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 property destruction and loss of life. We construct an 80 year panel data set that includes the universe of natural disasters in the United States from 1930 to 2010 and study how these shocks affected migration rates, home prices, and poverty rates at the county level. Severe disasters increased out-migration rates by 1.5 percentage points and lowered housing prices/rents by 2.5–5.0 percent, but milder disasters had little effect on economic outcomes.

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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 extensive 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 natural disasters in the United States from 1920 to 2010. Figure 1 displays annual counts of disaster events at the county level using this new series. Data is based on reports from the American National Red Cross (ARC) from 1920 to 1964, combined with counts from Federal Emergency Management Agency (FEMA) and its predecessors starting in the 1950s.[1] Though most of the century, the US experienced around 500 county-level disaster events each year. 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.[2]

With this extensive new data in hand, we ask: what happens to local economies that are hit by a natural disaster? We view disasters as negative amenities or negative productivity shocks that, in spatial equilibrium, should encourage existing residents to leave (or prospective residents not to move in), leading to net out-migration and reductions in housing prices. We find that the presence of a severe disaster in a given decade led to heightened out-migration rates and lower housing prices/rents at the county level. Out-migration increases by 1.5 percentage points (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

[1] 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.

[2] 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. 2013, 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).

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), but results are quite robust to choice of fatality threshold. Residents do not seem to be responding to the share of the population killed by the event, but rather to the salience of a disaster with a high death count (25 or more).

We also find that 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 increase 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 out-migration of households above the poverty line, in-migration of the poor (perhaps in response to lower housing prices), or a transition of the existing population into poverty. Our estimates capture the net effect of disasters on local economies, after any rebuilding, new investments, or disbursement of disaster relief funds.[3]

The out-migration response to disasters increased after 1980, despite the growing coordination of federal disaster relief through FEMA (founded in 1979), which might root residents in place. One possibility is that the rising frequency of disaster events encourages residents to respond more readily to any *given* disaster, inferring from one event that future disasters may occur. In addition, rising disaster-related migration is consistent with Deryugina’s (2017) finding that non-disaster-related transfer payments increase substantially following disaster events, mainly in the form of unemployment insurance and medical spending. The presence of a safety net and of relief payments may allow residents of disaster-affected areas to relocate to another county.

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).[4] We provide suggestive evidence that our results are not being driven by biases that would arise if disaster events are declared more often in politically connected states. 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-

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

[4] 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.

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 all received federal disaster designations.[5] 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 holds also when instrumenting for disaster activity with climate variables that are available historically (e.g., maximum and minimum temperatures), 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 affects economic growth (Dell, Jones and Olken 2012, 2014, Cavallo, et al. 2013, Hsiang and Jina 2014, Burke, Hsiang and Miguel 2015, Kocornik-Mina et. al. 2015, Cattaneo and Peri 2016).[6] These studies have not led to consensus, finding results ranging from long-lasting effects 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).

A second set of papers study the effect of specific major disasters in the US on existing residents (see, for example, Smith and McCarty (1996) and Hallstrom and Smith (2005) on Hurricane Andrew; Hornbeck (2012) and Long and Siu (2016) 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

[5] 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.

[6] There is some prior work using multiple disasters striking the same country. Feng, Oppenheimer and Schlenker (2012) study the effect of temperature on migration from rural US counties. Anttila-Hughes and Hsiang (2013) analyze more than 2,000 typhoons that struck the Philippines over 60 years.

Katrina). 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 a county-level panel of US counties and find that hurricanes reduce local economic growth and affected population in some areas 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. Natural Disaster Risk in a Static Spatial Equilibrium Model

Classic models of spatial equilibrium guide our empirical predictions (Rosen 1978, Roback 1982). In the simplest version of these models, all people have the same preferences over private consumption and local public goods and face zero migration costs. Geographic areas differ by one exogenous attribute – say, winter temperature. From this local variation, a hedonic rental price equilibrium arises mapping out the representative agent's indifference curve between private consumption and temperature. There is no migration in equilibrium because utility is equalized across all locations. Residents of colder places are compensated in the form of lower rents.

Now suppose that a county experiences a natural disaster. A disaster event could disrupt local supply chains and product infrastructure (Carvalho, et al. 2016), thereby lowering local labor market demand. In addition, the occurrence of a natural disaster could decrease the local amenity level – for example, by imposing some risk of mortality or property damage. All else equal, such natural disasters should push people to leave and discourage outsiders from moving in (Topel 1986). In an economy featuring durable local housing, the housing supply will be inelastic in the medium run and this means that a downward shock to local quality of life will depress local home prices (Glaeser and Gyourko 2005).[7] 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 high real income for higher disaster risk. We thus predict that areas that are routinely hit by natural disasters will experience out migration, but such migration will be moderated by

[7] If disasters also destroy enough of the local housing stock, there could be a countervailing supply effect in the housing market, overwhelming the reduction in local housing demand.

declining home prices. Falling prices could thus generate shifts in the income distribution of a local area, resulting in a larger share of residents who are poor.

