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A CENTURY OF DATA

Leah Platt Boustan
Matthew E. Kahn
Paul W. Rhode
Maria Lucia Yanguas

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The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data
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ABSTRACT

More than 100 natural disasters strike the United States every year, causing extensive fatalities and damages. We construct the universe of US federally designated natural disasters from 1920 to 2010. We find that severe disasters increase out-migration rates at the county level by 1.5 percentage points and lower housing prices/rents by 2.5–5.0 percent. The migration response to milder disasters is smaller but has been increasing over time. The economic response to disasters is most consistent with falling local productivity and labor demand. Disasters that convey more information about future disaster risk increase the pace of out-migration.

Leah Platt Boustan
Princeton University
Industrial Relations Section
Louis A. Simpson International Bldg.
Princeton, NJ 08544
and NBER
lboustan@princeton.edu

Matthew E. Kahn
Department of Economics
Johns Hopkins University
3100 Wyman Park Drive
Baltimore, MD 21211
and NBER
mkahn10@jhu.edu

Paul W. Rhode
Economics Department
University of Michigan
205 Lorch Hall
611 Tappan St.
Ann Arbor, MI 48109-1220
and NBER
pwrhode@umich.edu

Maria Lucia Yanguas
Department of Economics
UCLA
Los Angeles
myanguas@ucla.edu

I. Introduction

Natural disasters regularly strike major cities in the United States, leading to numerous fatalities and billions of dollars of property and infrastructure damage each year. Recent examples include Hurricane Sandy, which hit New York City and the surrounding area in 2012, and Hurricane Harvey, which caused severe flooding in Houston in 2017, each resulting in more than 100 deaths. Climate science suggests that as global greenhouse gas emissions increase, so too will the number and severity of natural disasters (IPCC 2012). Furthermore, as more economic activity clusters along America's coasts, a greater share of the population is now at risk of exposure to natural disasters (Changnon et. al. 2000, Rappaport and Sachs 2003, Pielke et. al. 2008).

This paper analyzes an original dataset for which we compiled the universe of federally designated natural disasters in the United States from 1920 to 2010.¹ Figure 1 displays annual counts of disaster events at the county level using this new series, and Appendix Figure 1 breaks down the series by disaster type. From 1920 to 1964, observations are based on historical archival data from the American National Red Cross (ARC). We then combine this information with disaster counts from the Federal Emergency Management Agency (FEMA) and its predecessors starting in the 1950s.² Through most of the century, the US experienced around 500 county-level disaster events each year (one disaster can contribute to numerous county-level disaster events – for example, as a hurricane moves up the coast and strikes multiple counties). Since the early 1990s, there has been a clear acceleration in disaster counts, reaching around 1,500 county-level events per year by the 2000s. Winter storms and hurricanes contribute the most to this increase in frequency.³ Our extensive new data set aggregates these annual disaster events to the decadal level in order to investigate the effect of natural disasters on local economies.

¹ Our time series of disasters begins in 1920, but our analysis of the effect of disasters on migration starts in 1930, when the series of net migration by county is first available.

² By this measure, a disaster that affects multiple counties would be tallied multiple times. For example, the Great Mississippi Flood of 1927 affected 170 counties. Likewise, a county that experiences more than one disaster event in a decade would be counted more than once.

³ A rise in the frequency of disasters after 1990 is also evident in global series, suggesting that it reflects a real uptick in weather events (see Munich Re 2012, Gaiha et al. 2015, Kousky 2014). In addition, the federal government may have become more expansive in their declaration of disaster events after Hurricane Andrew, which was especially salient, taking place during the 1992 presidential election campaign (Salkowe and Chakraborty 2009).

A natural disaster event might affect the local economy in several ways: reducing firm productivity by destroying productive capital or disrupting supply chains, creating unanticipated disamenities for consumers, or demolishing part of the housing stock. Each of these channels implies a different relationship between disaster events and local wages, housing prices/rents, and net migration to an area. Furthermore, disasters could shock local areas out of an inefficient equilibrium established through path dependence, allowing the economy to reset to a new equilibrium (for example, by destroying outdated buildings and other durable capital such as in Hornbeck and Keniston (2017)).

We compare a series of economic outcomes within counties before and after a disaster strikes, relative to comparison counties that do not experience a natural disaster in the decade. The underlying assumption is that the presence of a disaster in a particular decade does not coincide with other economic changes at the county level. We find no evidence that disasters that will occur in the next decade (*leads*) have any effect on current out-migration. In some specifications, we also include county-specific trends to account for the fact that, for example, disasters are more common in coastal areas that might be otherwise attracting economic activity over time.

We find that a severe disaster event leads to lower family income, heightened out-migration rates and lower housing prices/rents in a county over the decade. Together, these results suggest that natural disasters reduce firm productivity, thereby lowering wages in the area, which encourages out-migration and falling housing prices. Local responses to disaster events increased after 1980 as national disaster activity has become more frequent in recent years, perhaps because residents infer that each event is associated with a higher risk of future disasters. The advent of FEMA in 1978 did not dampen this trend. If natural disasters were able to shock local areas out of inefficient equilibria regularly, we would expect a stronger out-migration response to disasters in slow-growing areas compared to areas that were experiencing faster economic or population growth. Yet, if anything, we find a stronger net out-migration response in growing areas, contrary to the idea that disasters regularly shock local economies off an inefficient path.

On average, net out-migration from a county increases by 1.5 percentage points during a decade facing a severe natural disaster (8 percent of a standard deviation). The migration response to one severe natural disaster is around half as large as the estimated migration effect of a one standard-deviation reduction in local employment growth. Our preferred specification considers a disaster to be “severe” if it leads to 25 or more deaths, the median value for disasters with known

fatality counts. Results are robust to alternative fatality thresholds (20 to 200 fatalities), but we find stronger out-migration from the most severe disasters (500 fatalities or more). In the full sample, there are small out-migration responses to milder disasters, especially hurricanes and wild fires. However, after 1980, a period of rising natural disaster frequency and intensity, we find a sizeable migration response to floods, hurricanes, and wild fires. The heightened response to smaller disasters in the more recent period is consistent with the possibility that these events confer more information about future disaster risk, given the growing frequency of disasters over time.

We also find that median housing prices/rents fall by 2.5 to 5 percent after a severe natural disaster, the same order of magnitude as the housing market response to a five percent decrease in school quality as measured by test scores (Black 1999; Black and Machin 2011). Poverty rates increase in areas hit by severe disasters, which is consistent with either an out-migration of households above the poverty line or in-migration of the poor (perhaps in response to lower housing prices), or a causal effect of natural disasters on the probability that the existing population falls into poverty. Our estimates capture the net effect of disasters on local economies, after any rebuilding, new investments, or disbursement of disaster relief funds.⁴

On the margin, FEMA disaster declarations and the extent of disaster relief payments are affected by the political process (Downton and Pielke 2001, Garrett and Sobel 2003).⁵ We provide suggestive evidence that our results are not being driven by biases that would arise if disaster events were declared more often in politically connected states (e.g., those controlled by the same party as the president). First, any political connection that would lead states to receive an unwarranted disaster designation and disaster relief should generate other flows of valuable discretionary federal funds, thereby, if anything, leading to net in-migration. Thus, we would expect the political component of disaster declarations to bias *against* finding that disasters lead to out-migration or falling housing prices. Second, although the official designation of mild weather events as “disasters” may be subject to political manipulation, the largest disasters have

⁴ Gregory (2017) and Fu and Gregory (2019) document that rebuilding grants have externality effects on the decision of neighboring households to remain in an area struck by a natural disaster.

⁵ These papers show that states politically important to the president have a higher rate of disaster declaration, and that disaster expenditures are higher in states having congressional representation on FEMA oversight committees and during election years.

all received federal disaster designations.⁶ We show that the estimated effect of “severe disasters” is robust to various definitions, ranging from a threshold of 10 to 500 deaths, suggesting that individuals respond similarly to any disaster that is sufficiently damaging. The association between large disasters and out-migration also holds when instrumenting for disaster activity with historically available climate variables (e.g., maximum and minimum temperatures) to account for any association between disaster declarations and local politics, and is present regardless of whether the political party of the state’s governor matches the party of the President.

Our work contributes to two strands of the literature in urban and environmental economics. First is a series of macroeconomic studies that use cross-country panel regressions to study how changing temperature, rainfall, and increased exposure to natural disasters conditions affect economic growth (Dell, Jones and Olken 2012, 2014; Cavallo, et al. 2013; Hsiang and Jina 2014; Burke, Hsiang and Miguel 2015; Cattaneo and Peri 2016; Kocornik-Mina et. al. Forthcoming). These studies have not led to a consensus. Results range from long-lasting effects of natural disasters on national income to near-immediate recovery. By analyzing the effect of many natural disasters within a single country (the United States) over many decades, we are able to hold constant many core institutional and geographic features of the economy that may be otherwise correlated with disaster prevalence in a cross-country setting (e.g., democracy, temperate climate). We add to a small body of work studying disasters within a country, including Anttila-Hughes and Hsiang (2013), which analyzes more than 2,000 typhoons in the Philippines.⁷ In our universe of US disasters, we document results more consistent with the finding of long-lasting disaster effects on local economies.

A second set of papers present case studies of specific major disasters on existing residents (see, for example in the US, Smith and McCarty 1996 and Hallstrom and Smith 2005 on Hurricane Andrew; Hornbeck 2012 and Long and Siu 2018 on the Dustbowl; Hornbeck and Naidu 2014 on the 1927 Mississippi flood; and Vigdor 2008, Sastry and Gregory 2014, Bleemer and Van der Klaauw 2017 and Deryugina, Kawano and Levitt 2018 on Hurricane Katrina; for disasters in other

⁶ Even Hurricane Maria, the severity of which was downplayed by the Trump administration after hitting Puerto Rico in 2017, did receive a disaster designation by FEMA and so would be included in our definition of a disaster event.

⁷ In work related to climate change (although not directly focused on natural disasters), Feng, Oppenheimer and Schlenker (2012) studies the effect of temperature-induced changes in crop yields on migration from rural US counties.

countries, see Nobles, Frankenberg, and Thomas 2015 and Groger and Zylberberg 2016). Most of these case studies find large effects of a major disaster on out-migration or population loss. While it is important to study these major cases, most disasters are not as severe as these notable outliers. Our comprehensive dataset allows us to examine a much wider universe of disasters. In two related papers, Strobl (2011) and Fussell, et al. (2017) use county-level panels of US counties and find that hurricanes reduce local economic growth and affected population in recent decades. Strobl leverages detailed data on wind speeds and a scientific model of hurricane intensity to generate a proxy for local damage. The (complementary) advantage of our paper is that we examine all disaster types – hurricanes represent less than 10 percent of disaster events – over a much longer historical period.

II. Theoretical Predictions

Natural disasters can have various effects on local economies, potentially reducing firm productivity, destroying housing stock and/or diminishing consumer amenities. Furthermore, one disaster event can change the expectations of residents or prospective residents about future disaster risk. We discuss each of these aspects in turn, as well as the case of a disaster shocking an area out of an inefficient equilibrium, and derive predictions that will guide our empirical exercise. Kocornik-Mina et al. (Forthcoming) discusses a set of similar channels.

