses requirements are not met. Given that natural disasters occur more frequently and become more devastating, thereby exacerbating the described consequences, an analysis of the impact of natural disasters is extremely relevant.

This paper analyzes the effects of natural disasters on the income distribution of the United States. The results suggest that natural disasters have a decreasing effect on incomes. In particular, the main results suggest that middle incomes are adversely more affected by natural disasters, which is also the main reason why there are only minor effects on inequality measures. These results implies that is very important to include the entire income distribution into the analysis. Another benefit of this analysis is that policy-makers can implement policies that have a more specific target. For instance, the results show that mandatory flood insurance in areas vulnerable to floods attenuates the effects of flooding on incomes.

In general, the effects are stronger for individual-based measures. Households are important smoothing tools for idiosyncratic shocks. The effects only appear in household-based measures if the shock is more systemic in nature. Similarly, welfare payments and disaster-related assistance programs mitigate some of the effects on earnings. In fact, natural disasters have no statistically significant effects on total labor income when social security payments are included. Another adaptation channel is migration. The findings suggest that the effects would have been larger in absence of migration. Thus, migration is used to mitigate the effects. The reassignment exercise yields upper and lower bounds for the magnitudes of the effects. Therefore, the true effects lie between the reassigned bottom 40% and the reassigned top 10% results.

The paper also confirms the intensification channel of natural disasters. Multiple as well as severe disasters lead to larger effects on incomes. In addition, Figure 7 shows that the effect of previous disasters is not linear. There is a surprise effect in counties that did not experience any disasters in the previous five years. However, if one or two disasters occurred in the last five years, then a county is less affected. The effect only intensifies for higher numbers of disasters. The analysis by types of natural disasters yield that the initial results are attributed to the strong effects of hurricanes and storms on middle incomes. Interesting income dynamics are also discovered for tornadoes that have inequality decreasing effects by strongly affecting the top income group.

Future research should further analyze the role of migration. The reassignment exercise in this paper provides some bounds on the effects. However, it would be interesting to see how these migration patterns evolve and how top incomes are affected by them. Another relevant topic is the effects of real estate prices and labor market outcomes on incomes and migration patterns. Does income homogenization occur in parts of the city? For instance, after Hurricane Katrina large parts of New Orleans were rebuilt, thereby increasing real estate prices. As a consequence, low income households could not afford to live in their former neighborhood anymore. In addition, it would be interesting and highly relevant to further explore the effects on different sectors of the economy. The construction sector is booming after a natural disaster. But which incomes exactly are benefiting from the boom? What about sectors that loose after a natural disaster? Finally, in order to pinpoint the effects on incomes more exactly, monthly data would be invaluable. As mentioned before, most natural disasters in the US occur in the second half of the year. By using annual data from January to December, the effects are underestimated by construction.

References

Abdullah, A. N. M., K. K. Zander, B. Myers, N. Stacey, and S. T. Garnett (2016). A Short-Term Decrease in Household Income Inequality in the Sundarbans, Bangladesh, following Cyclone Aila. *Natural Hazards 83*, 1103–1123.

Banerjee, L. (2007). Effect of Flood on Agricultural Wages in Bangladesh: An Empirical Analysis. *World Development 35*(11), 1989–2009.

Belasen, A. R. and S. W. Polachek (2008). How hurricanes affect wages and employment in local labor markets. *American Economic Review: Papers and Proceedings 98*(2), 49–53.

Bohra-Mishra, P., M. Oppenheimer, R. Cai, S. Feng, and R. Licker (2017). Climate Variability and Migration in the Philippines. *Population and Environment 38*, 286–308.

Boustan, L. P., M. E. Kahn, and P. W. Rhode (2012). Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century. *American Economic Review: Papers and Proceedings 102*(3), 238–244.

Boustan, L. P., M. E. Kahn, P. W. Rhode, and M. L. Yanguas (2017). The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data. *NBER Working Paper No. 23410*.

Bui, A. T., M. Dungey, C. V. Nguyen, and T. P. Pham (2014). The Impact of Natural Disasters on Household Income, Expenditure, Poverty and Inequality: Evidence from Vietnam. *Applied Economics 46*(15), 1751–1766.

Coffman, M. and I. Noy (2012). Hurricane Iniki: Measuring the Long-Term Economic Impact of a Natural Disaster using Synthetic Control. *Environment and Development Economics 17*, 187–205.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature 52*(3), 740–798.

Deryugina, T. (2017). The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance. *American Economic Journal: Economic Policy 9*(3), 168–198.

Felbermayr, G. and J. Gröschl (2014). Naturally Negative: The Growth Effects of Natural Disasters. *Journal of Development Economics 111*, 92–106.

Feng, S., M. Oppenheimer, and W. Schlenker (2012). Climate Change, Crop Yields, and Internal Migration in the United States. *National Bureau of Economic Research Working Paper Series No. 17734*, 1–43.