III. Econometric Framework

To study how natural disaster events affect local economies, we stack data from county *i* in state *j* for decade *t* (*t* = 1930-2010) and estimate:

$$Y_{ijt} = \mu_i + \xi_t + \beta_1 * Disasters_{ijt} + \beta_2 * \Delta employ_{ijt} + \beta_3 * (\boldsymbol{X}_{ij} * t) + U_{ijt} \qquad (1)$$

Our set of dependent variables Y include the net migration rate, the logarithm of median housing prices (or rents), and the poverty rate (available from 1970), all of which are measured at the decadal level from the Censuses of Population and Housing.[8] We control for county (μ_i) and decade (ξ_t) fixed effects, state-specific time trends and an interaction between initial county population and a linear time trend (both state fixed effects and initial county population are included in the vector X_{ij}). We control for differential trends by initial population to account for the fact that sparsely populated areas (e.g., in the Mountain West) were unlikely to have declared disasters. We also conduct several robustness checks, including country-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. Our main explanatory variables of interest is a vector of the number and severity of disasters in a local area ($Disasters_{ijt}$), 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). Standard errors are clustered by state.

Standard economic controls like the unemployment rate are not available at the county level over such a long period of time. 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

[8] Data on poverty rates and house values/rents by county are taken from the National Historical Geographic Information System (NHGIS).

follows standard proxies for local economic growth pioneered by Bartik (1991) and Blanchard and Katz (1992) and is defined as:

$$\Delta employ_{ijt} = \frac{\sum_{Ind=1}^{I}[\,EMPLOY_{\{i,1930,ind\}} * GR_{\{t,ind\}}]}{EMPLOY_{\{i,1930\}}} \tag{2}$$

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).[9]

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), disaster type, month and year of occurrence, and fatality count.

Our most recent data is drawn from the list of "major disaster declarations" posted by FEMA and its predecessors, which begins in 1964 (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.[10] We extend our series back to 1918 using data on the disaster relief efforts of the American National Red Cross (ARC) documented in their *Annual Reports* and in lists of disaster relief operations.[11] We link these lists with the ARC's case files to document the date, type, and location of each disaster.[12]

[9] 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.

[10] 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.

[11] 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).

[12] 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.

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.[13] 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 beaches 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.[14,15] We create measures of 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 1 presents a histogram of disasters by fatality count. There are 292 disasters with 25 or more deaths in our dataset which constitute 2.9 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.

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[13] 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 7 and they are unchanged.

[14] EM-DAT was created by the Centre for Research on the Epidemiology of Disasters (see http://www.emdat.be/).

[15] 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 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.

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 (see Appendix Table 7). 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 (see Appendix Table 9).

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. Appendix Figure 2 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 (Appendix Table 8). 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. Core results

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 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.

Some categories of milder disasters have additional effect on net migration to a county. Floods attract in-migrants to an area, while wildfires and hurricanes lead to net out-migration (although the coefficient on hurricanes is not significantly different from zero in the main specification). Storms and tornados have no effect on migration flows. The positive effect of floods on in-migration is consistent with our earlier work, in which we 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. Below, we show that the positive effect of floods on migration in this series is present only in the first part of the century.

B. Pre-trends before a disaster strikes

Our specification, which is based on variation in disaster incidence net of county and decade fixed effects, is akin to a difference-in-differences analysis, comparing migration rates within counties before and after a disaster strikes, relative to comparison counties that do not experience a natural disaster in the decade. To provide support for the assumptions underlying this specification, we include several robustness 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 3 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 4 includes both lags and leads of our disaster severity variable. We find that the disaster lead has a negative association with outmigration, 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. Population and underlying disaster risk

Thus far, we have estimated 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 5 aggregates counties into State Economic Areas and Appendix Table 6 instead 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. We prefer the unweighted results because weighted regressions put extra emphasis on large metropolitan areas. Appendix Table 7 uses a relative measure of disaster severity, defining severe disasters as any in the top 50 percent (or top 90 percent) of fatalities in a given decade. Results are nearly identical to the preferred specification.

Beyond weighting, there may be other population-based concerns. First, 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 8). 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. Secondly, 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 9 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.

