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THE EFFECT OF NATURAL DISASTERS ON ECONOMIC ACTIVITY IN US COUNTIES: A CENTURY OF DATA

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ABSTRACT

Major natural disasters such as Hurricanes Katrina and Sandy cause numerous fatalities, and destroy property and infrastructure. In any year, the U.S experiences dozens of smaller natural disasters as well. We construct a 90 year panel data set that includes the universe of natural disasters in the United States from 1920 to 2010. By exploiting spatial and temporal variation, we study how these shocks affected migration rates, home prices and local poverty rates. The most severe disasters increase out migration rates and lower housing prices, especially in areas at particular risk of disaster activity, but milder disasters have little effect.

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An online appendix is available at http://www.nber.org/data-appendix/w23410

I. Introduction

Major natural disasters such as Hurricanes Andrew, Katrina and Sandy cause numerous fatalities, and destroy private property and public infrastructure. As more economic activity clusters along America's coasts, the population is now at greater risk of exposure to natural disasters (Changnon et. al. 2000, Rappaport and Sachs 2003, Pielke et. al. 2005). Furthermore, climate science suggests that, as global greenhouse gas emissions increase, so too will the quantity and severity of certain types of natural disasters (IPCC 2012). This heightened disaster risk highlights the importance of having a better understanding of how natural disasters affect the economy.

In this paper, we study the universe of natural disasters in the United States from 1920 to 2010, from the most severe to the comparatively mild. By studying the full spectrum of such events, we can examine responses to both the *quantity* and *intensity* of natural disasters at the local level. Our unit of analysis is a US county. We assess whether counties that faced disasters lost population through net out-migration and experienced rising poverty rates, perhaps because of selective out-migration of the non-poor. We also ask whether population outflows were accompanied by falling housing prices and rents.

With access to disaster counts for almost a century, we are able to include a rich set of controls, including county fixed effects and state-specific time trends, which absorbs many attributes of disaster-prone areas on the coasts or in the flood plain of large rivers. We also control directly for changes in local labor demand by predicting employment growth using a county's baseline industrial structure interacted with national growth trends (the standard Bartik measure).

One of our paper's empirical contributions is to create a new long-run disaster data base at the county level in the United States spanning from 1920 to 2010. We combine data from the American Red Cross (ARC, 1920-64) and the Federal Emergency Management Agency and its predecessors (FEMA, 1950-2010). The mean county in our dataset faced two disasters in a typical decade, with floods being the most common event type followed by storms and hurricanes. In each decade, one in three counties experienced a severe disaster (with 10 or more deaths) and one in ten counties experienced a super-severe disaster (with 100 or more deaths).

We find that a one standard deviation increase in disaster count (2.4 disasters) heightens the out-migration rate from a county by 1 percentage point (5 percent of a standard deviation). The strongest migration response is to volcanos, hurricanes and forest fires. The effect of one super-severe disaster is twice as large as the response to the average disaster. The migration response to the most severe natural disasters is on the same order of magnitude as the effect of a one standard deviation increase in predicted employment growth. Poverty rates also increase in areas hit by super-severe disasters, which is consistent with out-migration of the non-poor, in-migration of the poor (perhaps in response to lower housing prices), or a transition of the existing population into poverty.

The migration response to disasters varies over the century and across locations. Of particular interest is how the 1978 advent of FEMA, which coordinated the federal response to natural disasters, may have influenced the likelihood of out-migration following a disaster event. One might expect that residents would be less likely to move out of disaster-struck areas after the creation of FEMA, if FEMA increased payments of federal disaster relief. This "moral hazard" effect has been extensively discussed in the popular media and has been the topic of some academic study (e.g., Gregory, 2014). Yet, we find that, if anything, out-flows in response to natural disasters were higher in recent decades, despite the advent of FEMA, perhaps because disaster events have been worsening in frequency over time. This pattern is also consistent with Deryugina's (2016) observation that transfer payments following disasters come mainly in the form of unemployment insurance and other non-place-based programs. It appears that many people in disaster affected areas take the money and move to another county.

Due to exogenous variation in geography, topography and climate conditions, counties differ with respect to their risk of natural disaster events. For example, coastal areas or areas in the flood plain of a river are more at risk of experiencing a natural disaster, whereas areas at higher elevation are at lower risk. We test whether migration rates are more responsive to disasters in areas that are less prone to experience them. One theory is that natural disasters have higher salience in "low risk" areas and residents are caught off guard when experiencing a shock that they were not prepared for. An alternative theory posits that since migration is a long run investment, it makes sense to migrate away from areas that have been shocked if such shocks are expected to be persistent over time. A forward-looking migrant will recognize that such areas are likely to suffer again and thus the long run present discounted value of benefits of remaining there is lower (Sjaastad 1962). Consistent with the second view, we find that net outmigration rates are higher in areas that are prone to suffer disasters when such areas experience a very severe shock.