Flood, S., M. King, R. Rodgers, S. Ruggles, and J. R. Warren (2019). Integrated Public Use Microdata Series, Current Population Survey: Version 7.0 [dataset]. *Minneapolis MN:IPUMS.*

Groen, J. A., M. J. Kutzbach, and A. E. Polivka (2019). Storms and Jobs: The Effect of Hurricanes on Individuals' Employment and Earnings over the Long Term Jeffrey. *Journal of Labor Economics DOI: 10.10*, 1–39.

Hornbeck, R. (2012). The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe. *American Economic Review 102*(4), 1477–1507.

Kahn, M. E. (2005). The Death Toll From Natural Disasters: the Role of Income, Geography, and Institutions. *The Review of Economics and Statistics 87*(2), 271–284.

Kaplan, G. and S. Schulhofer-Wohl (2017). Understanding the Long-Run Decline in Interstate Migration. *International Economic Review 58*(1), 57–94.

Karim, A. and I. Noy (2016). Poverty and Natural Disasters – a Qualitative Survey of the Empirical Literature. *The Singapore Economic Review 61*(1), 1640001–1–36.

Keerthiratne, S. and R. S. J. Tol (2018). Impact of Natural Disasters on Income Inequality in Sri Lanka. *World Development 105*, 217–230.

Klomp, J. (2016). Economic Development and Natural Disasters: A Satellite Data Analysis. *Global Environmental Change 36*, 67–88.

Loayza, N. V., E. Olaberría, J. Rigolini, and L. Christiaensen (2012). Natural Disasters and Growth: Going Beyond the Averages. *World Development 40*(7), 1317–1336.

Long, J. and H. Siu (2016). Refugees From Dust and Shrinking Land: Tracking the Dust Bowl Migrants. *National Bureau of Economic Research Working Paper Series No. 22108*, 1–50.

Lynham, J., I. Noy, and J. Page (2017). The 1960 Tsunami in Hawaii: Long-Term Consequences of a Coastal Disaster. *World Development 94*, 106–118.

Manski, C. F. (1990). Nonparametric Bounds on Treatment Effects. *American Economic Review: Papers & Proceedings 80*(2), 319–323.

Miljkovic, T. and D. Miljkovic (2014). Modeling Impact of Hurricane Damages on Income Distribution in the Coastal U.S. *International Journal of Disaster Risk Science 5*, 265–273.

Nordhaus, W. D. (2010). The Economics of Hurricanes and Implications of Global Warming. *Climate Change Economics 1*(1), 1–20.

Noy, I. (2009). The Macroeconomic Consequences of Disasters. *Journal of Development Economics 88*, 221–231.

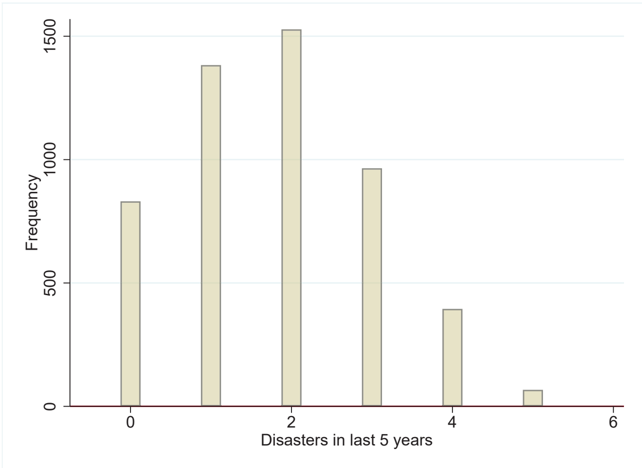
Sawada, Y. and S. Shimizutani (2008). How do People Cope with Natural Disasters? Evidence from the Great Hanshin-Awaji (Kobe) Earthquake in 1995. *Journal of Money, Credit and Banking 40*(2-3), 463–488.

Shaughnessy, T. M., M. L. White, and M. D. Brendler (2010). The income distribution effect of natural disasters: An analysis of hurricane katrina. *Journal of Regional Analysis and Policy 40*(1), 84–95.

Yamamura, E. (2015). The Impact of Natural Disasters on Income Inequality: Analysis using Panel Data during the Period 1970 to 2004. *International Economic Journal 29*(3), 359–374.