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 10).[16]

The distinction between disaster risk and disaster incidence merits further investigation. Some counties are more prone to disaster events than others (e.g., because they are on the coast or in a river basin). On the one hand, residents of these areas may have learned how to adapt to a disaster event and so may not be as responsive to any given disaster. On the other hand, disaster events have been increasing over time and so any given disaster event may be more predictive of future disasters in risk-prone areas, thereby prompting a larger out-migration response. Appendix Table 11 allows the response to a severe disaster to vary by risk exposure. We estimate a fixed risk exposure for the full century at the county level as a propensity score based on geographic characteristics and interact risk exposure with the incidence of a severe disaster in a given decade. Column 1 interacts the severe disaster dummy with a continuous measure of risk exposure, while

[16] Duflo and Pande (2005) 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.

columns 2 and 3 instead use an indicator for being above a certain threshold in exposure. In all three specifications, we find no evidence of a heterogeneous response by risk exposure. The lack of heterogeneity could be due to the fact that the two channels outlined above cancel each other out (residents of risk-prone areas have adapted, but also fear the uptick in disaster activity), or it could indicate that residents do not know their true risk profile.

D. Political vs. natural disasters

Our dataset is based on disaster declarations by the American 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 activity (for earthquakes), and so on. However, it is not possible to gather such data for five major disaster types over a 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 3 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 -0.011 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 12). 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 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 13.

Finally, we instrument for the presence of a severe disaster with the limited set of climatic variables that are available for the whole century. 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 14.

VI. Disasters, Home Prices and Poverty Rates

If natural disasters encourage net out-migration from a county, thereby lowering demand for the area, we would expect an associated effect of disaster activity on housing prices and rents. The second and third column of Table 2 document that the occurrence of a severe disaster lowers housing prices by 5.2 percent and rents by 2.5 percent. 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). Appendix Table 16 demonstrates that the estimated effect of severe disasters on housing prices is 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.

Residents who leave an area after a natural disaster may represent a select subsample of the incumbent population. We suspect that rich households would have greater resources to leave an area struck by disaster. In the climate change adaptation literature, there is a broad consensus that the wealthy can access a wide range of strategies ranging from owning a second home, to accessing better quality food, medical care and housing to protecting themselves from shocks; the poor are thus more likely to bear the incidence of natural disasters (Dasgupta 2001, Barreca, et. al. 2016, and Smith et. al. 2006). The poor may also be more willing to trade off a lower housing price for a heightened risk of disaster activity. If the rich are more likely to leave an area after a disaster, net out-migration may serve to increase the local poverty rate. The fourth column of Table 2 shows that the occurrence of a severe disaster increases the local poverty rate by 0.8 percentage points (10 percent of a standard deviation).

VII. Changing Responses to Disaster Events over Time

We may expect the effect of natural disasters on local economies to moderate as the federal response to disaster activity expanded over the century. From the 1920s through the 1950s, Washington responded to natural disasters on a case-by-case basis. In the 1950s, the federal government assumed a more systematic disaster relief role through a succession of Civil Defense agencies. The Federal Disaster Assistance Administration (FDAA) was created in 1973 under the Department of Housing and Urban Development and became an independent agency, the Federal Emergency Management Agency in 1978. We date the advent of a coordinated federal response to disaster activity (the creation of FDAA and FEMA) in the 1970s.

Table 4 tests for differences in the migration response to disaster events that occur before and after 1980, when a coordinated federal response to natural disasters began. If emergency management agencies increased the reliability of federal disaster relief, we might expect net out-migration to decline as the receipt of federal funds makes an area more attractive. However, we note that the frequency of disaster activity increased over time (Figure 1), especially after 1990, in part due to environmental change, and so it is hard to disentangle the effects of policy change from the environment.

We find no difference in the migration response to severe disasters before and after 1980. However, out-migration in response to mild disasters *increases* for nearly every disaster category after 1980, including floods, hurricanes, and wildfires. Although floods attracted in-migrants before 1980, they had no effect on migration in the latter part of the century. Any drag on migration from the establishment of FEMA was swamped by changes in the nature of disasters, which may be becoming more damaging or more salient to households over time.[17]

Our finding that the establishment of FEMA did not anchor residents in place is consistent with Deryugina (2017), which 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. Two-thirds of these funds were dispersed through unemployment insurance and income maintenance programs that are not tied to the recipient's location. The population in disaster-struck areas can move elsewhere and continue to receive income support.

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 these shocks affect the underlying spatial distribution of economic activity. We find that counties hit by severe disasters experienced greater out-migration, lower home prices and higher poverty rates. Given the durability of the housing capital stock, 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.

Contrary to recent cross-country studies like Cavallo et al. (2013) and Kocornik-Mina et al. (2015) which find near-immediate recovery from large natural disasters, we find long-term (decadal) effects of severe disasters 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, 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. Our estimates provide the net effect of disaster events on economic activity after all

[17] Any reduction 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 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).

private and government responses take place, which can include transfer payments and new infrastructure investments. 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.