Our work contributes to two strands of the climate and environmental economics literatures. 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, Galiani and Pantano 2013; Anttila-Hughes and Hsiang 2013; Hsiang and Jina 2014; Burke, Hsiang and Miguel 2015;

Kocornik-Mina et. al., 2015). By analyzing the effect of natural disasters in a single country over many decades, we are able to hold constant many core institutional and geographic features of the economy that may be correlated with disaster prevalence in a cross-country setting (e.g., democracy, temperate climate). The closest paper to ours in this respect is Strobl (2011), which uses a county-level panel of coastal US counties to study how hurricanes affected local economic growth during the years 1970 to 2005. A second set of papers uses case studies of specific major disasters to examine how shocks to a geographic area affect existing residents (see, for example, Smith and McCarty 1996 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 and Deryugina, Kawano and Levitt 2014 on Hurricane Katrina; Frankenberg et. al. 2011 examine the consequences of the Indian Ocean tsunami). While it is important to study these major cases, most disasters are not as severe as these notable outliers. Our data collection allows us to examine a much larger set of disasters, which includes – but is not limited to – some of the major disasters listed above.

Throughout this paper, we view local labor demand shifts and natural disasters as shocks to the underlying spatial equilibrium. We thus start by discussing an augmented Rosen/Roback spatial equilibrium model to introduce such shocks. We then present our estimating equation and core hypotheses, our data and our main results.

II. Natural Disaster Risk in a Static Spatial Equilibrium Model

In the simplest version of the spatial equilibrium model, all people have the same preferences over private consumption and local public goods and face zero migration costs (Roback 1982). Geographic areas differ by one exogenous attribute such as winter temperature. From this local variation, a hedonic rental price equilibrium arises mapping out the representative agent's indifference curve between private consumption and (say) outdoor 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 counties are at risk of experiencing two types of shocks: shifts in local labor market demand and the occurrence of natural disasters. In each decade, some counties enjoy an increase in local labor demand, while others face declining local labor demand. Furthermore, some counties experience a natural disaster, while others do not.

An increase in local labor market demand will lower unemployment risk and raise local wages. This positive shock should attract migrants to the area (Topel 1986). In contrast, the occurrence of a natural disaster will decrease the local amenity level – for example, by imposing some extra mortality risk. All else equal, such natural disasters should push people to leave and discourage outsiders from moving in. In an economy featuring durable local housing, the housing supply will be inelastic and this means that a downward shock to local quality of life will depress local home prices (Glaeser and Gyourko 2005). Lower home prices act to anchor the poor as their real purchasing power increases as rents decline. We thus predict that areas that are routinely hit by natural disasters will experience out migration but such migration will be slowed down by declining home prices and this will shift the area's composition such that a larger share of the residents are poor.

III. Econometric Framework

In our main regression specifications, we study how economic activity changes in response to the quantity and severity of natural disasters. Our unit of analysis will be a county/decade and the data will cover the decades 1930 to 2010. We measure economic activity using dependent variables such as a county's net migration rate, poverty rates and home prices/rents. A second set of results then tests for heterogeneous responses to natural disasters. For example, we test if high amenity or high productivity places experience more/less negative effects when disasters occur. We further explore whether the effects of disasters differ by disaster category (floods, hurricanes, etc.) and whether these relationships are stable over time.

Our main specification is an unweighted regression, in which each county contributes equally to the estimation. This approach considers each county to be a separate place that may be subject to a location-specific shock in a given period. Our interest then is in observing how these places are affected by (and potentially recover from) local shocks. In this way, our main specification corresponds to the cross-country regressions common to the climate economics literature. For completeness, we also present results weighted by a county's population in the year 1930 (see Web Appendix). This specification puts more weight on disasters that take place in heavily populated urban areas.

Define county i in State Economic Area (SEA) z in state j in decade t. Our core econometric results will be based on estimating equation (1).[1]

$$Y_{ijzt} = \mu_i + \xi_t + \pi_j * Time\ Trend_{jt} + B_1 * Disasters_{ijzt} + B_2 * Bartik_{ijzt} + U_{ijzt} \quad (1)$$

In this equation, Y represents a set of dependent variables that includes a county's migration rate, housing prices/rents, and the poverty rate. We include county and decade fixed effects and state specific time trends. Disasters is a vector of the quantity and severity of disasters in a local area. We discuss this vector in depth after we introduce our disaster data. The variable 'Bartik' is an estimate of employment growth in county i during the period t-10 to t using initial industrial composition to weight national employment trends. This is the standard proxy for exogenous shifts in local labor demand introduced by Bartik (1991) and Blanchard and Katz (1992). This variable's construction is presented in equation (2). U is the error term and it is clustered at the county group (SEA) level. We report results collapsed to the SEA level in the Web Appendix.

$$Bartik_{ijzt} = \frac{\sum_{Ind=1}^{I}[\,PEOPLE_{\{i,1930,ind\}} * NGR_{\{t,ind\}}]}{PEOPLE_{\{i,1930\}}} \quad (2)$$

Equation (2) provides the formula for our Bartik measure. We weight the national growth rate (NGR) in employment in industry I for decade t by the share of people in county i who worked in this industry in the base year (1930).

[1] SEAs are either single counties or groups of contiguous counties within the same state that had similar economic characteristics when they were originally defined, just prior to the 1950 census (Bogue, 1951). https://usa.ipums.org/usa-action/variables/SEA#description_section.