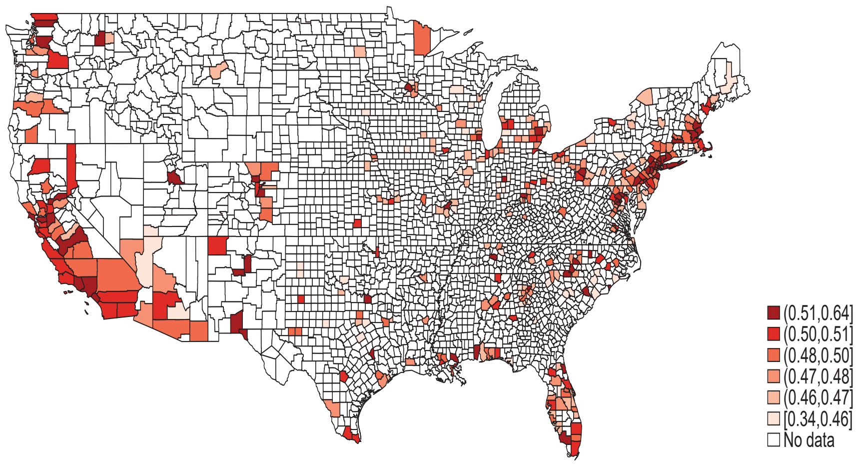
Appendix

Figure A1: Histogram Previous Disasters



Notes: Graph shows the frequency of previous disasters.
Source: OpenFEMA Dataset by the Federal Emergency Management Agency (FEMA).

Figure A2: Counties in CPS Data



Notes: Graph shows individual-based Gini-coefficients for the 400 counties that are included in the estimations.
Source: Current Population Survey (CPS).

Table A1: Disaster Types for Estimation

Type in Estimation	Type in FEMA data
Hurricane	Hurricane Typhoon Coastal Storm
Storm	Severe Storm
Flood	Flood Tsunami
Fire	Fire Drought
Winter Storm	Freezing Severe Ice Storm Snow
Tornado	Tornado
Geophysical	Earthquake Volcano Mud/Landslide

Table A2: Components of Total Income

Labor	Capital
Wage	Interest
Non-Farm Business	Dividends
Farm	Rent
Social Security	Other Sources not specified
Welfare (public assistance)	
Retirement	
Supplemental Security	
Unemployment Benefits	
Worker's Compensation	
Veteran's Benefits	
Survivor's Benefits	
Disability Benefits	
Educational Assistance	
Child Support	
Alimony	
Assistance	

Notes: Table shows the different components of total income. Wage, non-farm business and farm income constitutes earnings.
Source: Current Population Survey (CPS).

Table A3: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini-coefficient (Ind)	5169	.49	.05	.28	.74
Gini-coefficient (HH)	5169	.43	.06	.2	.72
Palma Ratio (Ind)	5169	5.79	4.47	1.32	148.5
Palma Ratio (HH)	5168	2.39	1.05	.26	17.28
Mean Total Income (Ind)	5169	33713.34	10282.92	9835.06	126170.4
Mean Total Income (020) (Ind)	5169	1458.89	1345.94	0	16366.73
Mean Total Income (2040) (Ind)	5169	11105.88	3875.13	1216.64	47576.11
Mean Total Income (4060) (Ind)	5169	23220.95	6890.68	6133.31	81691.11
Mean Total Income (6080) (Ind)	5169	40284.08	11744.63	11744.42	137759
Mean Total Income (8090) (Ind)	5169	62827.1	19051.9	21442.21	193364.3
Mean Total Income (80100) (Ind)	5169	94871.57	33583.76	28641.34	536494.7
Mean Total Income (95100) (Ind)	5168	172024.8	80989.29	39825.23	1100136
Mean Total Income (040) (Ind)	5169	6216.43	2461.21	178.75	30521.51
Mean Total Income (4090) (Ind)	5169	37950.76	10942.77	11352.99	127516
Mean Total Income (90100) (Ind)	5169	128192.6	51663.4	36545	895051.9
Mean Total Income (HH)	5169	68190.35	22040.27	20388.12	234902.3
Mean Total Income (020) (HH)	5169	13940.1	6075.49	0	64236.88
Mean Total Income (2040) (HH)	5169	32790.44	12040.57	7016.52	130514.4
Mean Total Income (4060) (HH)	5169	53263.26	17972.35	13447.7	176417.7
Mean Total Income (6080) (HH)	5169	81926.58	25850.86	27613.5	241654.9