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

	(1) Event count (1930-2010)	(2) Average num. of disasters, by county-decade	(3) Any disaster, by county-decade
Panel A: Disaster by type			
Flood	3,927	0.484	0.319
		(0.851)	(0.466)
Storm	1,667	0.724	0.301
		(1.57)	(0.459)
Hurricane	742	0.312	0.176
		(0.913)	(0.381)
Tornado	2,845	0.207	0.154
		(0.572)	(0.361)
Forest fire	910	0.095	0.0545
		(0.528)	(0.227)
Other disasters	67	0.010	0.010
		(0.105)	(0.098)
Total disasters	10,158	1.830	0.639
		(2.340)	(0.480)
Panel B: Disaster by severity			
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. In this specification, a disaster qualifies as "severe" if it was associated with 25 or more deaths.

Table 2: Effect of Disasters on County-Level Net Migration by Disaster Type and Severity

	(1) Migration rate	(2) House value (log median)	(3) House rent (log median)	(4) Poverty Rate
Severe disaster	-0.015***	-0.052***	-0.025**	0.008***
	(0.005)	(0.016)	(0.011)	(0.003)
Flood count	0.006**	0.007	0.007*	-0.002
	(0.003)	(0.006)	(0.004)	(0.001)
Storm count	-0.001	0.000	0.002	-0.000
	(0.002)	(0.005)	(0.003)	(0.001)
Tornado count	-0.002	0.011	0.015	-0.005**
	(0.004)	(0.011)	(0.010)	(0.002)
Hurricane count	-0.008	-0.005	-0.010	0.001
	(0.008)	(0.007)	(0.007)	(0.002)
Fire count	-0.013*	0.002	0.001	-0.004**
	(0.006)	(0.008)	(0.008)	(0.002)
Other disasters count	-0.029	-0.004	-0.022	0.005
	(0.030)	(0.030)	(0.021)	(0.008)
Employment growth rate	0.267***	0.264	0.234	-0.139***
	(0.028)	(0.174)	(0.140)	(0.028)
County FE	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y
State FE * time trend	Y	Y	Y	Y
1930s population * time trend	Y	Y	Y	Y
Decades included	1930-2010	1970-2010	1970-2010	1970-2010
Observations	24,408	15,154	15,152	15,162

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). Housing values, rents and poverty rates are from NHGIS. 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 (column 1) and in 1970 (column 2). Standard errors are clustered by state.

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

Table 3: Effect of Severe Disasters on Migration for Different Severity Thresholds

Dependent variable = Migration rate

	Severe Disasters	
Fatality Threshold	Coefficient	Standard Error
10	-0.008*	(0.004)
20	-0.015***	(0.005)
30	-0.012**	(0.005)
40	-0.015**	(0.006)
50	-0.012**	(0.006)
60	-0.012*	(0.007)
70	-0.014*	(0.007)
80	-0.014*	(0.007)
90	-0.016*	(0.009)
100	-0.017**	(0.008)
200	-0.013	(0.009)
500	-0.051**	(0.021)

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 were associated with more than 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. Standard errors are clustered by state.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

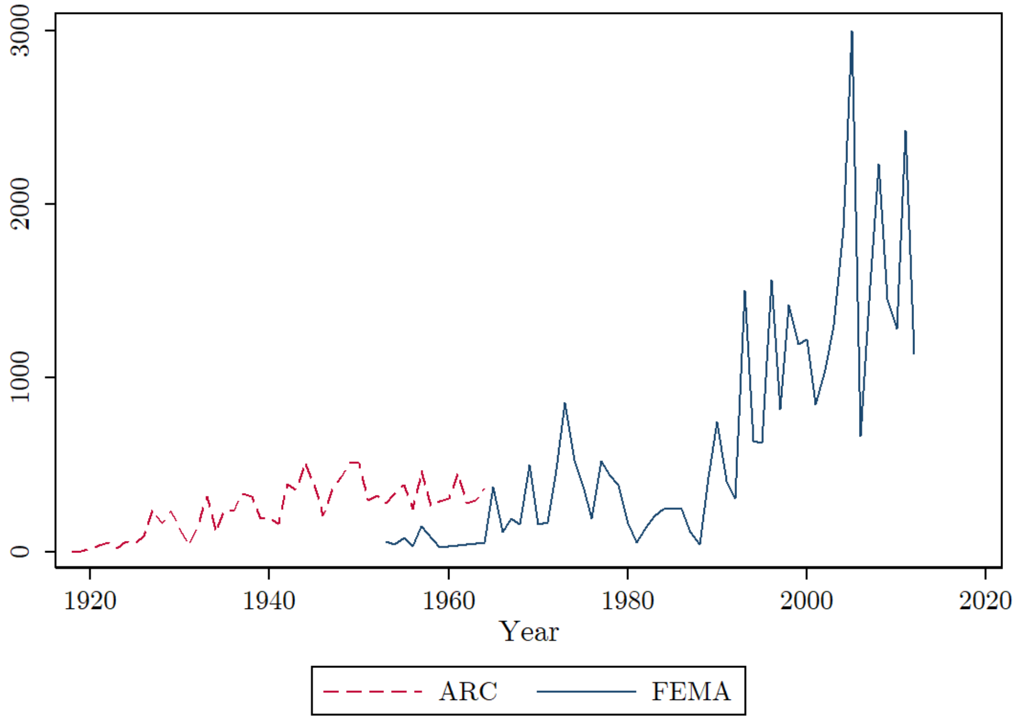
Table 4: Effect of Disasters on Net Migration Rates Before and After 1980