We use the effect of disasters on local wages, housing prices/rents, and net migration to distinguish the relative strength of the various channels by which disaster events can affect local economies. Consider the case in which a natural disaster reduces firm productivity– for example, by destroying productive capital or disrupting local supply chains (Carvalho, et al. 2016), thereby reducing labor demand. All else equal, natural disasters would lower wages, encouraging existing residents to leave the area and/or discouraging outsiders from moving in (Rosen 1974; Roback 1982; Topel 1986). In an economy with durable local housing, this out-migration would depress local home prices in the medium run until the existing housing stock has a chance to depreciate (Glaeser and Gyourko 2005).⁸ Lower home prices encourage some residents to stay in an area and others to move in; the price effect will be strongest for the poor who are more willing to trade off

⁸ If instead disasters result in extensive rebuilding projects, thereby temporarily increasing labor demand, population and housing prices will increase. We estimate the net effect of disasters including any effect on reconstruction.

high real income for higher disaster risk. Thus, if disasters reduce firm productivity, we expect they will be associated with lower wages, higher out-migration and lower housing prices. If instead disasters weaken local amenities, residents will also leave the area and housing prices will fall as a result, but, if anything, wages might rise as a result, as firms seek to attract workers back to the region.

Natural disasters may also destroy a substantial portion of the housing stock or reduce the willingness of homeowners to invest in ongoing maintenance, thereby reducing the quality of the existing stock (Bunten and Kahn, 2017). If the only effect of a disaster is to contract the housing stock, then we would expect housing prices to rise in the short run. More generally, the short run effect of a disaster on housing prices will depend on the relative strength of declining demand for living in the area (which will reduce prices) and a reduction in housing supply (which will raise prices). In the longer run, if prices rise above construction costs for some period of time, developers may build new housing, thereby moderating any initial increase in housing prices. Given the decadal frequency of data on housing prices taken from the Censuses of Population and Housing, housing supply destruction may have no estimated effect even if prices did rise for a few years. If a disaster event encourages local politicians to change land use regulations – for example, by expanding the zone considered at high risk of flooding or wild fires –the long-run housing supply in an area may end up lower than before. In that case, natural disasters could increase housing prices even at the decadal level.

The effect of a disaster on local amenities will depend on whether the event was anticipated by local residents– for example, in areas that are known for having a high hurricane risk. An anticipated disaster event would have no effect on the valuation of local amenities. The case of a fully anticipated disaster is analogous to a one-time shock that is expected not to recur, in the sense that both such events convey no new information about future risk. Davis and Weinstein (2002) document that even a severe (but temporary and non-recurrent) shock like the firebombing of Japanese cities during World War II did not lead to a long-term change in population levels across cities. Likewise, we would not expect an effect of disaster events on migration if: (a) disaster events are common and thus fully anticipated, or (b) a disaster is considered idiosyncratic and thus contains no new information about future disaster risk.

Although few disasters are entirely anticipated, the degree of new information about disaster risk contained in each event can vary across locations and over time. All else equal, we

predict that disasters that convey more new information about the increased likelihood of a future disaster in the area will lead to greater increases in out-migration. One corollary of this information channel is that a disaster may convey more “new news” if it strikes an area that otherwise has faced a low underlying disaster risk, as compared to an area that is regularly hit by disasters. Another corollary is that a given disaster event may convey more information about the likelihood of future reoccurrence in recent decades, when the severity and regularity of disasters has increased, as compared to the early- to mid-twentieth century.

In theory, local areas can persist for long periods in inefficient equilibria, due to historical path dependence or development delays stemming from coordinated rebuilding decisions. In this scenario, a natural disaster could be the catalyst shifting an area onto a new path, leading the effect of a disaster shock to differ in productive and unproductive areas. Siodla (2015) and Hornbeck and Keniston (2017) find that productive cities such as San Francisco and Boston respectively suffered from an inefficiently low quality building stock as they began to grow. Both cities then experienced large urban fires in the late nineteenth/early twentieth centuries that “reset” the area to a new equilibrium. In growing areas, then, natural disasters could even (counterintuitively) encourage population growth. In contrast, low productivity places can retain inefficiently high population levels for decades because of the existence of a long-lived housing stock. In this case, a natural disaster could “reset” the equilibrium to a permanently lower population if it destroyed a sufficient share of the housing stock, as in the case of Hurricane Katrina (Fussell 2015). We thus expect more out-migration from slow-growing areas if natural disasters regularly shock areas off of an inefficient path.

III. Econometric Framework

To study how natural disaster events affect local economies, we stack data from county i in state j for decades ending in year t ($t = 1940-2010$) and estimate:

$$Y_{ijt} = \mu_i + \xi_t + \beta_1 * Disasters_{ijt} + \beta_2 * \Delta employ_{ijt} + \beta_3 * (X_{ij} * t) + U_{ijt} \quad (1)$$

Our set of dependent variables Y include the net migration rate from year $t-10$ to year t , the logarithm of median housing prices (or rents) in year t , and a series of other economic attributes such as the logarithm of median family income and the poverty rate (available from 1970) in year

t , all of which are measured at the decadal level from the Censuses of Population and Housing.⁹ Our main explanatory variable is a vector of the number and severity of disasters in a local area ($Disasters_{ijt}$) from year $t-10$ to year t , which we will discuss in depth in the next section. In particular, we include an indicator for the presence of any severe disaster in the county and decade and counts of all other disasters by type (e.g., hurricanes, fires).

Our coefficient of interest β_1 compares counties that experienced a severe disaster to those that did not in a particular decade. We control for county (μ_i) and decade (ξ_t) fixed effects, state-specific linear time trends and an interaction between initial county population and a linear time trend (included in the vector X_{ij}). We allow for differential trends by initial population to account for the fact that sparsely populated areas (e.g., in the Mountain West) were less likely to have declared disasters, and include state-specific linear time trends because disaster events are more common in coastal areas that were otherwise attracting population over time. Standard errors account for spatial and temporal dependence as discussed in Conley (1999) and implemented by Hsiang (2010) and Fetzer (2014). We assume that spatial dependence is linearly decreasing in distance from the county centroid up to 1,000 km.

Standard economic controls like the unemployment rate are not available at the county level over such a long period of time and, in addition, are potentially endogenous outcomes of natural disaster activity. Instead, we control for time-varying economic conditions by constructing an estimate of county employment growth from $t-10$ to t using initial industrial composition at the county level to weight national employment trends ($\Delta employ_{ijt}$). This measure follows standard proxies for local economic growth pioneered by Bartik (1991) and Blanchard and Katz (1992) and is defined as:

$$\Delta employ_{ijt} = \frac{\sum_{l=1}^L [EMPLOY_{\{i,1930,l\}} * GR_{\{t,l\}}]}{EMPLOY_{\{i,1930\}}} \quad (2)$$

⁹Data on population, poverty rates, family income, housing stock and house values/rents by county are taken from the National Historical Geographic Information System (NHGIS). For stock variables like family income or population, we associate disasters over a given decade ($t-10$ to t) to attributes of a county at the decade's end (year t). So, for example, we imagine that housing prices in a county in 1970 would be affected by disasters in that location from 1960-69, and so on.

Equation (2) weights the national growth rate (GR) in employment in industry l for decade t by the share of workers in county i who worked in industry l in the base year (usually: 1930).¹⁰

We also conduct several robustness checks, including county-specific fixed effects instead of state fixed effects, controlling for county population by decade instead of initial population interacted with a time trends, and including a lag and lead term of the dependent variable on the right hand side to check for pre-trends before the disaster event. We also try excluding all controls beyond state and county fixed effects; the only control that is central to our main result is the inclusion of state-specific linear time trends.

IV. Data

A. Natural Disasters

We combine data from several sources to create a consistent series of disaster counts at the county level over the twentieth and the early twenty-first centuries. For each disaster, we record the geographic location (county), month and year of occurrence, type of event (e.g., flood, hurricane), and fatality count.

Our most recent data are drawn from the list of “major disaster declarations” posted by FEMA and its predecessors, which begins in 1964 ([fema.gov/disasters](https://www.fema.gov/disasters)). We supplement the FEMA roster with information on disaster declarations published in the *Federal Register* back to 1958 and with archival records back to the early 1950s.¹¹ We extend our series to 1918 using data on the disaster relief efforts of the American National Red Cross (ARC) documented in their *Annual*

¹⁰ We calculate employment in 143 industries by county using the 1930 IPUMS data and rely on the standardized 1950-based industry codes. Goldsmith-Pinkham and Sorkin (2018) emphasize the identifying assumptions needed to use Bartik-style shift-share variables as instruments. In this case, we are simply using the shift-share measure to create a proxy for employment growth.

¹¹ We use the archival records of the Office of Emergency Preparedness (Record Group 396) and of the Office of Civil and Defense Mobilization, the Office of Defense and Civil Mobilization, and the Federal Civil Defense Administration (Record Group 397) held at National Archives II at College Park, Maryland. The “State Disaster Files” in RG 396, Boxes 1-4 were especially useful.

Reports and in lists of disaster relief operations available in the National Archives.¹² We link these lists with the ARC's case files to document the date, type, and location of each disaster.¹³

Table 1 reports the number of disaster events in our dataset by type, as well as decadal averages of disaster counts at the county level.¹⁴ The most common disaster types in the data are floods and tornados, representing around 70 percent of the 10,158 total events. The typical county in our sample had 1.83 declared disasters in a decade, with the most common disasters being storms (0.73 in the typical county-decade), floods (0.49 in the typical county-decade) and hurricanes (0.31 in the typical county-decade).

Appendix Table 1 provides geographic and economic correlates of disaster incidence. Places with more coastline are more likely to experience a severe disaster than not, while high elevation, number of lakes, and being in the dustbowl area are comparatively protective. This is mainly driven by the fact that the coasts are more disaster prone. For similar reasons, population and median home value are positively correlated with severe disasters, and poverty is negatively correlated. A good weather index, which accounts for winter lows and summer highs, is positively related to disaster incidence. Because the US population has been moving toward the coasts over time and coastal areas are more disaster prone, we try a specification with county-specific time trends below.

Information on fatalities are drawn from the EM-DAT dataset or from the ARC records and are only available for disasters resulting in 10 or more deaths.^{15,16} We create measures of

¹² We use various versions of the ARC's "List of Disaster Relief Operations by Appropriation Number," held in Record Group 200 at National Archives II in College Park, MD (Records of the American National Red Cross, 1947-1960, Boxes 1635-37).

¹³ The case files are located in RG200 Records of the American National Red Cross, 1917-34, Box 690-820; 1935-46, Boxes 1230-1309; 1947-60, Boxes 1670-1750.

¹⁴ All disasters that may be influenced by economic activity, such as mine collapses, explosions, transportation accidents, arsons and droughts are excluded from the analysis. There is a debate about the extent to which droughts are caused by environmental conditions versus decisions about water use. We report results that include droughts in Appendix Table 19 and they are unchanged.

¹⁵ We incorporate information on fatalities for each disaster by merging in fatality counts from the American Red Cross by disaster type, state and start date of event, or from the EM-DAT dataset by state and event month. We use the maximum of the two fatality counts for disasters that are recorded in both data set. EM-DAT was created by the Centre for Research on the Epidemiology of Disasters (see <http://www.emdat.be/>).

¹⁶ Our measure of fatalities includes the number of people who lost their lives because the event happened (dead) and the number of people whose whereabouts since the disaster are unknown, and presumed dead based on official figures (missing). In the majority of cases, a disaster will only

disaster severity using fatality counts above various thresholds. Our preferred measure of a “severe” disaster is one with 25 or more deaths, the median count for disasters with known fatality numbers. Appendix Figure 2 presents a histogram of disasters by fatality count. There are 151 disasters with 25 or more deaths in our dataset which constitute 1.5 percent of all events. These disasters tend to be geographically extensive, so that around 30 percent of counties experience a severe disaster in a given decade.

For a given disaster event, the number of fatalities is determined in part by the level of economic development in the location and the period (Kahn 2005; Lim 2016). For this reason, we avoid using actual fatality counts to measure the intensity of disaster severity in favor of a simple fatality threshold. Results are nearly identical if we instead define disaster severity as any disaster with fatalities above the 50th or above the 90th percentile of the decade average to allow for endogenous declines in fatalities over time. The number of fatalities resulting from any given event may also be mechanically correlated with the population at a given time (the population “at risk” of death from a disaster). To address this mechanical effect, we also try including controls for county population by decade. These results are reported in Appendix Tables below.