Mean Total Income (8090) (HH)	5169	119151	39125.57	36962.92	468039.8
Mean Total Income (80100) (HH)	5169	165639.6	61138.14	38952.14	956489.3
Mean Total Income (95100) (HH)	5121	280712.7	142072.5	43000	2200237
Mean Total Income (040) (HH)	5169	23148.83	8706.28	3373.08	87013.19
Mean Total Income (4090) (HH)	5169	77934.9	24616.71	27864.12	253109.2
Mean Total Income (90100) (HH)	5168	216301.4	92006.56	42231.34	1540115
Mean Capital Income (Ind)	5169	1733.44	1246.81	-176.17	11044.99
Mean Capital Income (040) (Ind)	5169	.55	3.53	0	116.52
Mean Capital Income (4090) (Ind)	5132	606.01	615.49	1	7811.63
Mean Capital Income (90100) (Ind)	5169	16037.37	11483.09	4	148998.5
Mean Capital Income (95100) (Ind)	5162	27046.29	19410.49	4	183497
Mean Capital Income (020) (Ind)	5169	.01	.21	0	10.46
Mean Capital Income (2040) (Ind)	1006	9.23	16.79	1	228.15
Mean Capital Income (4060) (Ind)	3593	39.41	85.69	1	2007.71
Mean Capital Income (6080) (Ind)	4967	314.21	439.65	1	5774.52
Mean Capital Income (8090) (Ind)	5132	1869.28	2065.9	1	27861.32
Mean Capital Income (80100) (Ind)	5169	8764.6	6213.74	4	53315.22
Mean Capital Income (Ind)	5169	3525.65	2551.12	-385.6	20325.04
Mean Capital Income (040) (HH)	5169	7.29	25.61	0	658.49
Mean Capital Income (4090) (HH)	5149	1756.38	1786.52	1	30569.36
Mean Capital Income (90100) (HH)	5168	30301.94	22279.44	4	297997
Mean Capital Income (95100) (HH)	5104	47931.35	34294.48	4	328193
Mean Capital Income (020) (HH)	5169	.33	3.1	0	98.43
Mean Capital Income (2040) (HH)	2646	33.21	67.68	1	1391.92
Mean Capital Income (4060) (HH)	4545	181.14	316.72	1	5387.85
Mean Capital Income (6080) (HH)	5090	1219.06	1512.8	1	25109.96
Mean Capital Income (8090) (HH)	5149	5501.17	5600.24	1	100000
Mean Capital Income (80100) (HH)	5169	17271.88	12411.13	4	104871.1
Mean Earnings (Ind)	5169	26960.56	9318.58	6691.7	116546.5
Mean Earnings (040) (Ind)	5169	965.21	1462.76	0	21886.09
Mean Earnings (4090) (Ind)	5169	31591.86	10033.14	8058.52	121887.7
Mean Earnings (90100) (Ind)	5169	118862.8	50276.78	29807.19	933811.9
Mean Business Income (4090) (Ind)	5169	1386.71	1170.5	-221.6	15521.35
Mean Wage Income (4090) (Ind)	5169	30147.87	9775.53	7033.81	121887.7
Mean Farm Income (4090) (Ind)	5169	57.27	219.44	-611.49	2919.62
Mean Labro Income (040) (Ind)	4182	5463.22	2102.73	243.58	30063.87
Mean Labor Income (4090) (Ind)	4182	34518.34	9338.54	10925.64	99079.61
Mean Labor Income (90100) (Ind)	4182	115174.4	44458.48	35181.88	396149
Mean Unemployment Benefits (Ind)	5169	148	178.29	0	1977.06
Mean Assistance Income (Ind)	5169	78.79	183.71	0	3666.94
Disaster	5169	.38	.49	0	1
Disaster Assistance (dummy)	5169	.26	.72	0	8