IV. Data

Natural Disasters

Creating a consistent data set of natural disasters at the county level over the twentieth and the early twenty-first centuries requires combining data from several sources. The list of "major disaster declarations" posted by FEMA and its predecessors begins in 1964 (https://www.fema.gov/disasters). We supplement the FEMA roster with information published in the *Federal Register* back to 1958 and with archival records back to 1950s.[2] For each disaster, we recover the geographic location (county), disaster type, and month and year of occurrence. We expand our coverage back to 1918 by using data from the disaster relief efforts of the American National Red Cross (ARC). These efforts are documented in their *Annual Reports* and in various versions of the ARC's ""List of Disaster Relief Operations by Appropriation Number,", held in Record Group 200 at the National Archives in College Park, MD.[3] We link these lists with the ARC's case files to document the date, type, and location of each disaster.[4] We identify the larger-scale disasters using the ARC's *Circulars*, which were published from the early 1920s on whenever the ARC engaged in major relief efforts.

Our dataset includes the following set of natural disasters: floods (including tidal waves), storms, hurricanes, tornadoes, earthquakes, volcanic eruptions, droughts and other natural disasters such as forest fires, extreme temperatures and landslides. All human-related disasters

[2] Specifically, 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 i (Record Group 397) held in the National Archives at College Park, Maryland. The "State Disaster Files" in RG 396, Boxes 1-4 were especially used.
[3] See Record Group 200, Records of the American National Red Cross, 1947-1960, Boxes 1635-37, held in the National Archives at College Park, Maryland
[4] 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.

such as mine collapses, explosions, transportation accidents and arsons are excluded from the analysis.

In addition to counting the number of declared disasters in an area, we also rank disasters by fatalities, one measure of their intensity. Death counts for most severe disasters in the United States are available from EM-DAT, the International Disaster Database, which was created by the Centre for Research on the Epidemiology of Disasters (CRED). (See http://www.emdat.be/ for details.) The EM-DAT lists the date, type, location, and death tolls of all major natural disasters over the twentieth and twenty-first centuries.[5] Although EM-DAT has coverage back to 1900, its historical data is less comprehensive. We supplement EM-DAT with information on death counts from the American Red Cross for earlier years.

With these data in hand, we create four measures of the frequency and intensity of disasters in a county/decade. We start by simply counting the number of declared disasters in an area. We then include two indicators of disaster intensity, the first equal to one if a natural disaster led to ten or more deaths ("severe") and the second equal to one if the disaster resulted in 100 or more deaths ("super-severe"). Finally, we code a dummy variable equal to one if the county experienced *any* disasters in a decade. We observe that sparsely populated places have few recorded disasters (see, for example, the Mountain West in Figure 2), presumably because disaster declarations are based not only on the severity of a storm but also on the number of people likely affected. This indicator is an important control given that there was net migration away from these unpopulated places over time.

[5] To be included in EM-DAT, disasters must fit at least one of the following criteria: ten or more reported deaths, one hundred or more people reported affected, declaration of a state of emergency, or call for international assistance.

Figure 1 displays annual counts of disaster events at the disaster-by-county level from 1920-2010. By this measure, a disaster that affects multiple counties would be tallied multiple times, and a county that is struck by more than one disaster in a given year would also count more than once. The first half of the time series records data from the American Red Cross (1920-64), while the second half includes data from FEMA and its predecessors. From 1920-1980, around 500 separate county-disaster events took place in a given year. From 1980 to the present, and especially after the early 1990s, there has been a clear acceleration in disaster counts, reaching around 1,500 county-level events per year by the 2000s.

Our reading of the evidence is that some of this acceleration is capturing a real increase in the underlying frequency of storms. An uptick in disaster events is evident in comparable global series as well, suggesting that we are not merely picking up a change in US government policy toward disaster relief (see Munich Re, 2012; Gaiha, et al., 2013; Kousky 2014). Yet, we also suspect that the federal government became more expansive in the declaration of disaster events after Hurricane Andrew, which was notably destructive and especially salient, given that it took place during the 1992 presidential election campaign (Salkowe and Chakraborty 2009). Political science research has investigated the determinants of FEMA disaster declarations. Garrett and Sobel (2003) and Downton and Pielke (2001) find that the president and Congress affect the rate of disaster declaration and the allocation of FEMA disaster expenditures across states. States politically important to the president have a higher rate of disaster declaration, and disaster expenditures are higher in states having congressional representation on FEMA oversight committees and during election years. Garrett and Sobel suggest that nearly half of all disaster relief is motivated politically rather than by need.

Figures 2-4 present maps of the spatial distribution of the count of total disasters, severe disasters and super severe disasters. 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. As we emphasized earlier, there are comparatively few disasters in the West, with the exception of California, which is affected primarily by droughts and fires. The paucity of disaster declarations in the Mountain West, as noted above, suggests that having a disaster declaration is correlated with county population. Severe and super-severe disasters, mapped in Figures 3 and 4, follow similar geographic patterns but are less common than the typical disaster in California or the Midwest. The geographic location of disaster events suggests that disasters are strongly spatially correlated. This high degree of collinearity between a county's disaster indicators and those of its adjacent counties implies that we cannot test hypotheses about cross-elasticities between locations – namely, that we might expect in-migration to a place when a nearby county suffers a disaster.

To address spatial correlation in disaster events, we create a weighted index of disaster prevalence that puts more weight on disasters that occur in county *i* but also puts some weight on those that occur in "nearby" counties *l*. Proximity is measured according to the weighting function $weight_{il}$ defined in equation (4).[6]

$$Disaster\ Index_{ijt} = .75 * Disaster_{it} + .25 * \sum_{l=1}^{M} weight_{il} * Disaster_{lt} \qquad (3)$$

$$weight_{il} = \frac{\frac{1}{(distance\ from\ i\ to\ l)^{.5}}}{\sum_{l=1}^{M} \frac{1}{(distance\ from\ i\ to\ l)^{.5}}} \qquad (4)$$

[6] We do not impose a distance cutoff in defining neighboring counties. For each county *i*, we calculate the distance from its centroid to the centroid of every other county *l*.