Figure 2 presents maps of the spatial distribution of disaster prevalence. The first map reports the cumulative count of disasters of any type during the century, and the second map reports the number of decades in which the county experienced a severe disaster. Disasters are prevalent throughout Florida and on the Gulf of Mexico, an area typically wracked by hurricanes; in New England and along the Atlantic Seaboard, locations battered by winter storms; in the Midwest, a tornado-prone region; and along the Mississippi River, an area subject to recurrent flooding. There are comparatively few disasters in the West, with the exception of California, which is affected primarily by fires and earthquakes. Severe disasters follow similar geographic patterns but are more concentrated on the Atlantic Coast, in the Gulf of Mexico, and in large river valleys. It may be noted in Figure 2 that disaster counts drop significantly when crossing certain borders, for instance when crossing from the Dakotas into eastern Montana or crossing into Iowa. These can be attributed to state-level variation in the disaster-declaration process.¹⁷ Appendix Figure 3

be entered into EM-DAT if at least two independent sources confirm the fatality count. Note that the final fatality figures in EM-DAT may be updated even long after the disaster has occurred.

¹⁷ According to the FEMA disaster declaration process, all disaster declarations are made solely at the discretion of the President of the United States. Before submitting a request for declaration, the state government must determine that the damage exceeds their resources. Thus, differences in

displays the count of decades with a severe disaster event *after* including state fixed effects. We can more readily see the vulnerability of counties along the path of hurricanes that originate in the Gulf of Mexico or that suffer from winter storms in the Snow Belt.

B. Migration

We obtain age-specific net migration estimates by decade for US counties from 1950 to 2010 from Winkler, et al. (2013a, b). Gardner and Cohen (1992) provide similar estimates for 1930 to 1950. These data include estimates of net migration for each decade from US counties by five-year age group, sex, and race. The underlying migration numbers are estimated by comparing the population in each age-sex-race cohort at the beginning and end of a Census period (say, 1990–2000) and attributing the difference in population count to net migration, after adjusting for births and mortality. Any net inflow of immigration from abroad would be captured in this measure as an increase in the county’s rate of net in-migration. This method has become standard practice to estimate internal migration in the United States, as originated by Kuznets and Thomas (1957). We divide estimated net migration to or from the county from time t to $t+10$ by population at time t to calculate a migration rate. To address any inaccuracies in the incorporation of birth and death rates, we also estimate net-migration using the population between ages 15–64 per decade below. At the lower end, these individuals are too old to have been affected by the disaster’s effect on birth rates, and at the upper end, we drop the elderly, who are more vulnerable to disaster-induced mortality. Summary statistics of our outcome variables at the county-by-decade level are reported in Appendix Table 2.

V. Disasters and Out Migration

A. The effect of disasters on out-migration in the full sample

We document in this section that severe natural disasters are associated with net out-migration from a county. Table 2 reports our main specification, which defines “severe disaster” as an event resulting in 25 or more deaths. The first column considers a county’s net migration rate

state resources may result in differences in the probability of requesting a federal disaster declaration. These state-level differences are accounted for in our analysis with state and county fixed effects, and in some cases with state time trends. (<https://www.fema.gov/disaster-declaration-process>).

as an outcome. By this measure, experiencing a severe disaster leads to a 1.5 percentage point increase in net out-migration (8 percent of a standard deviation). Severe disasters are around half as disruptive to local population as a large negative employment shock. A one standard deviation decline in local employment growth increases out-migration by 3 percentage points.

Over the full century, we find that some categories of milder disasters affect net migration to a county but these effects are small. Below, we show that the migration response to these milder disasters has increased over time. In the full sample (Table 2), wildfires and hurricanes encourage out-migration, while floods actually *attract* in-migrants to an area. Storms and tornados have no effect on migration flows. The positive effect of floods on in-migration is consistent with earlier work by part of our research team, which found that migrants moved toward flooded counties before 1940 (Boustan, Kahn and Rhode 2012). We speculated that areas prone to flooding received new infrastructure in this period, which may have encouraged new use of previously marginal land. Here, we find that the positive effect of floods on migration in this series is present only in the first part of the century. Appendix Table 3 excludes each of the control variables in turn: controls for expected employment growth, linear time trends by initial population and linear time trends by state. Migration responses to milder disasters are robust to dropping each control, whereas migration responses to severe disasters are observed only when allowing for state-specific time trends (but are robust to excluding other controls). Appendix Table 4 replaces the standard errors that correct for spatial dependence with standard errors clustered by state and results look similar.

B. Pre-trends before a disaster strikes

Our specification compares migration rates within counties before and after a disaster strikes, relative to comparison counties that do not experience a natural disaster in the decade. The underlying assumption is that disasters do not coincide with other economic changes at the county level. To provide support for this assumption, we include several specification checks. First, we check for parallel trends by including county-specific trends as additional control variables (county fixed effects interacted with a linear time trend). If disaster-prone counties became increasingly undesirable for reasons other than disaster incidence, we would find that out-migration is correlated with disaster incidence, even if this relationship is not causal. Appendix Table 5 finds similar results after including county-specific time trends.

Second, we directly investigate whether disasters that *will occur* in the next decade (leads) appear to affect out-migration from the county in the current decade. Appendix Table 6 includes both lags and leads of our disaster severity variable. We find that the disaster lead has a negative association with net migration, but the estimated effect is only one-third the size of the contemporaneous effect (0.6 percentage point increase in out-migration, compared to 1.6 percentage point increase) and is not statistically significant. Including lags and leads has no effect on our estimate of interest.

C. New information about disasters and net out-migration

A disaster that is fully anticipated – and thus already built into a resident’s decision to locate in an area – should have no effect on migration decisions. Although climate and weather models are not reliable enough for the frequency or exact location of any disaster to be entirely known in advance, some disasters are more anticipated than others. Furthermore, some unanticipated disasters are perceived to be idiosyncratic events, while others are perceived to contain new information about the heightened risk of future disaster events. We test for the role of “new news” in the out-migration response to disaster activity in two ways, first by examining the changing response to disasters over time, and then by considering differences in response to disasters that strike areas at high vs. low risk of disaster activity. Because we are only able to measure net migration flows, we cannot allow for (or test) the possibility that existing residents and prospective new residents to an area glean more or less information from a given disaster event.

The regularity of disasters increased dramatically after 1980 (Figure 1). As a result, disasters that struck in recent years may contain more information about future disaster risk. Table 3 tests for differences in the migration response to disaster events that occur before and after 1980. We find no difference in the migration response to severe disasters over this period. However, out-migration in response to mild disasters increased for nearly every disaster category after 1980, including floods, hurricanes, and wildfires. As disasters have become more frequent over time, even milder disasters may become more salient or may actually convey more new information to households now than in the past.¹⁸

¹⁸ Any changes in general migration costs would be absorbed into decade fixed effects. Yet national trends suggest that, if anything, internal migration has been falling over time, especially

An alternative explanation for changes in the responsiveness to disaster events over time is the advent of coordinated federal disaster management. The Federal Disaster Assistance Administration (FDAA) was founded in 1973 and became an independent agency, renamed the Federal Emergency Management Agency (FEMA), in 1978. Before that time, the federal government responded to disasters on a case-by-case basis. However, if emergency management agencies increased the reliability or generosity of federal disaster relief, we might expect out-migration in response to disasters to decline over time.¹⁹ If anything, we see the opposite pattern, with the out-migration response to disasters increasing after 1980. Appendix Table 7 investigates the relationship between disaster events and FEMA relief payments at the county level. Counties that faced storms or hurricanes received more FEMA transfers in a given decade, but there is no association between a severe disaster event and the extent of FEMA funding. As a result, controlling for FEMA payments does not affect the coefficient of interest in our migration regression.

A disaster may convey more “new news” if it strikes an area that otherwise has faced a low underlying disaster risk. In areas that are regularly hit by disasters, local residents may come to expect disaster events and may undertake public or private investments to protect themselves from their consequences. Alternatively, disaster events may be perceived as idiosyncratic events – flukes of nature – in areas with low disaster risk, and thus may not change expectations of future events. Table 4 allows the response to a severe disaster to vary by county risk exposure. We estimate a fixed risk exposure for the full century at the county level as a propensity score based on geographic characteristics. Column 1 interacts disaster measures with a continuous measure of risk exposure, while column 2 instead interacts each measure with an indicator for being in the top quartile of risk exposure. We find no evidence of a heterogeneous out-migration response by risk exposure for severe disasters. Instead, severe disasters appear to influence location decisions in-and-of-themselves, rather than providing new information about future realizations of disaster risk (we note that the main effect of severe disasters is not statistically significant in this specification, although the magnitude is similar to the core result in Table 2).

in the 1990s, and so we are unlikely to just be picking up greater responsiveness to any decline in local amenities (Molloy, Smith and Wozniak 2011).

¹⁹ Deryugina (2017) documents that counties struck by hurricanes in the 1980s and 1990s received around \$1,000 (2008 dollars) of additional federal transfers per capita in the decade after a hurricane event.

D. Local economic growth and net out-migration following a disaster

The effect of a disaster shock may differ in productive and unproductive areas. Productive areas may have an inefficiently low density of housing or an inefficient mix of commercial and residential space due to path dependence. In this case, a natural disaster could allow the area to “reset” and may thus attract new population. In contrast, otherwise unproductive areas may have an inefficiently high level of population because of the existing and long-lived housing stock. If the disaster destroys some housing, the area may instead “reset” to a lower level of population. If these forms of historical path dependence or hysteresis are common across areas, we would expect to find a stronger out-migration response from otherwise unproductive areas than from otherwise productive areas. We define local productivity in two ways: first, by using local employment growth in the past decade, as estimated by our Bartik estimate in equation (2), and secondly by using local population growth in the past decade. We split the sample at the median in each decade into high and low growth areas, and then interact this indicator with each disaster measure.

Table 5 contains the main effects of each disaster type on the interactions between being a high-growth area and responsive out-migration. If anything, we find *stronger* out-migration from areas that were otherwise experiencing high rates of employment or population growth in the previous decade. This pattern is contrary to the hypothesis that many local areas in the US are stuck in inefficient local equilibria, despite the few cases of this phenomenon that have been documented. We speculate that high growth areas have more scope to respond to local shocks via net out-migration because they are experiencing both in- and out-migration at baseline, whereas slower growing areas that are not attracting in-migrants can only respond to shocks if existing residents choose to leave (see Long and Siu 2018 on this phenomenon after the Dust Bowl). Another possibility is that residents in high growth areas have lived in the area for fewer years on average, and so have more potential for learning new information about the local environment (Kocornik-Mina, et al. Forthcoming).

VI. Home Prices, Family Income and Poverty Rates

Thus far, we have assumed that out-migration following a disaster event is a proxy for falling firm productivity without considering alternative channels for the out-migration responses, including reductions in consumer amenities or direct effects of disasters on destruction of the

housing stock. A disaster that destroys a significant amount of housing but has little impact on the demand for a location should lead to an increase in housing prices, at least in the short run. Conversely, a disaster that reduces demand for the location should cause a decline in housing prices.²⁰ Moreover, a decline in demand driven by lower local amenity levels should be, if anything, associated with rising wages, whereas a drop in firm productivity should be associated with falling wages.