Notes: Table shows the summary statistics for all variables used in the main analysis for the estimation sample from 1996 to 2017.

Table A4: Summary statistics for Non-Movers

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini-coefficient (Ind)	5095	.49	.05	.28	.75
Gini-coefficient (HH)	5095	.43	.06	.2	.73
Mean Total Income (Ind)	5095	33908.61	10387.87	9705.3	127215
Mean Total Income (020) (Ind)	5095	1508.29	1385.4	0	18001.14
Mean Total Income (2040) (Ind)	5095	11219.01	3918.24	1216.64	58263.21
Mean Total Income (4060) (Ind)	5095	23384.05	6966.65	6133.31	89113.75
Mean Total Income (6080) (Ind)	5095	40544.05	11910.66	11744.42	141716.1
Mean Total Income (8090) (Ind)	5095	63178.88	19279.68	21006.95	202600.1
Mean Total Income (80100) (Ind)	5095	95317.28	33914.76	28463.73	556135.1
Mean Total Income (95100) (Ind)	5094	172871.1	82106.67	40271.43	1100136
Mean Total Income (040) (Ind)	5095	6296.4	2503.41	178.75	37037.64
Mean Total Income (4090) (Ind)	5095	38185.84	11059.51	11352.99	129354
Mean Total Income (90100) (Ind)	5095	128797.5	52099.3	36545	895051.9
Mean Total Income (HH)	5095	68662.86	22224.11	21455.61	241576.7
Mean Total Income (020) (HH)	5095	14224.38	6194.76	0	67279.41
Mean Total Income (2040) (HH)	5095	33158.38	12225.31	7360.39	130514.4
Mean Total Income (4060) (HH)	5095	53740.53	18170.61	13447.7	176417.7
Mean Total Income (6080) (HH)	5095	82527.47	26072.35	27772.84	241654.9
Mean Total Income (8090) (HH)	5095	119935.6	39581.67	37434.42	529054.4
Mean Total Income (80100) (HH)	5095	166496.8	61655.04	39417.14	1048394
Mean Total Income (95100) (HH)	5042	281923.4	142023.2	43000	2200237
Mean Total Income (040) (HH)	5095	23457.71	8865.02	3447.5	87013.19
Mean Total Income (4090) (HH)	5095	78534.48	24873.9	27812.63	253109.2
Mean Total Income (90100) (HH)	5094	217605.4	92932.92	42231.34	1540115
Mean Capital Income (Ind)	5095	1765.16	1277.39	-199.56	11086.4
Mean Capital Income (040) (Ind)	5095	.66	3.93	0	103.09
Mean Capital Income (4090) (Ind)	5057	636.1	665.94	1	10639.94
Mean Capital Income (90100) (Ind)	5095	16253.67	11564.27	4	100389.4
Mean Capital Income (95100) (Ind)	5089	27338.86	19570.38	4	183497
Mean Capital Income (020) (Ind)	5095	.01	.25	0	12.19
Mean Capital Income (2040) (Ind)	1058	10.17	17.87	1	202.23
Mean Capital Income (4060) (Ind)	3577	43.35	94.75	1	1880.17
Mean Capital Income (6080) (Ind)	4899	336.93	483.33	1	7737.02
Mean Capital Income (8090) (Ind)	5057	1961.37	2206.79	1	34962.45
Mean Capital Income (80100) (Ind)	5095	8912.85	6335.49	4	53615.42
Mean Capital Income (Ind)	5095	3578.96	2596.63	-437.62	20503.67
Mean Capital Income (040) (HH)	5095	8.29	29.53	0	659.03
Mean Capital Income (4090) (HH)	5079	1821.8	1869.82	1	30569.36
Mean Capital Income (90100) (HH)	5093	30601.08	22191.81	4	188997
Mean Capital Income (95100) (HH)	5024	48280.64	34338.32	4	328193
Mean Capital Income (020) (HH)	5095	.42	3.51	0	106.26
Mean Capital Income (2040) (HH)	2637	36.82	77.68	1	1397.01
Mean Capital Income (4060) (HH)	4486	193.69	342.65	1	5886.1
Mean Capital Income (6080) (HH)	5014	1280.49	1618.52	1	25109.96
Mean Capital Income (8090) (HH)	5078	5677.74	5804.76	1	100000
Mean Capital Income (80100) (HH)	5095	17499.08	12538.65	4	104871.1
Mean Earnings (Ind)	5095	27031.73	9422.33	6584.17	118230.3
Mean Earnings (040) (Ind)	5095	935.1	1456.98	0	18139.08
Mean Earnings (4090) (Ind)	5095	31721.5	10139.8	6598.79	120335.8
Mean Earnings (90100) (Ind)	5095	119382.7	50832.85	30596.47	933811.9
Mean Business Income (4090) (Ind)	5095	1415.01	1198.41	-243.56	17886.53
Mean Wage Income (4090) (Ind)	5095	30248.62	9877.65	6089.43	120335.8
Mean Farm Income (4090) (Ind)	5095	57.88	225.56	-632.1	3119.79
Mean Labro Income (040) (Ind)	4137	5536.61	2149.77	232.6	33702.25
Mean Labor Income (4090) (Ind)	4137	34786.59	9547.02	11223.26	103975.2
Mean Labor Income (90100) (Ind)	4137	115943.1	45410.58	35873.09	419602.8
Mean Unemployment Benefits (Ind)	5095	147.75	181.21	0	2025.7
Mean Assistance Income (Ind)	5095	71.59	174.36	0	3782.59
Disaster Assistance (dummy)	5095	.26	.71	0	8
Disaster	5095	.38	.49	0	1

Notes: Table shows the summary statistics for non-movers for the estimation sample from 1996 to 2017.

Table A5: Summary statistics (Top 10% Reassigned)