The weights in equation (4) add up to one and the resulting index in equation (3) varies between 0 and 1. An index value equal to zero means that neither the county itself nor its neighbors experienced a natural disaster in that decade. The Web Appendix reports results based only on the count of disasters occurring in own county i. We follow the procedure described above for each of our disaster variables.

Migration

We obtain age-specific net migration estimates for US counties from 1950-2010 from the University of Wisconsin-Madison and from 1930-50 through ICPSR. 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 likely mortality. 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.

Other Data

The county-by-decade prediction of employment growth in equation (2) is constructed by first calculating employment shares by industry in a base year (1930), and then using these share to weight national rates of employment growth by industry and decade. Our measure relies on individual data on employment in 143 industries in the IPUMS dataset using the standardized 1950-based industries codes. We also use data on poverty rates and house values/rents (1960-2000/1970-2010) by county from NHGIS. The geography variables used in our prediction of local disaster risk, such as elevation and distance to the coast, are from Fishback et. al. (2006). We classify counties into "good" and "bad" weather areas (our measure of local amenities) using an index comparing average January and July temperatures from NOAA.[7]

V. Results

We begin in Table 1 by reporting summary statistics for our sample of nearly 25,000 county-by-decade level observations. The typical county in our sample had 1.97 declared disasters in a decade, with the most common disasters being storms (0.79), floods (0.49) and hurricanes (0.31). Three out of ten counties experience a severe disaster, while one out of ten experience a super-severe disaster. One percent of the population, or around 2,000 residents, left the average county in a decade, but there is substantial variation around this mean. Table 1 also reports summary statistics for poverty rate and housing values.

Each local disaster declaration is associated with a small increase in net out-migration at the county level, with a substantially larger effect of super-severe disasters. Table 2 reports our main estimates of equation (1). Each declared disaster increases net out-migration by 0.5 percentage points (2.5 percent of a standard deviation). There is no additional effect on out-migration if a disaster is considered severe (10 or more deaths). But a super-severe disaster (100 or more deaths) has a much larger effect on population loss, increasing net out-migration by almost 3 percentage points (15 percent of a standard deviation).[8] For comparison, our estimates

[7] Our good weather index is: [mean average daily January temperature/standard deviation – mean average daily July temperature/standard deviation]. We classify counties as being "good weather" areas if their index value is above the median.

[8] We also control for an indicator equal to one in counties that faced at least one disaster in the decade. We find net in-migration to counties that had at least one declared disasters, perhaps counties with no

suggest that a one standard deviation decline in the estimated employment growth in a county would increase out-migration by 3 percentage points (= -0.12 x 0.276). Experiencing one super-severe disaster is as disruptive to a local population as a large negative employment shock. The Web Appendix reports results for the subsample of young men, who tend to be more mobile, and implied effects (in standard deviation terms) are similar.

We note that our estimates are net effects of a 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 Web Appendix).[9]

Changing Migration Response to Disaster Events over Time

From the 1920s through the 1950s, the federal government 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. During the 1970s, Washington coordinated its response to disaster events, first by creating the Federal Disaster Assistance Administration in 1973 under the Department of Housing and Urban Development and then by

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disasters tended to be sparsely populated and population has been moving away from rural areas over time. Excluding this indicator does not affect the coefficient on super-severe disasters, but does bias the coefficient on disaster count toward zero.

[9] 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.

creating an independent agency, the Federal Emergency Management Agency (FEMA) in 1978. In Table 3, we test for a difference in the migration response to disaster events that occur before and after these policy changes. If FEMA increased the federal disaster relief available in a county, we might expect the net out-migration to decline as residents are anchored to an area by receipt of federal funds. However, we note that the intensity of disaster activity increased over time, especially after 1990, in part due to environmental change (Figure 1), and so it is hard to disentangle the effects of policy change from the environment.

Table 3 documents that there was little migration response to disasters before 1980. The main results for the century presented in Table 2 are primarily picking up the heightened out-migration response to disaster events after 1980. In this period, each disaster increased net out-migration from a county by 1 percentage point, although this outflow was mitigated in the case of severe disasters. Each super-severe disaster increased out-migration by 4 percentage points. 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.

Our finding that the establishment of FEMA did not anchor residents in place is consistent with Deryugina (2011), which documents that counties struck by hurricanes in the 1980s and 1990s received around $1,000 (2008 dollars) per capita in additional federal transfers 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.