	Migration rate	
	Coefficient	Standard Error
Severe disaster	-0.017**	(0.008)
Severe disaster, after 1980	0.003	(0.013)
Flood count	0.008**	(0.003)
Flood count, after 1980	-0.008*	(0.004)
Storm count	-0.006	(0.006)
Storm count, after 1980	0.005	(0.007)
Tornado count	-0.001	(0.005)
Tornado count, after 1980	-0.006	(0.010)
Hurricane count	0.006	(0.009)
Hurricane count, after 1980	-0.018***	(0.005)
Fire count	0.018	(0.013)
Fire count, after 1980	-0.031**	(0.015)
Other disasters count	0.005	(0.046)
Other count, after 1980	-0.047	(0.065)
Exp. employment growth rate, 1930 weights	0.266***	(0.028)
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 (1930–2010). 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. Standard errors are clustered by state. We interact each disaster variable with an indicator for decade equal to or after 1980 (after the creation of FEMA). Standard errors are clustered by state.

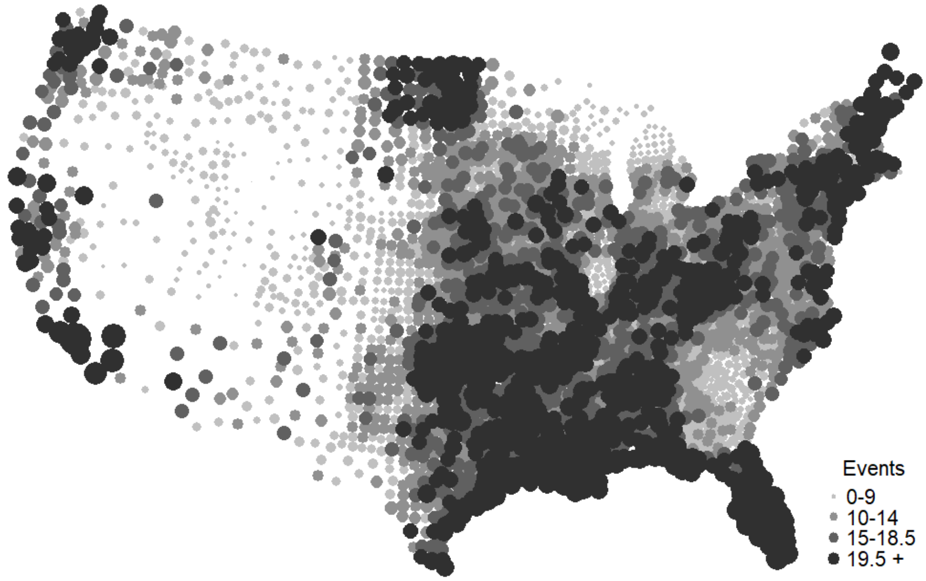
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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



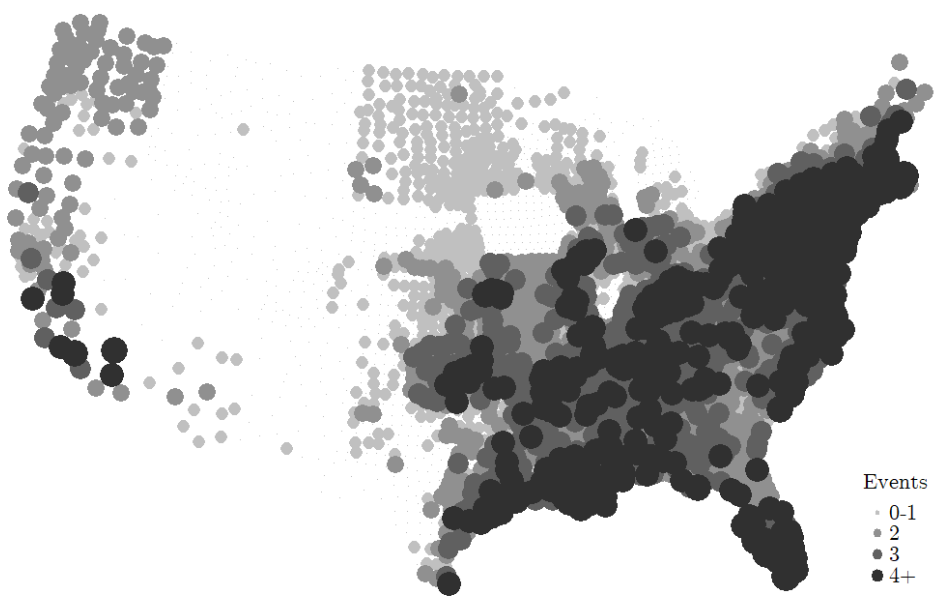
Notes: This graph plots the sum of county-level disaster counts by year and source between 1918 and 2012. Note that this measure will treat a given natural event that occurred in two separate counties as two different disaster events. The disaster count is truncated at 3000. Sources: American National 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 quartiles. 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 2019