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini-coefficient (Ind)	5163	.5	.05	.28	.75
Gini-coefficient (HH)	5163	.43	.06	.2	.73
Mean Total Income (Ind)	5162	39882.87	11290.98	14809.49	127215
Mean Total Income (020) (Ind)	5162	1852.91	1581.77	0	18001.14
Mean Total Income (2040) (Ind)	5162	12543.09	4186.89	2640.75	58749.77
Mean Total Income (4060) (Ind)	5162	26431.28	7749.41	8381.14	95698.64
Mean Total Income (6080) (Ind)	5162	47548.14	13858.64	15684.91	148028.2
Mean Total Income (8090) (Ind)	5162	75653.14	21831.3	26257.17	236771.9
Mean Total Income (80100) (Ind)	5162	113796.2	36459.89	41255.06	556135.1
Mean Total Income (95100) (Ind)	5162	206472.3	87960.55	50421.8	1100136
Mean Total Income (040) (Ind)	5162	7135.23	2711.8	567.88	37737.01
Mean Total Income (4090) (Ind)	5162	44725	12527.96	14998.27	144988.5
Mean Total Income (90100) (Ind)	5162	153688	55645.61	48027.63	895051.9
Mean Total Income (HH)	5163	69717.72	21769.67	24776.23	241576.7
Mean Total Income (020) (HH)	5163	14378.1	6199.1	0	67279.41
Mean Total Income (2040) (HH)	5163	33599.22	12109.49	7360.39	130514.4
Mean Total Income (4060) (HH)	5163	54647.46	17836.55	16607.71	176417.7
Mean Total Income (6080) (HH)	5163	83908.4	25509.69	31175.32	241654.9
Mean Total Income (8090) (HH)	5163	121758	38999.85	40700.75	529054.4
Mean Total Income (80100) (HH)	5163	168963.1	60868.05	48929.77	1048394
Mean Total Income (95100) (HH)	5102	286054.3	140819.7	65000	2200237
Mean Total Income (040) (HH)	5163	23753.27	8788.02	3447.5	87013.19
Mean Total Income (4090) (HH)	5163	79816.71	24349.36	29345.5	253109.2
Mean Total Income (90100) (HH)	5163	220825.3	92403.01	57609.87	1540115
Mean Capital Income (Ind)	5162	2107.32	1347.75	-195.85	12026.58
Mean Capital Income (040) (Ind)	5162	.81	4.78	0	184.73
Mean Capital Income (4090) (Ind)	5154	736.37	685.77	1	10486.48
Mean Capital Income (90100) (Ind)	5162	19260.27	12120.17	90.44	101588.6
Mean Capital Income (95100) (Ind)	5154	32238.89	20155.42	106.5	183497
Mean Capital Income (020) (Ind)	5162	.01	.3	0	12.19
Mean Capital Income (2040) (Ind)	1236	10.69	20.1	1	364.53
Mean Capital Income (4060) (Ind)	3963	47.94	97.86	1	2024.57
Mean Capital Income (6080) (Ind)	5084	396.44	510.64	1	7553.52
Mean Capital Income (8090) (Ind)	5154	2312.92	2332.66	1	34962.45
Mean Capital Income (80100) (Ind)	5162	10570.75	6688.17	61.57	60013.89
Mean Capital Income (Ind)	5163	3633.09	2589.55	-385.6	20503.67
Mean Capital Income (040) (HH)	5163	8.31	29.26	0	638.71
Mean Capital Income (4090) (HH)	5154	1842.93	1860.65	2	29428.32
Mean Capital Income (90100) (HH)	5162	31048.6	22368.18	4	275344
Mean Capital Income (95100) (HH)	5085	48993.57	34335.86	4	328193
Mean Capital Income (020) (HH)	5163	.41	3.31	0	98.43
Mean Capital Income (2040) (HH)	2715	36.38	75.7	1	1272.9
Mean Capital Income (4060) (HH)	4610	193.63	337.65	1	5387.85
Mean Capital Income (6080) (HH)	5102	1294.25	1586.1	1	23181.76
Mean Capital Income (8090) (HH)	5154	5758.56	5808.13	2	100000
Mean Capital Income (80100) (HH)	5163	17759.75	12576.37	4	120497.7
Mean Earnings (Ind)	5162	32629.29	10196.31	11806.37	118230.3
Mean Earnings (040) (Ind)	5162	1341.53	1767.17	0	19666.91
Mean Earnings (4090) (Ind)	5162	37753.63	11389.16	12404.36	135259.4
Mean Earnings (90100) (Ind)	5162	144094.5	55318.32	42732.04	933811.9
Mean Business Income (4090) (Ind)	5162	1679.69	1576.39	-172.48	20123.97
Mean Wage Income (4090) (Ind)	5162	36009.21	10916.06	11750.88	135259.4
Mean Farm Income (4090) (Ind)	5162	64.73	240.54	-550.44	4615.4
Mean Labro Income (040) (Ind)	4185	6335.84	2382.31	493.11	33702.25
Mean Labor Income (4090) (Ind)	4185	40819.5	10866.92	15009.16	111209.8
Mean Labor Income (90100) (Ind)	4185	140784.8	50345.92	48100.1	470644.3
Mean Unemployment Benefits (Ind)	5163	148.06	175.43	0	1864.96
Mean Assistance Income (Ind)	5163	76.27	167.81	0	3471.33
Disaster Assistance (dummy)	5163	.26	.71	0	8
Disaster	5163	.38	.49	0	1

Notes: Table shows the summary statistics when individuals and households with top 10% incomes are reassigned.