Heterogeneous Migration Responses to Disaster Events

Low Risk vs. High Risk Areas

The remainder of the paper explores heterogeneous responses to disaster events by disaster risk, disaster type, urban status, amenity level and racial composition. We start by considering whether disasters have a differential effect on economic outcomes in areas that face higher disaster risk given their local geography and climate. We create a propensity score measuring the likelihood that county *i* suffers a severe natural disaster in decade *t*. In particular, we estimate a linear probability model using exogenous geographical and topographical attributes included in the vector Z and use this regression to predict the county-specific propensity score $p(Z_j)$.[10]

$$Severe\ Natural\ Disaster\ Dummy_{ijt} = \mu_t + B_1 * Z_{ijt} + e_{ijt} \qquad (5)$$

In Table 4, we interact this regressor with the indicators for severe and super-severe disasters. Recall that the level of *p(Z)* is captured by the county fixed effects. We find evidence of greater out migration from areas that suffer extreme natural disasters (either severe or super-severe) if these areas are at a higher propensity for disaster events. This pattern suggests that migrants respond more to a given shock in areas with geography prone to such shocks, such as low elevation areas on a coastline or in a river plain. This pattern might arise because current shocks are more likely to predict future shocks in areas that are prone to disaster activity. We do not find evidence consistent with the idea that residents of high-risk areas anticipate such events

[10] In the Web Appendix, we present the first stage regression for creating the propensity score. The major predictors of a severe disaster are proximity to a coast or a river, or being at low elevation.

and thus invest in effective disaster prevention, such as moving out of mobile homes or retro-fitting their house for earthquake safety (see, for example, Lim, 2016 on tornadoes).

Productive Places and Areas with High Amenity Levels

Areas with strong productivity fundamentals should be more easily able to rebound from natural disasters than local economies that are otherwise waning. During the twentieth century, urban and metropolitan areas were gaining population and economic activity at the expense of rural areas. We thus expect that natural disasters that hit these less-productive rural counties may have larger effects on the net out-migration rate than similar disasters that strike more populated counties.

We construct two definitions of urban/metropolitan counties to apply throughout the century. The first definition contains all counties that were part of a metropolitan statistical area in 1970. The second definition instead includes all counties with a population density greater than the national median in 1930.

We find that the effect of disaster events on net out-migration is two to three times as large in rural counties than in their urban counterparts. Table 5 reports results that split the sample according to the first definition; a similar table using the second definition is included in the Web Appendix. This finding is consistent with Feng, Oppenheimer and Schlenker (2012) who find significant out-migration from rural counties in the Corn Belt following climate-driven drops in crop yields and with Cattaneo and Peri (2015), who find that higher temperatures due to global warming increase emigration rates from rural to urban areas in middle income economies.

Following the same logic, we expect less outflow in response to a given natural disaster that strikes an area that is otherwise attracting population due to high levels of local amenities.

One local amenity that unambiguously attracted population over the twentieth century was pleasant weather (Gyourko and Tracy, 1991; Gyourko, Kahn and Tracy, 1999). Table 6 splits the sample into counties that are above and below the median on a "good weather" index. We find no significant difference in the response to severe or super-severe disasters by local climate. If anything, and contrary to our reasoning, it appears that residents are *more* likely to move away from good weather areas for a given number of mild disaster events. However, this differential responsiveness to mild disasters is driven by the composition of disaster types in good and bad weather areas. Good weather counties are more likely to face hurricanes and disasters in the "other" category (landslides, forest fires), which have the strongest effect on out-migration (see Table 8 below). The Web Appendix includes a version of Table 6 that separately controls for event counts by disaster type.

Blacks vs. Whites

In the early twentieth century, the majority of blacks lived in the rural South, many in the flood plain of the Mississippi River. More than half of southern blacks moved to other regions, particularly in the years 1940 through 1970 (Boustan, 2017). Hornbeck and Naidu (2014) examine the impact of the Great Mississippi Flood of 1927 and find that flooded counties experienced an immediate and persistent out-migration of black population. However, it is hard to draw inferences on black migration response to natural disasters from one extreme event alone. In Table 7, we report results separately for whites and blacks. Although the coefficients are not individually statistically significant, it appears that the black migration response to total disaster count and to extreme disaster events is substantially larger than the white response.

Disaster Category

Certain disaster types have much stronger effects on out-migration than others. In Table 8, we break out the disaster count variable by category. The overall effect of disasters on migration activity – a 0.5 percentage point increase in net out-migration – is a weighted average of more and less destructive disaster types. The migration response is strongest to volcanic eruptions, hurricanes, and the "other" disaster category, which includes forest fires and landslides. Storms also encourage net out-migration. On the other hand, and surprisingly, tornados and earthquakes appear to have no effect on mobility flows, and floods actually encourage some net in-migration. The pattern for floods is consistent with our earlier work, in which we found that migrants moved toward counties that experienced floods in the 1920s and 1930s (Boustan, Kahn and Rhode, 2012). We posited that areas prone to flooding received new infrastructure in this period, which may have encouraged new use of previously marginal land. However, it appears that in-migration to flooded areas continued throughout the century. Furthermore, the positive effect of flooding on in-migration is present even when we control for the construction of new dams during the decade. We also note that migrants are very strongly attracted to areas experiencing drought. Drought are associated with low precipitation and higher-than-average temperatures, two amenities that attract residents (even if they may be detrimental for local agriculture).

Measuring the Impact of Disasters on Home Prices and Poverty Rates

If natural disasters encourage net out-migration from a county, lowering demand for the area, we would expect an associated effect of disaster activity on housing prices and rents (see

Hallstrom and Smith 2005). In rare cases, disasters also destroy a substantial portion of the housing stock, in which case the effect on housing prices would be ambiguous. The first two columns of Table 9 analyze the effect of disasters on median housing values and monthly rents in a county. The total number of declared disasters has no effect on local housing prices and rents, despite encouraging a mild amount of net out-migration. Yet, the occurrence of a super-severe disaster lowers housing prices by 6 percent and rents by 3 percent. The implied elasticity of housing prices with respect to population loss – a 3 percent decline in rents for out-migration representing 2 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).