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Appendix Table 1: Descriptive Statistics by Disaster Occurrence in Decade

	Difference Severe – Non-severe		Severe disaster	No severe disasters	No disasters
Geographic					
Max elevation in county	-838	(43.2)	1,665	2502	2,897
Number lakes in county	-3.998	(0.896)	18.09	23.17	21.66
Number beaches in county	0.468	(0.06)	0.850	0.391	0.287
Dustbowl area	-0.012	(0.00168)	0.007	0.013	0.027
Time-varying					
Good weather index	0.166	(0.0125)	-6.562	-6.683	-6.694
Population	35,635	(4277)	91,600	63,537	37,320
Poverty Rate	-0.00423	(0.00158)	0.160	0.172	0.175
Median House Value	23,217	(1285)	88,846	53,090	37,182
Exp. employment growth rate, 1930 weights	-0.0085	(0.00201)	0.048	0.046	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
Persons: Total [NHGIS]	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
Poverty rate	0.168	0.0835	15,222
Median house value (dollars)	62,416	61,347	15,164
Median house rent (dollars)	247	181	15,162
Log median house value	10.7	0.926	15,164
Log median house rent	5.2	0.864	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 and values are measured at the end of each decade from 1960 to 1990.

Appendix Table 3: Effect of Disasters on Migration Rates with County-Specific Trends

	Migration rate
Severe disaster	-0.016**
	(0.007)
Flood count	0.004
	(0.003)
Storm count	-0.002
	(0.002)
Tornado count	-0.003
	(0.004)
Hurricane count	-0.009
	(0.009)
Fire count	-0.015
	(0.010)
Other disasters count	-0.037
	(0.039)
Exp. employment growth rate, 1930 weights	0.177***
	(0.025)
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. Standard errors are clustered by state.

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

Appendix Table 4: Effect of Disasters on Migration Rates, with Lags and Leads

	Migration rate
Severe disaster	-0.016^{***}
	(0.006)
Severe disaster (lag)	0.003
	(0.009)
Severe disaster (lead)	-0.006
	(0.008)
Flood count	0.006^{**}
	(0.003)
Storm count	-0.006^{**}
	(0.003)
Tornado count	-0.003
	(0.005)
Hurricane count	-0.009
	(0.008)
Fire count	-0.041^{***}
	(0.012)
Other disasters count	-0.000
	(0.024)
Exp. employment growth rate, 1930 weights	0.290^{***}
	(0.038)
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. Standard errors are clustered by state. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 5: Effect of Disasters on County-Level Migration by Disaster Type
Regression at the SEA level

	Migration rate
Severe disaster	-0.020^{**}
	(0.009)
Flood count	0.006^{**}
	(0.002)
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 (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. Standard errors are clustered by state.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 6: Effect of Disasters on County-Level Migration by Disaster Type Weighted by County Population in 1930

	Migration rate
Severe disaster	-0.011
	(0.009)
Flood count	0.008**
	(0.003)
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 (1930-2010). 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.

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

Appendix Table 7: Effect of Disasters on Migration by Disaster Type
Top 50 and Top 10 percent of Severe Disasters in Decade

	(1) Top 50%	(2) Top 10%
Severe disaster	-0.015**	-0.017**
	(0.006)	(0.007)
Flood count	0.006**	0.005*
	(0.003)	(0.003)
Storm count	-0.001	-0.001
	(0.002)	(0.002)
Tornado count	-0.003	-0.004
	(0.004)	(0.004)
Hurricane count	-0.009	-0.008
	(0.008)	(0.008)
Fire count	-0.012*	-0.012*
	(0.006)	(0.006)
Other disasters count	-0.028	-0.029
	(0.031)	(0.031)
Employment growth rate	0.267***	0.267***
	(0.028)	(0.028)
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 (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 a number of deaths higher than the median in each decade (column 1) or higher than the 90th percentile (column 2) 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 8: Effect of Disasters on Migration Rates of People Aged 15–64

	Migration rate (15–64)
Severe disaster	-0.017***
	(0.006)
Flood count	0.007**
	(0.003)
Storm count	-0.001
	(0.002)
Tornado count	-0.003
	(0.005)
Hurricane count	-0.009
	(0.009)
Fire count	-0.014**
	(0.007)
Other disasters count	-0.032
	(0.032)
Exp. employment growth rate, 1930 weights	0.342***
	(0.036)
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. Standard errors are clustered by state.