Table A6: Summary statistics (Bottom 40% Reassigned)

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini-coefficient (Ind)	5230	.53	.05	.31	.77
Gini-coefficient (HH)	5230	.43	.06	.2	.73
Mean Total Income (Ind)	5230	28301.16	9806.72	7969.78	115482.7
Mean Total Income (020) (Ind)	5230	662.94	898.39	0	5992.96
Mean Total Income (2040) (Ind)	5228	7398.59	3703.5	1	25741.21
Mean Total Income (4060) (Ind)	5230	17026.23	6563.72	2091.24	47514.4
Mean Total Income (6080) (Ind)	5230	32943.15	11654.93	7563.61	90121.65
Mean Total Income (8090) (Ind)	5230	55103.86	18446.64	15087.3	165982.1
Mean Total Income (80100) (Ind)	5230	85315.31	31261.2	24761.29	497032.1
Mean Total Income (95100) (Ind)	5230	156484.7	72527.47	38399.34	1100136
Mean Total Income (040) (Ind)	5230	3966.35	2230.62	0	15370.48
Mean Total Income (4090) (Ind)	5230	30994.21	10617.46	7353.63	82333.35
Mean Total Income (90100) (Ind)	5230	116502.3	47236.85	33006.84	895051.9
Mean Total Income (HH)	5230	67842.87	21518.47	21455.61	234980
Mean Total Income (020) (HH)	5230	13640.76	5711.4	0	59121.77
Mean Total Income (2040) (HH)	5230	32368.16	11551.16	7009.22	107393.7
Mean Total Income (4060) (HH)	5230	52889.54	17455.37	14165.04	159556.3
Mean Total Income (6080) (HH)	5230	81627.35	25345.67	27567.5	223564
Mean Total Income (8090) (HH)	5230	118905.5	38233.3	37434.42	468039.8
Mean Total Income (80100) (HH)	5230	165279.5	59982.86	39417.14	956489.3
Mean Total Income (95100) (HH)	5174	280818.5	140915.2	43000	2200237
Mean Total Income (040) (HH)	5230	22777.46	8291.63	3640.28	77125.67
Mean Total Income (4090) (HH)	5230	77634.73	24031.68	27898.09	217813.8
Mean Total Income (90100) (HH)	5229	216041.9	90639.93	42231.34	1540115
Mean Capital Income (Ind)	5230	1430.07	1013.56	-183.63	8667.27
Mean Capital Income (040) (Ind)	5230	.17	1.86	0	72.37
Mean Capital Income (4090) (Ind)	5208	431.44	403.12	1	3969.77
Mean Capital Income (90100) (Ind)	5230	13484.82	9392.5	4	74093.48
Mean Capital Income (95100) (Ind)	5230	23205.44	16529.77	4	183497
Mean Capital Income (020) (Ind)	5230	0	.1	0	5.97
Mean Capital Income (2040) (Ind)	546	6.14	12.55	1	139.29
Mean Capital Income (4060) (Ind)	3037	22.98	55.43	1	1160.82
Mean Capital Income (6080) (Ind)	5006	189.27	271.89	1	3038.72
Mean Capital Income (8090) (Ind)	5208	1279.15	1342.98	1	15582.67
Mean Capital Income (80100) (Ind)	5230	7274.41	5062.21	4	44811.51
Mean Capital Income (Ind)	5230	3487.37	2504.27	-421.13	20704.02
Mean Capital Income (040) (HH)	5230	6.6	22.29	0	379.39
Mean Capital Income (4090) (HH)	5212	1737.29	1752.57	1	30569.36
Mean Capital Income (90100) (HH)	5228	30053.36	22060.06	4	297997
Mean Capital Income (95100) (HH)	5161	47333.26	33736.31	4	328193
Mean Capital Income (020) (HH)	5230	.27	2.36	0	78.85
Mean Capital Income (2040) (HH)	2657	31.09	59.51	1	761.29
Mean Capital Income (4060) (HH)	4610	172.48	294.76	1	4527.93
Mean Capital Income (6080) (HH)	5152	1195.84	1449.29	1	25109.96
Mean Capital Income (8090) (HH)	5211	5457.31	5557.36	1	100000
Mean Capital Income (80100) (HH)	5230	17101.35	12163.18	4	109020.3
Mean Earnings (Ind)	5230	22432.85	8718.95	4405.12	107054.3
Mean Earnings (040) (Ind)	5230	441.52	844.9	0	10033.03
Mean Earnings (4090) (Ind)	5230	25208.12	9477.7	3887.57	78173.58
Mean Earnings (90100) (Ind)	5230	107502.6	45625.41	26541.52	933811.9
Mean Business Income (4090) (Ind)	5230	1111.84	869.46	-250.18	7723.88
Mean Wage Income (4090) (Ind)	5230	24054.33	9202.85	3711.49	78173.58
Mean Farm Income (4090) (Ind)	5230	41.95	167.25	-586.79	2956.31
Mean Labro Income (040) (Ind)	4236	3392.91	1912.59	0	13428.56
Mean Labor Income (4090) (Ind)	4236	27838.2	9046.45	6807.71	70467.05
Mean Labor Income (90100) (Ind)	4236	103771.4	39572.21	28048.43	379669
Mean Unemployment Benefits (Ind)	5230	141	160.18	0	1790.15
Mean Assistance Income (Ind)	5230	83.45	137.51	0	3006.53
Disaster Assistance (dummy)	5230	.26	.73	0	8
Disaster	5230	.38	.49	0	1

Notes: Table shows the summary statistics when individuals and households with bottom 40% incomes are reassigned.