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 protective strategies ranging from owning a second home, to accessing better quality medicine, food and 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.). If the rich are more likely to leave an area after a disaster, net out-migration may serve to increase the local poverty rate. We test this hypothesis in the third column of Table 9. While each declared disaster slightly reduces area poverty, the occurrence of a super-severe disaster increases the local poverty rate by 1.1 percentage points (13 percent of a standard deviation).

VI. Conclusion

During the past century, the United States has experienced more than 5,000 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.

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 to live in an area due to persistent natural disasters leads to falling rents and acts as a poverty magnet. This dynamic is particularly apparent in areas that face high disaster risk or that lack other productivity advantages. Glaeser and Gyourko (2005) documented a similar spiral in declining cities (i.e., Detroit). In their setting, the cause of declining housing demand was a persistent decline in local labor demand following the contraction of the US auto industry.

Our estimate of the average effect of super-severe disasters (those with 100 or more deaths) on out-migration is much lower than estimates arising from case studies of the nation's most extreme events. We find a 3 percentage point increase in net out-migration in disaster struck counties, which is substantially lower than the 12 point increase in out-migration from New Orleans after Hurricane Katrina (Deryugina, et al., 2014); the 12 point increase in the out-migration rate from flooded counties in the 1927 flood (Hornbeck and Naidu, 2014); and a 12 percent reduction in the population of counties facing high erosion during the Dustbowl (Hornbeck 2012; Long and Siu 2016).

In recent years, two independent literatures have emerged studying the population responses to large local shocks, including natural disasters and war-time bombing. Population appears to quickly recover after an area is bombed (Davis and Weinstein 2002; Brakman, Garretsen and Schramm 2004; Miguel and Roland 2011, but see also Schumann, 2014). Yet war and natural disasters differ in their expected persistence. Coastal areas and flood plains are shocked again and again by natural disasters, whereas, in the case of war, the shocks end with a peace treaty and investors can invest with confidence. The expectation of future shocks in areas hit by natural disasters raises the likelihood of disinvestment both in terms of labor and capital from such increasingly vulnerable areas. Whether the federal government seeks to counter such a trend through local stimulus, and what are the equilibrium impacts on labor and capital flows remains an open question.

VII. References

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Table 1: Descriptive Statistics

	Mean	Std.Dev.	N
Total population	62713	219101	24432
Population (black share)	0.110	0.180	24432
Migration rate	-0.010	0.200	24432
Migration rate (black)	0.700	6.230	20580
Migration rate (white)	-0.010	0.200	21378
Flood count	0.410	0.790	24432
Storm count	0.710	1.580	24432
Hurricane count	0.290	0.890	24432
Tornado count	0.150	0.460	24432
Earthquake count	0.000	0.060	24432
Volcano count	0.000	0.040	24432
Drought count	0.080	0.290	24432
Other disasters (count)	0.100	0.550	24432
Any flood	0.280	0.450	24432
Any storm	0.280	0.450	24432
Any hurricane	0.160	0.370	24432
Any tornado	0.120	0.330	24432
Any earthquake	0.000	0.060	24432
Any volcano	0.000	0.040	24432
Any drought	0.080	0.270	24432
Any other	0.060	0.230	24432
Disaster count	1.750	2.350	24432
Any disaster	0.610	0.490	24432
Severe disaster (dummy)	0.290	0.450	24432
Super-severe disaster (dummy)	0.100	0.300	24432
Fatalities count (>=10)	262	602	7091
Disaster count [weighted]	1.750	2.090	24432
Severe disaster dummy [weighted]	0.290	0.380	24432
Super-severe disaster dummy [weighted]	0.100	0.240	24432
Expected employment growth rate, 1930 weights	0.040	0.120	24408
Expected employment growth rate, 1970 weights	0.290	0.220	24320
Poverty Rate	0.170	0.080	15222
Median House Value ($)	45603	39233	12131
Median House Rent ($)	192.13	136.49	12130
Good Weather Index	-6.650	0.680	20992

Black migration rates available for all decades except 1980. Unless clarified by [weighted], all disaster variables are county-specific and not weighted. When clarified, the weighted disaster variables are computed as described in equation (3). Expected employment growth rates are computed using equation (2). The Good Weather Index is defined in footnote 5.

Table 2: Effect of Disasters on Migration

	(1) Migration rate
Super-severe disaster	-0.0228**
	(0.00889)
Severe disaster	0.00416
	(0.00594)
Disaster count	-0.00434***
	(0.00165)
Disaster count >=1	0.0104**
	(0.00525)
Exp. employment growth rate, 1930 weights	0.276***
	(0.0229)
Observations	24408
R^2	0.523

This table reports our main estimates of equation (1). We study the migration of the entire population. Regressions include decade and county fixed effects, as well as state-specific time trends. All disaster variables are computed as shown in equation (3). Standard errors clustered at the SEA level.