We collect measures of median wages and housing prices and rents at the county level from Census data, using measures of family income as a proxy for wages. These variables are compiled at the county level by National Historical Geographic Information System (NHGIS) from 1970-2010, and so we focus on the more recent decades here. Table 6 reports the relationship between disaster activity and this broader set of economic outcomes. We start in column 1 by reproducing the association between severe disaster events and out-migration. This relationship is mirrored in column 2 by a negative relationship between severe disasters and local population, although this coefficient is not statistically significant. The out-migration following natural disasters does not appear to be a response to the rising housing prices that would follow destruction of the local housing stock. At least at the decadal level, the occurrence of a severe disaster lowers housing prices by 5.2 percent and rents by 2.5 percent (columns 3 and 4).²¹ (We note that the housing stock in areas hit by a natural disaster does contract, as seen in column 5, but, at the decadal level, there is enough time for the number of housing units to adjust to track declines in population). Furthermore, the falling demand for living in areas hit by natural disasters does not seem to be due to declines in local amenities. If anything, wages in the area appear to decline, as proxied by falling median family income (column 6).

Out-migration after a natural disaster may be selective by income level. If rich households have greater resources to leave an area struck by disaster, out-migration may lead to a higher

²⁰ Predictions about the effect of natural disasters on housing prices at the decadal level also depend on whether disasters affect the local elasticity of housing supply (e.g., by encouraging stricter land use regulations), a factor that we discuss in Section II but do not directly observe.

²¹ The implied elasticity of housing prices with respect to population – a 2.5 percent decline in rents for out-migration representing 1.7 percent of the population – is similar to standard estimates in the literature (e.g., Saiz, 2007, which looks at the effect of foreign in-migration on rents).

poverty rate among those residents who remain in the area.²² The poor may also be more willing to trade off a lower housing price for a heightened risk of disaster activity. Alternatively, natural disasters may have a causal effect on the probability of falling into poverty for the existing population, if, for example, some local residents lose their jobs due to falling labor demand in the area. Column 7 shows that the occurrence of a severe disaster increases the local poverty rate by 0.8 percentage points (10 percent of a standard deviation). We cannot differentiate here between changes in poverty due to selective out-migration versus causal effects of disaster activity on income and poverty.

VII. Addressing concerns

A. Robustness to geography and population

We made a number of choices about variable definitions and specification for our core results. In this section, we test the robustness of our findings to alternative choices. First, our core results estimate unweighted regressions, allowing each county to contribute equally to the analysis. In this way, we treat each county as a separate economy that may be subject to a location-specific shock in a given period, corresponding to the cross-country regressions common to the climate economics literature. Appendix Table 8 instead aggregates counties into State Economic Areas and Appendix Table 9 weights the county-level results by county population in 1930. This specification puts more weight on disasters that take place in heavily-populated urban areas. In both cases, the effect of a severe disaster on net migration is similar, but the coefficient is no longer statistically significant after weighting by county population.²³ We prefer the unweighted results because weighted regressions put what we feel is excessive emphasis on large metropolitan areas. Second, our measure of disaster severity is based on a threshold defined according to an absolute number of fatalities. However, for a given disaster intensity, fatalities have declined over time as infrastructure and construction have improved (Kahn, 2005). Appendix Table 10 uses a relative measure of disaster severity, defining severe disasters as any in the top 50 percent (or top 10 percent) of fatalities in a given decade. Results are nearly identical to the preferred specification.

²² In the climate change literature, there is a broad consensus that the wealthy can access a wide range of adaptation strategies – of which migration may be one – to protect themselves from shocks (Dasgupta 2001, Barreca, et. al. 2016, and Smith et. al. 2006).

²³ In Appendix Table 9, standard errors are clustered by state; our implementation of the Conley standard errors does not support weights.

Third, population dynamics after a disaster may bias our measurement of migration. Our specification assumes that disasters do not have long-term effects on birth rates or death rates over a decade, which is plausible but not certain. Therefore, we run an additional specification using migration defined for the population between 15-64 (Appendix Table 11). This subset is too old to be affected by changes in birth rate and excludes the oldest, who are most likely to be affected by a change in mortality rates. We find similar results in terms of magnitude and significance. Appendix Table 12 subdivides the population by 10-year age categories. We find that strong out-migration responses to severe disasters up through middle age (age 35-44), and monotonically declining responses thereafter, which is consistent with the low mobility rates of older individuals.

Fourth, counties with larger populations may be more likely to suffer from a severe disaster (defined as any disaster with 25 or more deaths) because any given disaster event will likely have a higher death count in a more populated area. Appendix Table 13 reports estimates of the effect of severe disasters on out-migration, controlling for county population at the start of each decade. This will absorb the variation in death count due to differences in county levels of population. Again, the results are qualitatively similar.

Fifth, we note that our estimates are net effects of disaster on migration activity after all private and government responses to the disaster event take place (e.g., infrastructure investment, transfer payments). A disaster at the start of a given decade may trigger infrastructure investments in flood control or early warning systems that mitigate future risk. New investments may attract people to an area both because of declines in natural disaster risk and because of short run jobs stimulus. Our results are unchanged by controlling for new dam construction in the decade, the largest of such infrastructure projects (see Appendix Table 14).²⁴

B. Robustness to the political process

Our dataset is based on disaster declarations by the American National Red Cross or various federal agencies. There is a political process governing whether the government declares an official disaster or state of emergency after a given weather event. Ideally, we would have detailed climatological data to measure the intensity of wind speeds (for hurricanes), seismic

²⁴ Duflo and Pande (2007) study the productivity and distributional effects of large irrigation dams in India. They find that rural poverty declines in downstream districts but increases in the district where the dam is built.

activity (for earthquakes), and so on. However, it is not possible to gather such data for five major disaster types over a full century. Instead, we present suggestive evidence that the coefficients are not driven by political factors.

First, we argue that any political connection that would lead states to receive an unwarranted disaster designation should generate other sources of discretionary federal funds, thereby, if anything, leading to net in-migration. Thus, we would expect the political component of disaster declarations to bias *against* finding that disasters lead to out-migration or falling housing prices.

Second, although the official designation of a mild weather event may be subject to political manipulation, it is hard to believe that the largest disasters (e.g., Hurricane Katrina) could be left without a federal declaration. It is not clear *a priori* how large an event would need to be before the disaster declaration was effectively depoliticized. Table 7 reports the coefficient on “severe disaster” for various fatality thresholds, starting with a threshold of only 10 fatalities, and increasing to an extreme threshold of 500 fatalities. We find a very consistent effect of facing a severe disaster on net out-migration (coefficients range from -0.012 to -0.017) for all definitions ranging from 20 deaths to 100 deaths. For larger thresholds, standard errors increase and the estimates are no longer statistically significant. We find similar results when including county-specific trends (see Appendix Table 15).²⁵ Appendix Table 16 demonstrates that the estimated effect of severe disasters on housing prices and other economic outcomes are also robust to thresholds between 20 and 100 deaths (ranging from 3.8-5.3 percent); the estimated effect on rents is more sensitive but generally ranges between -1.0 and -2.6 percent. Above a certain severity threshold, it appears that households are equally responsive to large disasters and additional fatalities do not elevate the out-migration rate (except the very largest disasters that were associated with 500 or more fatalities).

Third, we split the sample into disasters occurring in a state-year in which the state governor was of the same party as the President, and state-years in which he/she was not. If disaster declarations are driven by political considerations, we would expect that state-years with a same party governor would get more disaster declarations and the actual weather events underlying those declarations should be weaker, and thus should be less associated with out-migration. We find no

²⁵ Appendix Table 15 reports standard errors that are clustered by state because of the computational time required for spatially-dependent standard errors with county-specific trends.

relationship between having a same-party governor and the strength of the out-migration response to a severe disaster. Results are presented in Appendix Table 17.

Finally, we instrument for the presence of a severe disaster with the limited set of climatic variables that are available for the whole century to account for any association between disaster declarations and local politics. Our instruments are average maximum daily temperature, minimum daily temperatures and total precipitation by county and decade. Although the instruments do not rise to conventional levels of statistical power (F-statistics are around 5), we continue to find an association between the presence of a severe disaster and net out-migration from a county. Temperature and precipitation may have direct effects on migration decisions, beyond any effect on disaster prevalence, and so we caution that the instruments may not meet the necessary exclusion restriction. We include IV results for completeness in Appendix Table 18.²⁶

VIII. Conclusion

During the past century, the United States has experienced more than 10,000 natural disasters. Some have been major newsworthy events, while others have been comparatively mild. We compile a near-century long series on natural disasters in US counties, distinguishing severe events by death toll, and find that tAppese shocks affect the underlying spatial distribution of economic activity. Counties hit by severe disasters experienced greater out-migration, lower home prices and higher poverty rates. Given the durability of housing capital, lower demand due to persistent natural disasters leads to falling rents and acts as a poverty magnet. We find little effect of milder disasters on population movements or housing prices in the full sample, but document a growing migration response to mild disasters over time and a stronger response in areas at high-risk of disaster activity.

Contrary to recent cross-country studies like Cavallo et al. (2013) and Kocornik-Mina et al. (Forthcoming) that find near-immediate recovery from large natural disasters (mostly in developing countries), we find long-term effects of severe disaster events on economic activity at the county level in the US. Yet, our estimates are much smaller than those arising from case studies of the nation's most extreme events, including Hurricane Katrina and the 1927 Great Mississippi Flood, both of which led to 12 percentage point increases in out-migration (Deryugina et al. 2018;

²⁶ This table is based on state-clustered standard errors; the function *ivreg* is not compatible with spatial and time correlation adjustments.

Hornbeck and Naidu 2014). Instead, we find that the typical severe disaster in the US was associated with a 1.5 percentage point increase in net out-migration from a county, and corresponding declines in housing prices/rents. This comprehensive analysis, which is based on the universe of disaster activity in the US over nearly a century, provides a valuable benchmark against which future case studies of extreme disaster events can be compared.

Our finding that severe natural disasters are associated with both out-migration and falling housing prices suggests that, in the US context, disasters reduce productivity in local areas, outweighing any destruction of the housing stock. We do not find evidence that disasters shift local areas out of inefficient equilibria established through path dependence.

Net out-migration responses have increased over time, which is consistent with larger responses to disaster events that convey more information about the degree of future disaster risk. Rapidly growing locations experience a stronger net out-migration response to disaster events, perhaps because prospective residents choose not to move in. Studying the differential effect (if any) of natural disasters on in- and out-migration to an area is possible in more recent data and would be a fruitful area of future research.

Disaster activity has been increasing over time due to climate change. The National Oceanic and Atmospheric Administration (NOAA) tallies that the number of “billion dollar disasters” (adjusted for inflation) held relatively steady in the 1990s and 2000s at around 55 disasters per decade, but then doubled to 115 disasters in the 2010s. If these 60 additional disasters occurred in productive coastal places that otherwise would have been attracting in-migration, our estimates suggest that they will be a drag on these local economies, reducing productive economic activity and encouraging net out-migration.

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Table 1: Summary Statistics for Natural Disasters Occurring in the US 1930–2010

	(1) Event count (1930-2010)	(2) Average number of disasters, by county-decade	(3) Mean of =1 if any disaster, by county-decade
<u>Panel A: Disaster by type</u>			
Flood	3,927	0.484 (0.851)	0.319 (0.466)
Winter storm	1,667	0.724 (1.57)	0.301 (0.459)
Hurricane	742	0.312 (0.913)	0.176 (0.381)
Tornado	2,845	0.207 (0.572)	0.154 (0.361)
Forest fire	910	0.095 (0.528)	0.0545 (0.227)
Other disasters	67	0.010 (0.105)	0.010 (0.098)
Total disasters	10,158	1.830 (2.340)	0.639 (0.480)
<u>Panel B: Disaster by severity</u>			
Severe disasters	292	- -	0.307 (0.461)
Observations		24,432	24,432

Notes: Column (1) counts the number of individual disaster events registered in the ARC, FEMA or EM-DAT datasets. This tally counts each disaster once even if it affects multiple counties. Column (2) shows the average number of natural disaster events that occurred in a given county and decade between 1930 and 2010. Column (3) shows the average incidence of any disaster event occurring in a given county and decade. These tallies count disasters multiple times if they affect multiple counties. Standard deviations in parentheses. For completeness, a disaster qualifies as “severe” in this table if it was associated with 10 or more deaths.