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

Appendix Table 9: Effect of Disasters on Migration Rates Controlling for Population

	Migration rate
Severe disaster	-0.013**
	(0.005)
Flood count	0.005*
	(0.003)
Storm count	-0.001
	(0.001)
Tornado count	-0.003
	(0.004)
Hurricane count	-0.008
	(0.008)
Fire count	-0.002
	(0.007)
Other disasters count	-0.025
	(0.025)
Population at the start of the decade	-0.000***
	(0.000)
Exp. employment growth rate, 1930 weights	0.244***
	(0.028)
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. Standard errors are clustered by state.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 10: Effect of Disasters on Migration by Disaster Type Controlling for Dam Construction

	Migration rate
Severe disaster	-0.015***
	(0.005)
Flood count	0.006**
	(0.003)
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)
Exp. employment growth rate, 1930 weights	0.268***
	(0.029)
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. Standard errors are clustered by state.

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

Appendix Table 11: Effect of Disasters on Migration Rates as a Function of Geographic Risk Exposure

Dependent variable = Migration rate

	Risk exposure: propensity score		Risk exposure: propensity score above median		Risk exposure: propensity score above percentile 75	
Severe disaster	-0.014	(0.015)	-0.017^{**}	(0.007)	-0.016^{***}	(0.005)
Risk Exposure * Severe disaster	-0.002	(0.057)	0.004	(0.009)	0.004	(0.011)
County FE	Y		Y		Y	
Decade FE	Y		Y		Y	
State FE* time trend	Y		Y		Y	
1930's population * time trend	Y		Y		Y	
Observations	24,000		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. We estimate risk exposure as a propensity sore based on geographic characteristics (column 1); we also generate dummies for counties with high risk exposure (columns 2, 3). Standard errors are clustered by state.

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

Appendix Table 12: Effect of Severe Disasters on Migration for Different Severity Thresholds, with County-Specific Trends

Dependent variable = Migration rate

Fatality Threshold	Severe Disasters: Coefficient	Severe Disasters: 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 was larger than 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 13: Effect of Disasters on Migration by Political Alignment

	Migration rate	
	Coefficient	Standard Error
Severe disaster	-0.014*	(0.008)
Severe disaster, same party	-0.002	(0.011)
Flood count	0.005	(0.004)
Flood count, same party	0.001	(0.004)
Storm count	-0.001	(0.002)
Storm count, same party	-0.000	(0.003)
Tornado count	-0.004	(0.006)
Tornado count, same party	0.003	(0.007)
Hurricane count	0.002	(0.003)
Hurricane count, same party	-0.016*	(0.009)
Fire count	-0.014***	(0.005)
Fire count, same party	0.003	(0.008)
Other disasters count	-0.038	(0.032)
Other count, same party	0.018	(0.034)
Exp. employment growth rate, 1930 weights	0.268***	(0.028)
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 (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. 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. Standard errors are clustered by state.

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

Appendix Table 14: IV Effect of Disasters on Migration for Different Definitions of Severity

Dependent variable = Migration rate

	IV			OLS	
Fatality Threshold	Coefficients	Standard Errors	F	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 imitates Table 2 of the paper but omit 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 were associated with more than 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 15: Effect of Disasters on County-Level Migration by Disaster Type Including droughts

	Migration rate
Severe disaster	-0.014***
	(0.005)
Flood count	0.006**
	(0.003)
Drought count	0.018
	(0.011)
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	0.266***
	(0.029)
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. Standard errors are clustered by state.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