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

Table 3: Effect of Disasters on Migration Before and After 1980

	(1) Migration rate
Super-severe disaster	-0.000337
	(0.0130)
Super-severe disaster, Post 1970	-0.0411**
	(0.0182)
Severe disaster	-0.00950
	(0.0104)
Severe disaster, Post 1970	0.0252*
	(0.0139)
Disaster count	0.00424
	(0.00312)
Disaster count, Post 1970	-0.0120**
	(0.00479)
Disaster count >=1	0.00429
	(0.00633)
Disaster count >=1, Post 1970	-0.0151
	(0.0109)
Exp. employment growth rate, 1930 weights	0.271***
	(0.0224)
Observations	24408
R^2	0.525

Regressions include decade and county fixed effects, as well as state-specific time trends. All disaster variables are computed as shown in equation (3). Standard errors clustered at the SEA level.

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

Table 4: Effect of Disasters on Migration as a Function of Geographic Risk Exposure

	(1) Migration rate
Super-severe disaster	0.0274
	(0.0442)
Propensity score * Super-severe disaster	-0.116
	(0.131)
Severe disaster	0.0567^{***}
	(0.0168)
Propensity score * Severe disaster	-0.176^{***}
	(0.0581)
Disaster count	-0.00372^{**}
	(0.00157)
Disaster count >=1	0.00937^{*}
	(0.00507)
Exp. employment growth rate, 1930 weights	0.268^{***}
	(0.0233)
Observations	24000
R^2	0.527

Regressions include decade and county fixed effects, as well as state-specific time trends. All disaster variables are computed as shown in equation (3). Propensity score based on actual incidence of severe disasters. Severe disaster and its propensity score interaction are jointly significant (F-statistic=6, p-value = 0.0022). The same goes for super-severe disasters (F-statistic=3.5, p-value = 0.0245).

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

Table 5: Effect of Disasters on Migration in Urban versus Rural Areas

	Urban Migration rate	Rural Migration rate
Super-severe disaster	-0.0129*	-0.0552**
	(0.00746)	(0.0255)
Severe disaster	0.00104	0.00748
	(0.00541)	(0.0132)
Disaster count	-0.00427***	-0.00930
	(0.00127)	(0.00582)
Disaster count >=1	0.0143***	0.0111
	(0.00469)	(0.0118)
Exp. employment growth rate, 1930 weights	0.290***	0.118**
	(0.0249)	(0.0504)
Observations	18328	6080
R^2	0.557	0.505

Column (1) focuses on urban counties, while column (2) focuses on rural counties. Rural areas defined as counties with below-p(25) population in 1930. Regressions include decade and county fixed effects, as well as state-specific time trends. All disaster variables are computed as shown in equation (3). Standard errors clustered at the SEA level.

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

Table 6: Effect of Disasters on Migration - Good versus Bad Weather Areas

	(1) All	(2) Good weather	(3) Bad weather
Super-severe disaster	-0.0241**	-0.0186	-0.0227*
	(0.0101)	(0.0130)	(0.0117)
Severe disaster	0.00352	-0.00489	0.00757
	(0.00621)	(0.00925)	(0.00652)
Disaster count	-0.00538***	-0.00924***	-0.00197
	(0.00173)	(0.00271)	(0.00161)
Disaster count >=1	0.0125**	0.0191**	0.00369
	(0.00536)	(0.00873)	(0.00548)
Exp. employment growth rate, 1930 weights	0.270***	0.257***	0.284***
	(0.0246)	(0.0311)	(0.0380)
Observations	20976	10488	10488
R2	0.512	0.485	0.522

Column (1) focuses on all counties that have weather information. Column (2) focuses on counties that experience good weather, while column (3) focuses on counties that experience bad weather. Good weather areas are defined as counties with above median score in their good weather index, computed as: winter average temperature in year 2000 divided by its standard deviation cross-county, minus summer average temperature in year 2000 divided by its standard deviation cross-county. Regressions include decade and county fixed effects, as well as state-specific time trends. The first three disaster variables are computed as shown in equation (3). Standard errors clustered at the SEA level.

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

Table 7: Effect of Disasters on Migration by Race

	(1) Migration rate (black)	(2) Migration rate (white)
Super-severe disaster	-0.0911	-0.0203*
	(0.195)	(0.0117)
Severe disaster	-0.0948	-0.000794
	(0.221)	(0.00661)
Disaster count	0.0524	-0.00450**
	(0.0665)	(0.00193)
Disaster count >=1	-0.323	0.0147**
	(0.258)	(0.00662)
Exp. employment growth rate, 1930 weights	1.132**	0.273***
	(0.575)	(0.0228)
Observations	20567	21357
R^2	0.179	0.472

In column (1) we study migration patterns for blacks and in column (2) we focus on whites. Regressions include decade and county fixed effects, as well as state-specific time trends. All disaster variables are computed as shown in equation (3). Migration by race is not available in 1980. Standard errors clustered at the SEA level.

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

Table 8: Effect of Disasters on Migration by Disaster Type

	(1)
	Migration rate
Flood count	0.00393*
	(0.00230)
Storm count	-0.00262**
	(0.00115)
Tornado count	0.00153
	(0.00330)
Hurricane count	-0.0129**
	(0.00566)
Drought count	0.0184**
	(0.00784)
Volcano count	-0.0373**
	(0.0157)
Earthquake count	-0.00522
	(0.0282)
Other disasters (count)	-0.0139***
	(0.00467)
Disaster count >=1	-0.00270
	(0.00507)
Exp. employment growth rate, 1930 weights	0.272***
	(0.0227)
Observations	24408
R^2	0.525

We study the migration of the entire population. Regressions include decade and county fixed effects, as well as state-specific time trends. These disasters are not computed using equation (3). Standard errors clustered at the SEA level.