Table 2: Effect of Disasters on County-Level Net In-Migration Rate by Disaster Type and Severity in 1940–2010

	(1) Migration rate
Severe disaster = 1	-0.015*** (0.005)
Flood count	0.006** (0.002)
Storm count	-0.001 (0.002)
Tornado count	-0.002 (0.003)
Hurricane count	-0.008** (0.004)
Fire count	-0.013** (0.005)
Other disasters count	-0.029 (0.025)
Exp. employment growth rate	0.267*** (0.033)
County FE	Y
Decade FE	Y
State FE * time trend	Y
1930's population * time trend	Y
Observations	24,408

Notes: The reported regression of equation (1) is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of Disasters on Net In-Migration Rates Before and After 1980

	Migration rate	
	Coefficient	Standard Error
Severe disaster = 1	-0.017**	(0.008)
Severe disaster = 1, after 1980	0.003	(0.011)
Flood count	0.008***	(0.003)
Flood count, after 1980	-0.008*	(0.005)
Winter storm count	-0.006	(0.006)
Winter storm count, after 1980	0.005	(0.007)
Tornado count	-0.001	(0.004)
Tornado count, after 1980	-0.006	(0.008)
Hurricane count	0.006	(0.009)
Hurricane count, after 1980	-0.018*	(0.009)
Fire count	0.018	(0.017)
Fire count, after 1980	-0.031*	(0.018)
Other disasters count	0.004	(0.027)
Other count, after 1980	-0.047	(0.042)
Exp. employment growth rate, 1930 weights	0.266***	(0.032)
County FE	Y	
Decade FE	Y	
State FE * time trend	Y	
1930s population * time trend	Y	
Observations	24,408	

Note: The reported regression is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are collected from the ARC, FEMA and EM-DAT datasets. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment in 1930 by industry. We interact each disaster variable with an indicator for decade equal to or after 1980 (after the creation of FEMA). Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of Disasters on Net In-Migration Rates, by Geographic Risk Exposure

Dependent variable = Migration rate				
	Risk exposure: Propensity score		Risk exposure: Propensity score > 75 th	
Severe disaster = 1	-0.014	(0.013)	-0.013	(0.012)
Severe risk * Severe disaster = 1	-0.002	(0.048)	-0.004	(0.043)
Flood count	0.006	(0.005)	0.003	(0.003)
Flood risk * Flood	0.001	(0.023)	0.022*	(0.012)
Winter storm count	0.003	(0.003)	0.001	(0.002)
Storm risk * Winter storm	-0.014	(0.013)	-0.030	(0.019)
Tornado count	-0.023*	(0.012)	0.000	(0.004)
Tornado risk * Tornado	0.075*	(0.044)	-0.023	(0.028)
Hurricane count	0.004	(0.011)	-0.002	(0.004)
Hurricane risk * Hurricane	-0.035	(0.027)	-0.082**	(0.033)
Fire count	-0.019*	(0.011)	-0.004	(0.004)
Fire risk * Fire	0.024	(0.047)	-0.285**	(0.120)
Other disasters count	0.068	(0.045)	-0.042	(0.029)
Other risk * Other	-0.400*	(0.220)	0.128	(0.190)
Employment growth, 1930 weights	0.258***	(0.033)	0.258***	(0.033)
County FE	Y		Y	
Decade FE	Y		Y	
State FE* time trend	Y		Y	
1930's population * time trend	Y		Y	
Observations	24,000		24,000	

Notes: The reported regression of equation (1) with risk exposure interactions is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. We estimate risk exposure to different disasters as a propensity score based on geographic characteristics (column 1); we also generate dummies for counties with high risk exposure (column 2). Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of Disasters on Net Migration Rates, by Local Growth

Dependent variable = Migration rate

	Economic growth (previous decade)		Population growth (previous decade)	
Severe disaster = 1	-0.003	(0.006)	-0.009	(0.006)
High growth * Severe disaster = 1	-0.028***	(0.009)	-0.017**	(0.008)
Flood count	0.005*	(0.003)	0.002	(0.002)
High growth * Flood count	-0.000	(0.004)	0.005	(0.003)
Winter storm count	-0.001	(0.002)	0.002	(0.002)
High growth * Storm count	0.000	(0.002)	-0.008***	(0.002)
Tornado count	-0.013***	(0.004)	-0.012***	(0.004)
High growth * Tornado count	0.025***	(0.008)	0.019***	(0.005)
Hurricane count	-0.009**	(0.004)	-0.008**	(0.004)
High growth * Hurricane count	0.003	(0.004)	0.002	(0.004)
Fire count	-0.009	(0.009)	-0.004	(0.006)
High growth * Fire count	-0.006	(0.009)	-0.012*	(0.007)
Other disasters count	-0.016	(0.040)	-0.006	(0.025)
High growth * Other count	0.001	(0.044)	-0.010	(0.025)
High growth (previous decade)	0.015**	(0.007)	0.012*	(0.007)
Exp. employment growth rate	0.263***	(0.034)	0.261***	(0.032)
County FE	Y		Y	
Decade FE	Y		Y	
State FE* time trend	Y		Y	
1930's population * time trend	Y		Y	
Observations	21,357		21,357	

Notes: The reported regression of equation (1) with growth interactions is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. We define high growing counties as those with an expected employment growth rate (column 1) or population growth rate (column 2) above the median in previous decade. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect of Disasters on County-Level Economic Activity by Disaster Type and Severity in 1970-2010

	(1) Migration rate	(2) Population (log)	(3) House value (log med)	(4) House rent (log med)	(5) Housing stock (log)	(6) Family income (log med)	(7) Poverty Rate
Severe ==1	-0.011** (0.004)	-0.012 (0.008)	-0.052*** (0.012)	-0.025*** (0.008)	-0.014* (0.008)	-0.023* (0.012)	0.008*** (0.002)
Flood	-0.003 (0.003)	-0.001 (0.003)	0.007 (0.006)	0.007* (0.004)	-0.001 (0.003)	0.004 (0.006)	-0.002* (0.001)
Storm	0.001 (0.001)	0.001 (0.002)	0.000 (0.004)	0.002 (0.002)	0.002 (0.002)	0.001 (0.003)	-0.000 (0.001)
Tornado	0.001 (0.004)	-0.009 (0.008)	0.011 (0.009)	0.015** (0.007)	-0.007 (0.007)	0.018* (0.010)	-0.005** (0.002)
Hurricane	-0.007** (0.003)	0.004 (0.006)	-0.005 (0.007)	-0.010* (0.006)	0.001 (0.006)	-0.015** (0.007)	0.001 (0.002)
Fire	-0.013*** (0.005)	0.017** (0.007)	0.002 (0.007)	0.001 (0.005)	0.013** (0.007)	0.013** (0.006)	-0.004*** (0.001)
Others	-0.023 (0.023)	0.006 (0.020)	-0.004 (0.035)	-0.022 (0.022)	-0.004 (0.017)	0.006 (0.032)	0.005 (0.005)
Emp growth	0.385*** (0.066)	-0.638*** (0.201)	0.264 (0.198)	0.234* (0.142)	-0.601*** (0.185)	0.977*** (0.197)	-0.139*** (0.032)
County FE	Y	Y	Y	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y	Y	Y	Y
State FE * t	Y	Y	Y	Y	Y	Y	Y
1930 pop * t	Y	Y	Y	Y	Y	Y	Y
Observations	15,210	15,208	15,154	15,152	15,210	15,210	15,162

Notes: The reported regressions of equation (1) are at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Population, family income, poverty rates, housing stock, housing values, and housing rents are from NHGIS. Family income, housing values, and housing rents are expressed in 1982-84 dollars. Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1970. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

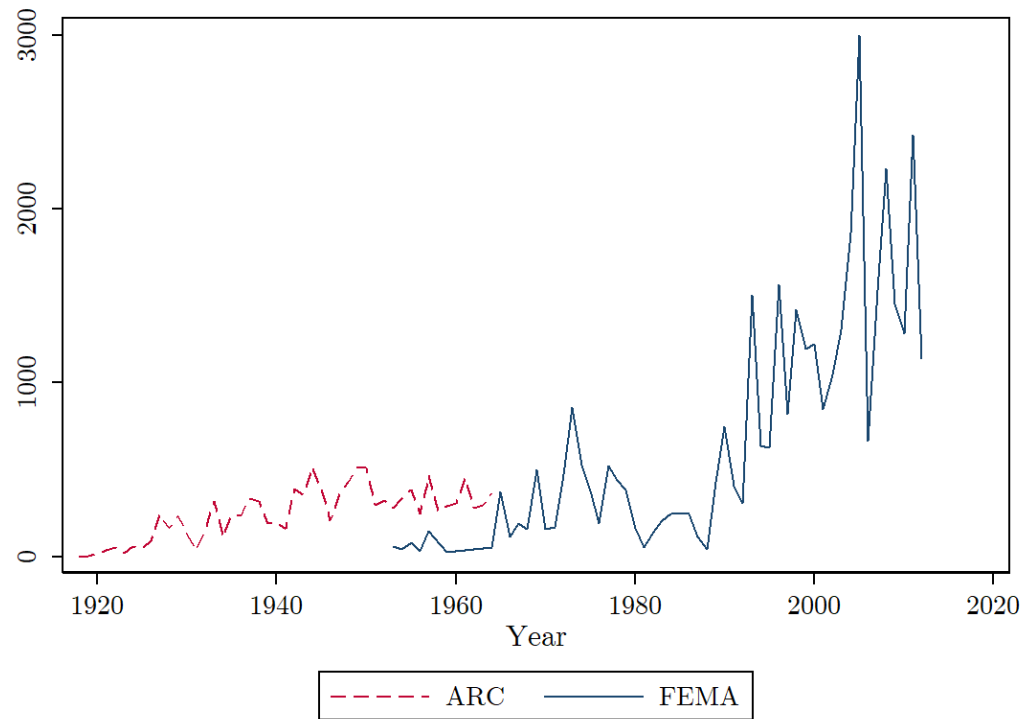
Table 7: Effect of Severe Disasters on Migration for Different Severity Thresholds

Dependent variable = Migration rate		
Fatality Threshold	Severe Disasters	
	Coefficient	Standard Error
10	-0.008	(0.005)
20	-0.015***	(0.005)
30	-0.012**	(0.005)
40	-0.015***	(0.005)
50	-0.012**	(0.006)
60	-0.012**	(0.006)
70	-0.014**	(0.006)
80	-0.013**	(0.006)
90	-0.016**	(0.007)
100	-0.017**	(0.007)
200	-0.013*	(0.007)
500	-0.051***	(0.019)

Notes: Each row corresponds to a separate regression that follows the format of Table 2. We report coefficients on the indicator for “severe” disasters, varying the threshold required for a disaster to qualify as severe. Disasters qualify as severe if they equaled or exceeded the number of fatalities reported in column (1). All regressions include as controls counts of natural disasters by type, county and decade fixed effects, state-specific time trends and a 1930 population time trend. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