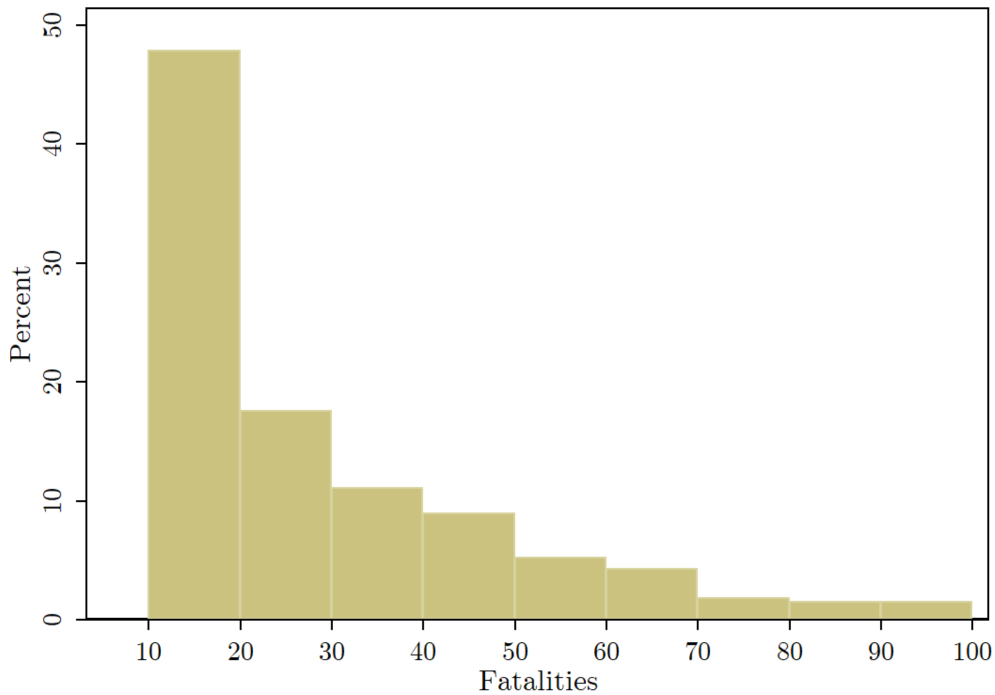
Appendix Table 16: Effect of Disasters on Poverty Rate and House Values for Different Definitions of Severity

Fatality Threshold	(1) House value (log median)		(2) House rent (log median)		(3) Poverty Rate	
10	-0.022	(0.016)	-0.007	(0.010)	0.005*	(0.003)
20	-0.038*	(0.019)	-0.016	(0.010)	0.007***	(0.003)
30	-0.053***	(0.017)	-0.026**	(0.012)	0.008***	(0.003)
40	-0.039**	(0.016)	-0.026**	(0.011)	0.008***	(0.003)
50	-0.042*	(0.021)	-0.021	(0.013)	0.010***	(0.004)
60	-0.034*	(0.020)	-0.008	(0.014)	0.007	(0.004)
70	-0.036*	(0.019)	-0.009	(0.014)	0.0062	(0.004)
80	-0.041**	(0.018)	-0.015	(0.012)	0.008*	(0.004)
90	-0.053**	(0.021)	-0.023	(0.014)	0.009*	(0.005)
100	-0.050**	(0.021)	-0.023	(0.015)	0.009*	(0.005)
200	-0.028	(0.022)	-0.016	(0.018)	0.008	(0.005)
500	-0.120**	(0.045)	-0.110**	(0.045)	0.034***	(0.012)

Notes: Each row corresponds to a separate regression hat 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 were associated with more than 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). Standard errors are clustered by state.

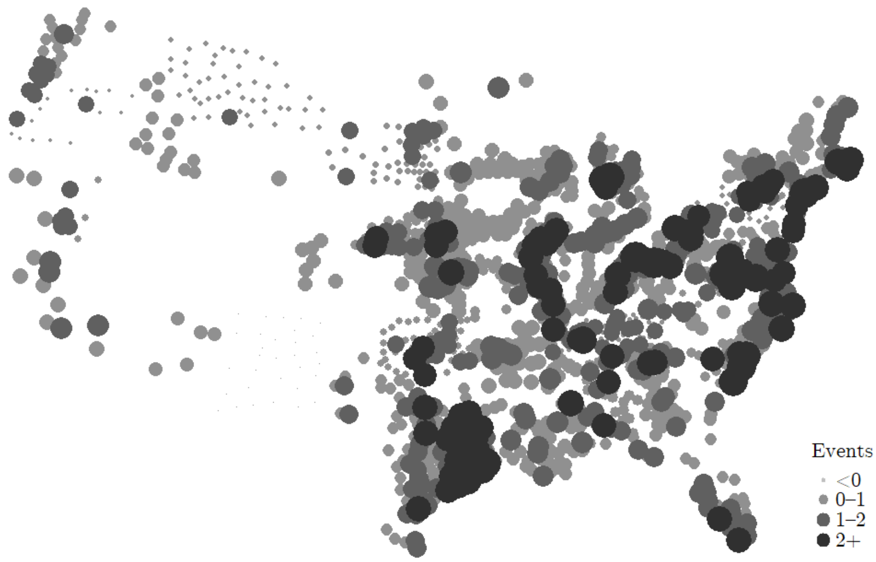
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figure 1: Histogram of Fatalities for Natural Disasters with more than 10 Deaths 1918–2012, by Data Source



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 1836. Source: EM-DAT. Disasters cross-verified with FEMA and ARC.

Appendix Figure 2: 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 to 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.