Table A7: Migration Reasons

Reason for moving	Freq.	Percent	Cum.
Change in marital status	10,192	5.61	5.61
Establish own household	15,816	8.71	14.32
Other family reason	22,678	12.49	26.81
New job or job transfer	17,500	9.64	36.44
To look for work or lost job	3,629	2.00	38.44
For easier commute	7,856	4.33	42.76
Retired	925	0.51	43.27
Other job-related reason	3,579	1.97	45.24
Wanted to own home, not rent	14,240	7.84	53.08
Wanted new or better housing	31,186	17.17	70.25
Wanted better neighborhood	7,247	3.99	74.24
For cheaper housing	13,992	7.70	81.95
Other housing reason	18,829	10.37	92.32
Attend/leave college	4,231	2.33	94.65
Change of climate	1,067	0.59	95.23
Health reasons	2,026	1.12	96.35
Other reasons	5,506	3.03	99.38
Natural disaster	299	0.16	99.54
Foreclosure or eviction	828	0.46	100.00
Total	181,626	100.00	

Notes: Table shows the given reasons for moving between 1996 and 2017.
Source: Current Population Survey (CPS).

Table A8: Interaction with Previous Disasters

	Total Income		Earnings			Capital
	0-100	40-90	0-100	40-90	90-100	0-100
Disaster=1	-1093.95**	-990.38**	-938.37**	-810.45*	-5337.98**	-137.04**
	(464.69)	(448.06)	(459.23)	(466.70)	(2679.69)	(65.71)
Disasters in last 5 years=1	-918.65*	-538.98	-986.22**	-678.55	-6826.02***	-39.60
	(496.55)	(521.36)	(488.22)	(531.67)	(2601.58)	(68.59)
Disasters in last 5 years=2	-426.54	68.79	-412.00	113.46	-4407.13	-63.39
	(589.95)	(624.01)	(559.71)	(613.99)	(2946.54)	(70.39)
Disasters in last 5 years=3	-416.38	63.32	-358.11	81.55	-5450.60*	-52.05
	(616.61)	(650.35)	(570.10)	(601.41)	(3293.42)	(77.09)
Disasters in last 5 years=4	-314.91	-152.27	-270.66	-134.84	-3358.11	56.67
	(735.37)	(791.00)	(663.37)	(760.17)	(3641.53)	(97.91)
Disasters in last 5 years=5	332.06	583.00	-53.26	-123.87	-2324.26	138.18
	(927.38)	(915.55)	(833.03)	(848.40)	(4975.83)	(129.56)
Disaster=1 × Disasters in last 5 years=1	1300.51**	1203.24**	1300.59**	1258.74**	6389.06*	103.44
	(553.29)	(533.27)	(551.66)	(566.24)	(3278.26)	(93.93)
Disaster=1 × Disasters in last 5 years=2	936.64*	631.68	897.06	629.31	4189.63	132.65
	(563.36)	(603.30)	(545.60)	(610.84)	(3113.19)	(81.70)
Disaster=1 × Disasters in last 5 years=3	990.63*	601.12	745.42	164.99	5518.44	121.20
	(596.78)	(590.06)	(582.86)	(590.06)	(3564.65)	(90.69)
Disaster=1 × Disasters in last 5 years=4	582.81	331.17	380.64	-72.26	3053.20	73.55
	(603.29)	(612.78)	(581.22)	(599.54)	(3322.93)	(93.28)
Disaster=1 × Disasters in last 5 years=5	719.23	668.00	805.96	772.29	5176.06	60.97
	(1125.76)	(1184.66)	(1091.10)	(1316.26)	(6499.32)	(211.46)
Observations	5169	5169	5169	5169	5169	5169

Notes: Table shows the results for Figure 7, namely the effects of natural disasters on individual-based mean total incomes, earnings and capital incomes for each number of previous disasters. The disaster dummy is equal to 1 if at least one disaster occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 385 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.

Table A9: Various Effects of Disaster Types

Dependent Variable	Disaster Type	Total	Income Groups		
		0-100	0-40	40-90	90-100
Total Labor Income	Flood	702.757*	-53.654	647.776*	3879.306
		(383.297)	(101.871)	(357.267)	(2574.857)
Observations		4182	4182	4182	4182
Capital Income	Fire	85.767*	.211	38.711***	621.608
		(46.230)	(.152)	(13.420)	(497.042)
Observations		5169	5169	5132	5169
Earnings	Fire	-113.038	-72.175*	-388.788*	63.763
		(213.791)	(42.327)	(233.569)	(1144.821)
Observations		5169	5169	5169	5169

Notes: Table shows the various results for the effects of different disaster types (second column) on various income measures (first column). The different types of disasters are dummies that are equal to 1 if at least one disaster of the type occurred in a county within a given year, otherwise the value is zero. The effects are estimated using population-weighted fixed effects regression with standard errors clustered at the county level. The estimations include 385 counties for 22 years (1996-2017). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. County- and year-fixed effects not shown.