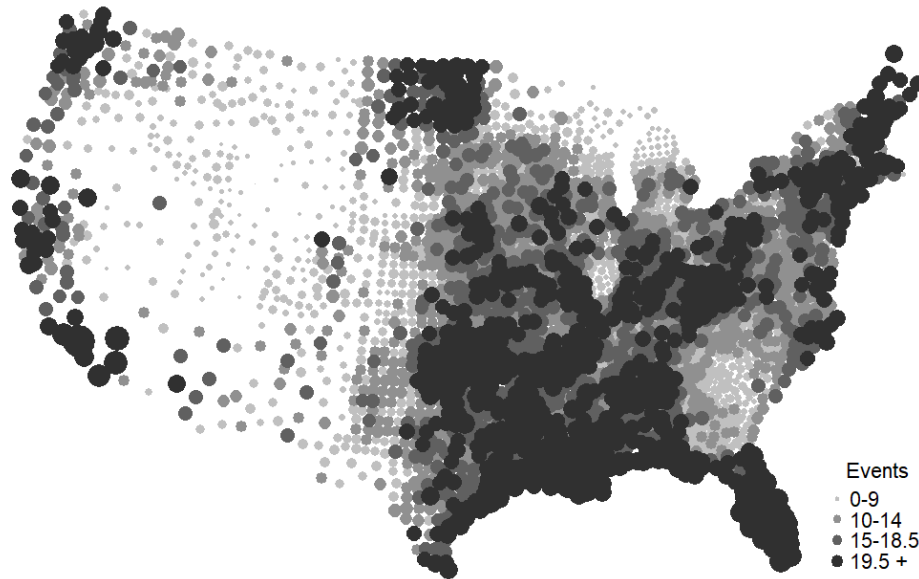
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Annual Disaster Count in the US 1918–2012, by Data Source



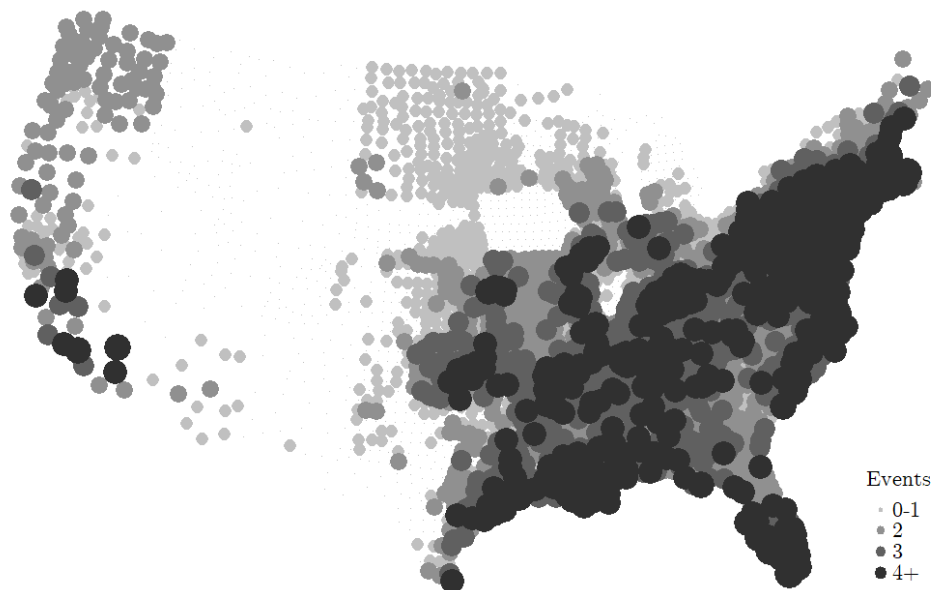
Notes: This graph plots the sum of county-level disaster counts by year and source between 1918 and 2012. Note that this measure will treat a given natural event that occurred in two separate counties as two different disaster events. The disaster count is truncated at 3000. Sources: American National Red Cross (ARC) and various federal sources, including Federal Emergency Management Agency (FEMA). See text for details.

Figure 2a: Disaster Count by US County, 1930-2010



Notes: This map plots disaster counts within each county for the whole period 1930–2010. The marker size is increasing in number of events, while color represents quartiles of disaster counts. The maximum number of occurrences is 87. Sources: American National Red Cross and various federal sources, including Federal Emergency Management Agency.

Figure 2b: Count of Decades with a Severe Disaster Event by US County, 1930–2010



Notes: This map shows the number of decades with severe events per county in the period 1930–2010. Severe events are disasters associated to 25 or more deaths. The marker size is strictly increasing in number of events, while color represents specific thresholds. The maximum number of occurrences is 7. Sources: American National Red Cross and various federal sources, including Federal Emergency Management Agency.

The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data

Web Appendix

April 2020

Leah Platt Boustan

Matthew E. Kahn

Paul W. Rhode

Maria Lucia Yanguas

Princeton & NBER

Johns Hopkins &

Michigan & NBER

Cornerstone Research

NBER

Appendix Table 1: Descriptive Statistics by Disaster Occurrence in Decade, 1930-2010

	Difference		Severe	No severe	No
	Severe – Non-severe		disaster	disasters	disasters
Geographic					
Max elevation in county	-838	(43.2)	1,572	2,410	2,897
Number lakes in county	-3.998	(0.896)	18.21	22.213	21.66
Number beaches in county	0.468	(0.06)	0.906	0.438	0.287
Dustbowl area	-0.012	(0.00168)	0.003	0.015	0.027
Time-varying					
Good weather index	0.166	(0.0125)	-6.520	-6.686	-6.694
Population	35,635	(4277)	99,462	63,826	37,320
Poverty rate	-0.00423	(0.00158)	0.163	0.167	0.175
Median house value	5,074	(574)	50,714	45,640	37,257
Housing stock (units)	15,084	(2314)	47,329	32,245	18,736
Exp. employment growth rate, 1930 weights	-0.0085	(0.00201)	0.042	0.05	0.032

Notes: Housing values and poverty rates are from NHGIS. Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. A disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Good weather index computed with data available from NOAA as: county-specific average daily temperature in the winter of year 2000 divided by its cross-county standard deviation, minus county-specific average daily temperature in the summer of year 2000 divided by its cross-county standard deviation. Standard errors from simple mean-tests are shown in parentheses.

Appendix Table 2: Summary Statistics for the US 1930–2010

	Mean	Std.Dev.	N
Population	62,713	219,101	24,432
Migration rate	-0.0119	0.198	24,432
Exp. employment growth rate, 1930 weights	0.0418	0.125	24,408
Exp. employment growth rate, 1970 weights	0.285	0.228	24,336
Median family income (dollars)	22,139	20,576	15,270
Poverty rate	0.168	0.0835	15,222
Housing stock (units)	32,911	104,239	15,270
Median house value (dollars)	44,781	27,447	15,164
Median house rent (dollars)	184	75	15,162
Log population	10.151	1.379	15,268
Log family income	9.876	0.402	15,270
Log housing stock	9.291	1.331	15,270
Log median house value	10.6	0.470	15,164
Log median house rent	5.1	0.413	15,162

Notes: All variables are at the county-by-decade level. Expected employment growth rates are a Bartik measure, computed using equation (2). House rents, house values, and family income are measured in Census years from 1970 to 2010 and expressed in 1982-84 dollars.

Appendix Table 3: Effect of Disasters on Migration Rates in 1940-2010 by Disaster Type

and Severity, Excluding Time-Varying Controls

	(1)	(2)	(3)	(4)
	Migration rate	Migration rate	Migration rate	Migration rate
Severe disaster	-0.015*** (0.005)	-0.014** (0.005)	-0.015*** (0.005)	-0.003 (0.006)
Flood count	0.006** (0.002)	0.008*** (0.003)	0.006** (0.002)	0.005** (0.002)
Storm count	-0.001 (0.002)	-0.002 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Tornado count	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.008** (0.003)
Hurricane count	-0.008** (0.004)	-0.008** (0.004)	-0.008** (0.004)	-0.006* (0.003)
Fire count	-0.013** (0.005)	-0.013** (0.005)	-0.013** (0.005)	-0.013*** (0.005)
Other disasters count	-0.029 (0.025)	-0.032 (0.025)	-0.028 (0.025)	-0.055** (0.022)
Exp. employment growth rate	0.267*** (0.033)		0.273*** (0.032)	0.317*** (0.034)
County FE	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y
State FE * time	Y	Y	Y	N
1930 population * time	Y	Y	N	Y
Observations	24,408	24,432	24,408	24,408

The reported regression of equation (1) is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Conley Standard errors using a distance threshold of 1,000 km and a time lag of 10 decades.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 4: Effect of Disasters on County-Level Net In-Migration Rate by Disaster Type and Severity in 1940–2010, Using State-Clustered Standard Errors

	(1) Migration rate
Severe disaster = 1	-0.015*** (0.005)
Flood count	0.006** (0.003)
Winter storm count	-0.001 (0.002)
Tornado count	-0.002 (0.004)
Hurricane count	-0.008 (0.008)
Fire count	-0.013* (0.006)
Other disasters count	-0.029 (0.030)
Employment growth rate	0.267*** (0.028)
County FE	Y
Decade FE	Y
State FE * time trend	Y
1930s population * time trend	Y
Observations	24,408

Notes: The reported regression of equation (1) is at the county-by-decade level. Net in-migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Standard errors are clustered by state.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Appendix Table 5: Effect of Disasters on Migration Rates in 1940-2010
with County-Specific Trends**

	Migration rate
Severe disaster = 1	-0.016*** (0.006)
Flood count	0.004 (0.003)
Winter storm count	-0.002 (0.002)
Tornado count	-0.003 (0.003)
Hurricane count	-0.009** (0.004)
Fire count	-0.015*** (0.006)
Other disasters count	-0.037 (0.026)
Exp. employment growth rate, 1930 weights	0.177*** (0.034)
County FE	Y
Decade FE	Y
County FE * time trend	Y
1930's population * time trend	Y
Observations	24,408

Notes: The reported regression of equation (1) is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 6: Effect of Disasters on Migration Rates in 1940-2010, with Lags/Leads

	Migration rate
Severe disaster = 1	-0.016*** (0.005)
Severe disaster (lag)	0.003 (0.007)
Severe disaster (lead)	-0.006 (0.006)
Flood count	0.006** (0.003)
Winter storm count	-0.006* (0.003)
Tornado count	-0.003 (0.003)
Hurricane count	-0.009 (0.007)
Fire count	-0.041*** (0.014)
Other disasters count	-0.000 (0.018)
Exp. employment growth rate, 1930 weights	0.290*** (0.040)
County FE	Y
Decade FE	Y
State FE * time trend	Y
1930's population * time trend	Y
Observations	18,306

Notes: The reported regression of equation (1) is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Appendix Table 7: Effect of Disasters on Migration Rates in 1940-2010
After Controlling for FEMA Transfers**

	(1) FEMA transfers per capita	(2) Migration rate
Severe disaster	1.212 (2.818)	-0.015*** (0.005)
Flood count	-0.649 (1.040)	0.006** (0.002)
Storm count	3.131* (1.680)	-0.001 (0.002)
Tornado count	-0.990 (1.203)	-0.003 (0.003)
Hurricane count	11.902** (5.241)	-0.008** (0.004)
Fire count	-3.226 (3.888)	-0.013** (0.005)
Other disasters count	-38.737* (22.259)	-0.029 (0.025)
Exp. employment growth rate	-34.403*** (11.793)	0.267*** (0.032)
FEMA transfers per capita (1982-84 dollars)	-	-0.000** (0.000)
County FE	Y	Y
Decade FE	Y	Y
State FE*time trend	Y	Y
1930's population*time trend	Y	Y
Observations	24,408	24,408

Notes: The reported regression of equation (1) is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. FEMA relief expenditures and obligations from Consolidated Federal Funds Reports are presented per capita in 1982-84 dollars. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930 (columns 1-4) and 1970 (columns 5-8). Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 8: Effect of Disasters on County-Level Migration by Disaster Type in 1940-2010, Regression at the SEA level

	Migration rate
Severe disaster = 1	-0.020 ^{**} (0.009)
Flood count	0.006 ^{**} (0.002)
Winter storm count	-0.001 (0.002)
Tornado count	-0.011 ^{***} (0.003)
Hurricane count	-0.015 (0.012)
Fire count	-0.007 [*] (0.004)
Other disasters count	0.001 (0.030)
Employment growth rate	0.262 ^{***} (0.060)
County FE	Y
Decade FE	Y
State FE * time trend	Y
1930s population * time trend	Y
Observations	2,527

Notes: The reported regression is at the SEA-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and incidence of severe disasters are obtained from merging data from the ARC, FEMA and EM-DAT. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. The employment growth rate is estimated (see equation 2); weights are based on county employment in 1930 by industry. Standard errors are clustered by state.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 9: Effect of Disasters on County-Level Migration by Disaster Type in 1940-2010, Weighted by County Population in 1930

	(1) Migration rate
Severe disaster = 1	-0.011 (0.009)
Flood count	0.008** (0.003)
Winter storm count	-0.003** (0.001)
Tornado count	-0.001 (0.003)
Hurricane count	-0.008** (0.004)
Fire count	-0.0002 (0.002)
Other disasters count	0.017 (0.026)
Exp. employment growth rate, 1930 weights	0.228*** (0.038)
County FE	Y
Decade FE	Y
State FE* time trend	Y
1930's population* time trend	Y
Observations	24,408

Notes: The reported regression is at the county-by-decade level. Counties are weighted by their population in 1930. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and incidence of severe disasters are obtained from merging data from the ARC, FEMA and EM-DAT. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. The employment growth rate is estimated (see equation 2); weights are based on county employment in 1930 by industry. Standard errors are clustered by state; our implementation of the Conley standard errors does not support weights.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 10: Effect of Disasters on Migration by Disaster Type in 1940-2010, Severe Disasters Redefined as Those with Highest Percent of Fatalities *in Decade*

	(1) Severe =Top 50%	(2) Severe =Top 10%
Severe disaster = 1	-0.015*** (0.005)	-0.017*** (0.006)
Flood count	0.006** (0.002)	0.005** (0.003)
Winter storm count	-0.001 (0.002)	-0.001 (0.002)
Tornado count	-0.003 (0.003)	-0.004 (0.003)
Hurricane count	-0.009** (0.004)	-0.008* (0.004)
Fire count	-0.012** (0.005)	-0.012** (0.005)
Other disasters count	-0.028 (0.025)	-0.029 (0.025)
Employment growth rate	0.267*** (0.032)	0.267*** (0.032)
County FE	Y	Y
Decade FE	Y	Y
State FE * time trend	Y	Y
1930s population * time trend	Y	Y
Observations	15,154	15,152

Notes: The reported regression is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and incidence of severe disasters are obtained from merging data from the ARC, FEMA and EM-DAT. In this specification, a disaster qualifies as “severe” if falls within the top 50 percent (column 1) or top 10 percent (column 2) of disaster-related fatalities in a given decade. The employment growth rate is estimated (see equation 2); weights are based on county employment in 1930 by industry. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 11: Effect of Disasters on Migration Rates of People Aged 15–64 in 1940-2010

	Migration rate (15–64)
Severe disaster = 1	-0.017*** (0.006)
Flood count	0.007** (0.003)
Winter storm count	-0.001 (0.002)
Tornado count	-0.003 (0.004)
Hurricane count	-0.009* (0.005)
Fire count	-0.014** (0.006)
Other disasters count	-0.032 (0.027)
Exp. employment growth rate, 1930 weights	0.342*** (0.041)
County FE	Y
Decade FE	Y
State FE * time trend	Y
1930's population * time trend	Y
Observations	24,408

Notes: The reported regression of equation (1) is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 12: Effect of Disasters on Migration Rates for Different Age Groups in 1940-2010

Dependent Variable = Migration Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	0-15	15-25	25-35	35-45	45-55	55-65	65-75
Severe disaster	-0.016*** (0.005)	-0.013* (0.008)	-0.018** (0.008)	-0.022*** (0.007)	-0.013** (0.005)	-0.009** (0.004)	-0.002 (0.005)
Flood count	0.006*** (0.002)	0.001 (0.004)	0.013*** (0.004)	0.008** (0.003)	0.004 (0.002)	0.003 (0.002)	0.002 (0.002)
Storm count	-0.002 (0.002)	-0.001 (0.002)	-0.000 (0.003)	0.000 (0.002)	0.001 (0.002)	-0.002 (0.001)	-0.002* (0.001)
Tornado count	0.000 (0.003)	-0.006 (0.005)	-0.004 (0.005)	-0.003 (0.004)	-0.003 (0.003)	0.000 (0.002)	0.002 (0.003)
Hurricane count	-0.007** (0.003)	-0.005 (0.005)	-0.001 (0.006)	-0.013** (0.005)	-0.009** (0.004)	-0.012** (0.006)	-0.012** (0.006)
Fire count	-0.008* (0.004)	-0.008 (0.005)	-0.012 (0.008)	-0.020*** (0.008)	-0.017*** (0.006)	-0.016*** (0.006)	-0.018*** (0.006)
Other count	-0.018 (0.016)	-0.024 (0.023)	-0.028 (0.034)	-0.035 (0.032)	-0.036 (0.026)	-0.043 (0.032)	-0.053 (0.035)
Emp growth	0.199*** (0.029)	0.400*** (0.057)	0.513*** (0.062)	0.273*** (0.038)	0.203*** (0.031)	0.184*** (0.026)	0.141*** (0.025)
County FE	Y	Y	Y	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y	Y	Y	Y
State FE * time trend	Y	Y	Y	Y	Y	Y	Y
1930's population * time trend	Y	Y	Y	Y	Y	Y	Y
Observations	24,408	24,408	24,408	24,408	24,408	24,408	24,408

Notes: The reported regression of equation (1) is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 13: Effect of Disasters on Migration Rates in 1940-2010, Controlling for Population

	Migration rate
Severe disaster = 1	-0.013** (0.005)
Flood count	0.005* (0.002)
Winter storm count	-0.001 (0.002)
Tornado count	-0.003 (0.003)
Hurricane count	-0.008** (0.004)
Fire count	-0.002 (0.008)
Other disasters count	-0.025 (0.022)
Population at the start of the decade	-0.000*** (0.000)
Exp. employment growth rate, 1930 weights	0.244*** (0.031)
County FE	Y
Decade FE	Y
State FE * time trend	Y
1930's population * time trend	Y
Observations	24,408

Notes: The reported regression of equation (1) is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and severity are assembled from the ARC, FEMA and EM-DAT data. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We control for population at the start of the decade. We estimate the employment growth rate from IPUMS data using industrial composition and national employment trends (see equation 2); weights are based on county employment by industry in 1930. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 14: Effect of Disasters on Migration by Disaster Type in 1940-2010, Controlling for Dam Construction

	Migration rate
Severe disaster = 1	-0.015*** (0.005)
Flood count	0.006** (0.002)
Winter storm count	-0.001 (0.002)
Tornado count	-0.002 (0.003)
Hurricane count	-0.008** (0.004)
Fire count	-0.013** (0.005)
Other disasters count	-0.028 (0.025)
Exp. employment growth rate, 1930 weights	0.268*** (0.033)
New dams constructed	0.00005*** (0.00004)
County FE	Y
Decade FE	Y
State FE* time trend	Y
1930's population* time trend	Y
Observations	24,408

Notes: The reported regression is at the county-by-decade level (1930-2010). Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and incidence of severe disasters are obtained from merging data from the ARC, FEMA and EM-DAT. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. The employment growth rate is estimated (see equation 2); weights are based on county employment in 1930 by industry. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 15: Effect of Severe Disasters on Migration for Different Severity Thresholds in 1940-2010, with County-Specific Trends

Dependent variable = Migration rate

Fatality Threshold	Severe Disaster ==1	
	Coefficient	Standard Error
10	-0.012*	(0.006)
20	-0.016**	(0.007)
30	-0.014**	(0.007)
40	-0.018**	(0.007)
50	-0.017**	(0.008)
60	-0.015**	(0.008)
70	-0.017**	(0.008)
80	-0.018**	(0.008)
90	-0.019*	(0.01)
100	-0.021**	(0.01)
200	-0.018*	(0.011)
500	-0.053**	(0.022)

Notes: This table follows the format of Table 3, after adding county-specific trends. Each row corresponds to a separate regression. We report coefficients on the indicator for “severe” disasters, varying the threshold required for a disaster to qualify as severe. Disasters qualify as severe if the percent of the county population affected by the disaster equaled or exceeded the thresholds reported in column (1). All regressions include as controls counts of natural disasters by type, county and decade fixed effects, county-specific time trends and a 1930 population time trend. Standard errors are clustered by state.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 16: Effect of Disasters on County-Level Economic Activity in 1970-2010 for Different Severity Thresholds

Fatality Threshold	(1) Migration rate	(2) Population (log)	(3) House value (log med)	(4) House rent (log med)	(5) Housing stock (log)	(6) Family income (log med)	(7) Poverty rate
10	-0.009** (0.004)	-0.006 (0.009)	-0.022** (0.011)	-0.007 (0.007)	-0.010 (0.010)	-0.017 (0.012)	0.005** (0.002)
20	-0.013*** (0.004)	-0.008 (0.007)	-0.038*** (0.014)	-0.016* (0.008)	-0.009 (0.007)	-0.018 (0.011)	0.007*** (0.002)
30	-0.010** (0.005)	-0.013 (0.008)	-0.053*** (0.012)	-0.026*** (0.008)	-0.013* (0.008)	-0.024** (0.012)	0.008*** (0.002)
40	-0.012** (0.005)	-0.004 (0.009)	-0.039*** (0.014)	-0.025*** (0.008)	-0.003 (0.008)	-0.023* (0.012)	0.008*** (0.002)
50	-0.014*** (0.005)	0.004 (0.010)	-0.042** (0.017)	-0.021** (0.009)	0.009 (0.010)	-0.028** (0.013)	0.010*** (0.002)
60	-0.015*** (0.005)	-0.000 (0.011)	-0.034** (0.017)	-0.008 (0.010)	0.007 (0.010)	-0.020 (0.015)	0.007*** (0.002)
70	-0.018*** (0.005)	-0.003 (0.010)	-0.036** (0.017)	-0.009 (0.010)	0.005 (0.010)	-0.014 (0.014)	0.006*** (0.002)
80	-0.018*** (0.005)	-0.002 (0.010)	-0.041** (0.016)	-0.015 (0.010)	0.005 (0.010)	-0.020 (0.013)	0.008*** (0.002)
90	-0.021*** (0.006)	-0.023*** (0.009)	-0.052*** (0.019)	-0.023* (0.012)	-0.016* (0.009)	-0.030** (0.015)	0.009*** (0.003)
100	-0.021*** (0.006)	-0.024*** (0.009)	-0.050** (0.019)	-0.022* (0.012)	-0.017* (0.009)	-0.026* (0.015)	0.009*** (0.003)
200	-0.017** (0.006)	-0.017* (0.010)	-0.027 (0.020)	-0.016 (0.013)	-0.012 (0.010)	-0.019 (0.014)	0.008*** (0.003)
500	-0.029* (0.016)	-0.027 (0.031)	-0.120*** (0.034)	-0.110*** (0.032)	-0.038 (0.030)	-0.159*** (0.037)	0.034*** (0.008)

Notes: Each row corresponds to a separate regression that follows the format of Table 2. We report coefficients on the indicator for “severe” disasters, varying the threshold required for a disaster to qualify as severe. Disasters qualify as severe if they exceeded the number of fatalities reported in column (1). All regressions include counts of natural disasters by type, county and decade fixed effects, state-specific time trends and a population time trend (using 1930's baseline values). Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 17: Effect of Disasters on Migration in 1940-2010, by Political Alignment

	Migration rate	
	Coefficient	Standard Error
Severe disaster = 1	-0.014*	(0.008)
Severe disaster = 1, same party	-0.002	(0.009)
Flood count	0.005	(0.003)
Flood count, same party	0.001	(0.004)
Winter storm count	-0.001	(0.002)
Winter storm count, same party	-0.000	(0.002)
Tornado count	-0.004	(0.006)
Tornado count, same party	0.003	(0.008)
Hurricane count	0.002	(0.004)
Hurricane count, same party	-0.016**	(0.007)
Fire count	-0.014**	(0.006)
Fire count, same party	0.003	(0.008)
Other disasters count	-0.038	(0.024)
Other count, same party	0.018	(0.034)
Exp. employment growth rate, 1930 weights	0.268***	(0.032)
Same party	0.004	(0.008)
County FE	Y	
Decade FE	Y	
State FE * time trend	Y	
1930s population * time trend	Y	
Observations	24,408	

Note: The reported regression is at the county-by-decade level. Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and incidence of severe disasters are obtained from merging data from the ARC, FEMA and EM-DAT. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. We interact each disaster variable with an indicator for whether the state’s governor belongs to the same party as the President. The employment growth rate is estimated (see equation 2); weights are based on county employment in 1930 by industry. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 18: IV Effect of Disasters on Migration in 1940-2010, for Different Severity Thresholds

Dependent variable = Migration rate

Fatality Threshold	IV		F	OLS	
	Coefficients	Standard Errors		Coefficients	Standard Errors
10	-0.054	(0.043)	10.7	-0.012**	(0.005)
20	-0.064	(0.052)	6.47	-0.018***	(0.006)
30	-0.041	(0.049)	6.86	-0.018***	(0.006)
40	-0.056	(0.050)	6.82	-0.021***	(0.007)
50	-0.082	(0.065)	5.47	-0.020***	(0.007)
60	-0.128	(0.080)	4.9	-0.021**	(0.008)
70	-0.127	(0.081)	5.01	-0.021**	(0.009)
80	-0.153	(0.094)	4.3	-0.021**	(0.009)
90	-0.135	(0.121)	2.16	-0.021*	(0.011)
100	-0.177	(0.138)	1.97	-0.021*	(0.011)
200	0.112	(0.182)	2.4	-0.018	(0.013)
500	0.758	(0.506)	1.61	-0.040	(0.028)

Notes: Each row corresponds to a separate regression. We report coefficients on the indicator for “severe” disasters for an IV specification and the corresponding OLS that follows Table 2 but omits the disaster counts by type. In each row we vary the threshold required for a disaster to qualify as severe. Disasters qualify as severe if they equaled or exceeded the number of fatalities reported in column (1). The instruments for “severe” disasters are the maximum and minimum daily temperatures recorded in the year and total annual precipitation averaged out across the decade. All regressions include counts of natural disasters by type, county and decade fixed effects, state-specific time trends and a population time trend (using 1930’s baseline values). Standard errors are clustered by state.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

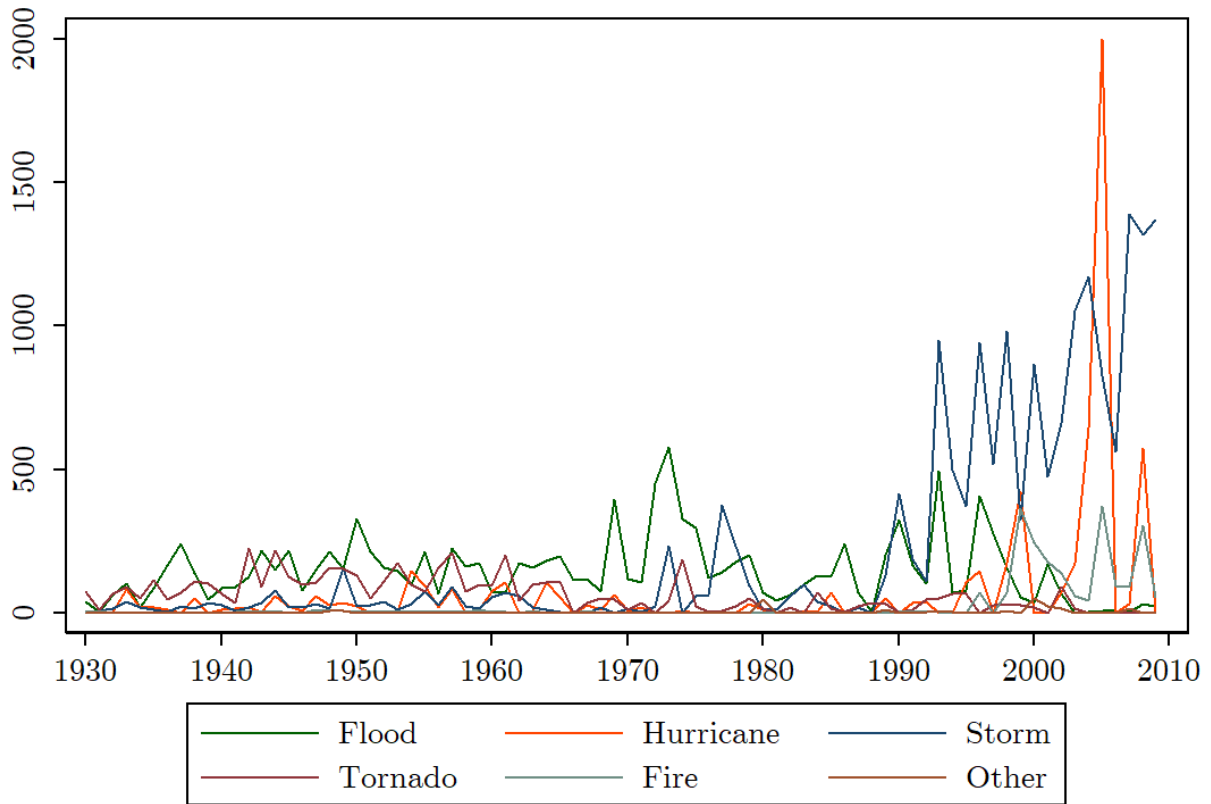
Appendix Table 19: Effect of Disasters on County-Level Migration by Disaster Type in 1940-2010, Including Droughts

	Migration rate
Severe disaster = 1	-0.014*** (0.005)
Flood count	0.006** (0.002)
Drought count	0.018* (0.01)
Winter storm count	-0.001 (0.002)
Tornado count	-0.002 (0.003)
Hurricane count	-0.008** (0.004)
Fire count	-0.013** (0.005)
Other disasters count	-0.029 (0.025)
Employment growth rate	0.266*** (0.032)
County FE	Y
Decade FE	Y
State FE * time trend	Y
1930s population * time trend	Y
Observations	24,408

Notes: The reported regression is at the county-by-decade level (1930-2010). Net migration rates are from Winkler, et al. (2013a, b) and Gardner and Cohen (1992). Counts of natural disasters by type and incidence of severe disasters are obtained from merging data from the ARC, FEMA and EM-DAT. In this specification, a disaster qualifies as “severe” if it was associated with 25 or more deaths. The employment growth rate is estimated (see equation 2); weights are based on county employment in 1930 by industry. Conley standard errors adjusted for spatial and temporal correlation within 1,000 km and 10 decades (see Hsiang, 2010).

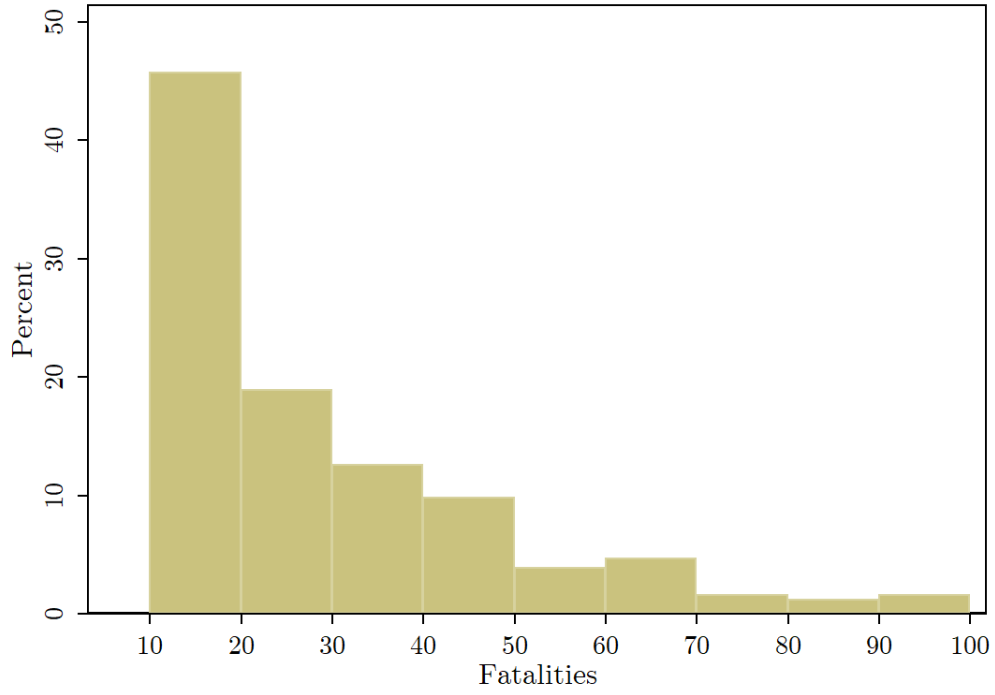
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figure 1: Annual Disaster Count in the US 1930–2012, by Type



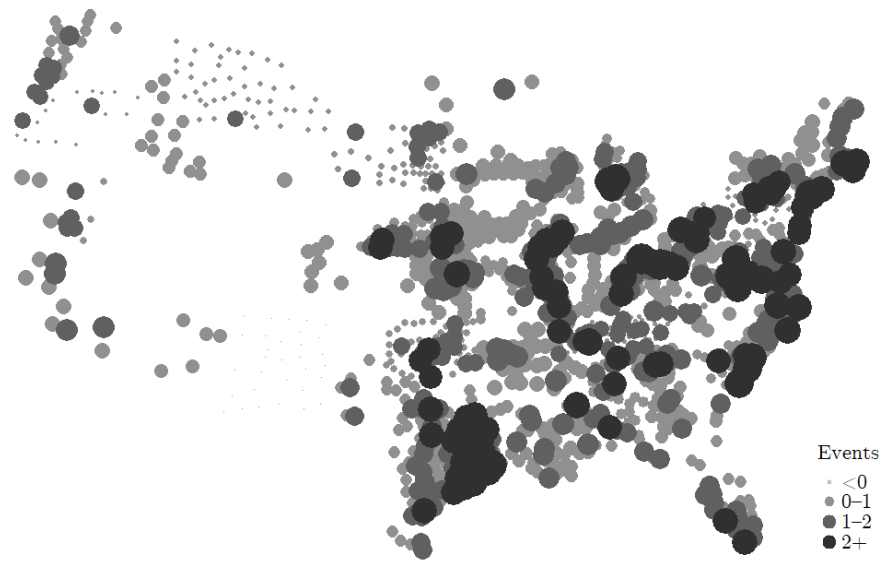
Notes: This graph plots the sum of county-level disaster counts by year and type between 1930 and 2012. Note that this measure will treat a given natural event that occurred in two separate counties as two different disaster events. The hurricane count is truncated at 2,000. Sources: American National Red Cross (ARC) and various federal sources, including Federal Emergency Management Agency (FEMA).

**Appendix Figure 2: Histogram of Fatalities for Natural Disasters with 10 or More Deaths
1930–2010**



This histogram shows the distribution of fatalities associated to natural disasters with at least 10 deaths affecting the US from 1930 to 2010. The histogram was capped at 100 fatalities. The maximum number of fatalities is 1833. Source: EM-DAT and ARC.

Appendix Figure 3: Count of Decades with a Severe Disaster Event by US County, 1930–2010, Accounting for State Fixed Effects



Notes: This map shows the number of decades with severe events per county in the period 1930–2010, as a residual after accounting for state fixed effects. Severe events are disasters associated with 25 or more deaths. The marker size and color are increasing in the number of events. The maximum number of occurrences is 3.75. Sources: American National Red Cross and various federal sources, including Federal Emergency Management Agency.