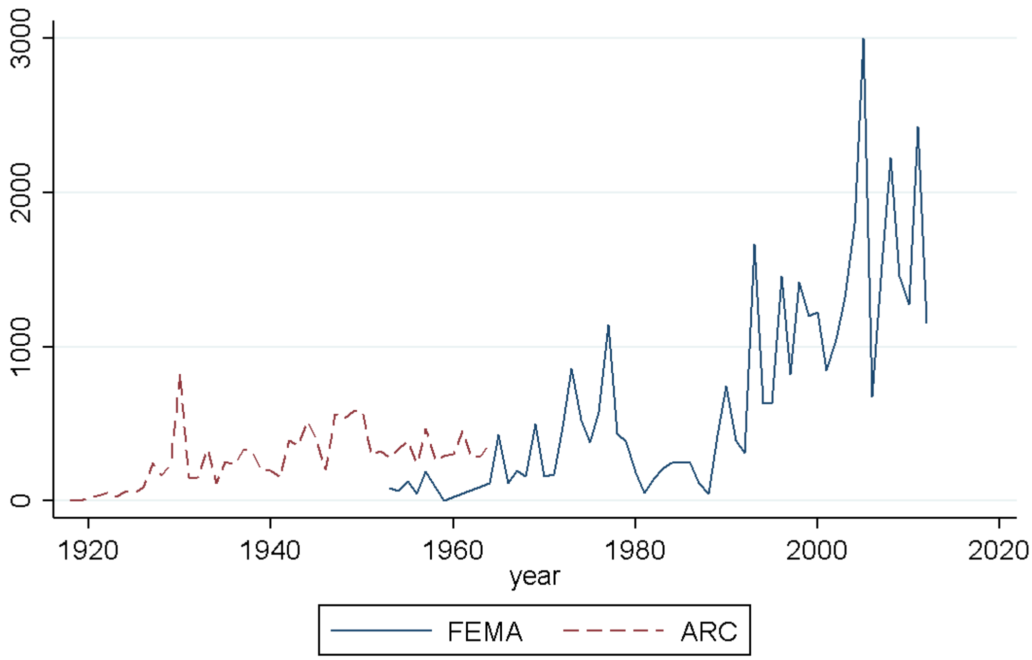
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effect of Disasters on Poverty Rate and House Values

	(1) House value (log median)	(2) House rent (log median)	(3) Poverty Rate
Super-severe disaster	-0.0669***	-0.0370***	0.0111***
	(0.0154)	(0.0109)	(0.00321)
Severe disaster	-0.0148	-0.00136	0.00312
	(0.0131)	(0.00948)	(0.00231)
Disaster count	0.000182	0.000776	-0.00103**
	(0.00237)	(0.00194)	(0.000513)
Disaster count >=1	0.00913	0.0111	-0.00236
	(0.00936)	(0.00780)	(0.00191)
Exp. employment growth rate,	0.243**	0.219**	-0.148***
1970 weights	(0.109)	(0.0936)	(0.0214)
Observations	15154	15152	15152
R2	0.977	0.974	0.870

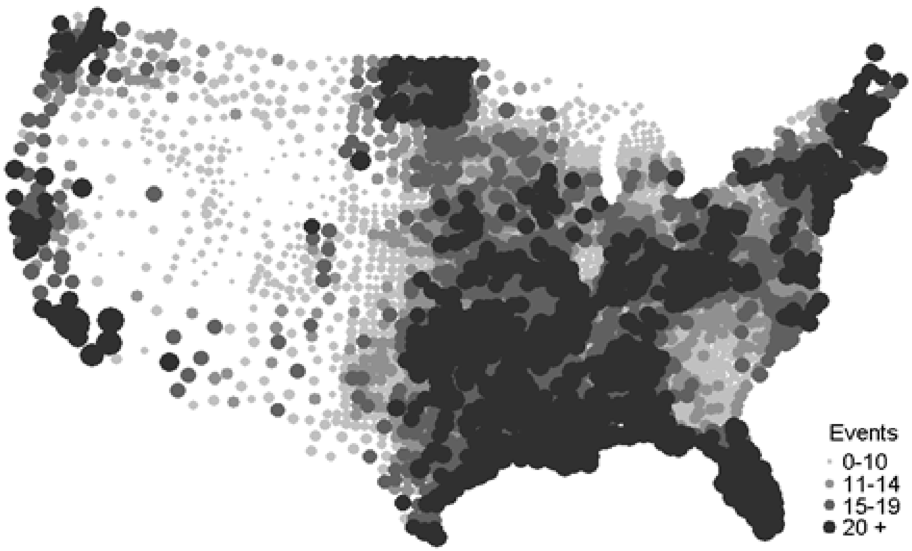
In column (1) we study county-level decade mean of poverty rates. In columns (2) and (3) we focus on (log) house values and monthly rents at the end of each decade. Regressions include decade and county fixed effects. All disaster variables are computed as shown in equation (3). Regressions encompass the period 1960-2000. Standard errors are clustered at the SEA level.
* p < 0.1, ** p < 0.05, *** p < 0.01

Figure 1: Annual disaster count by data source



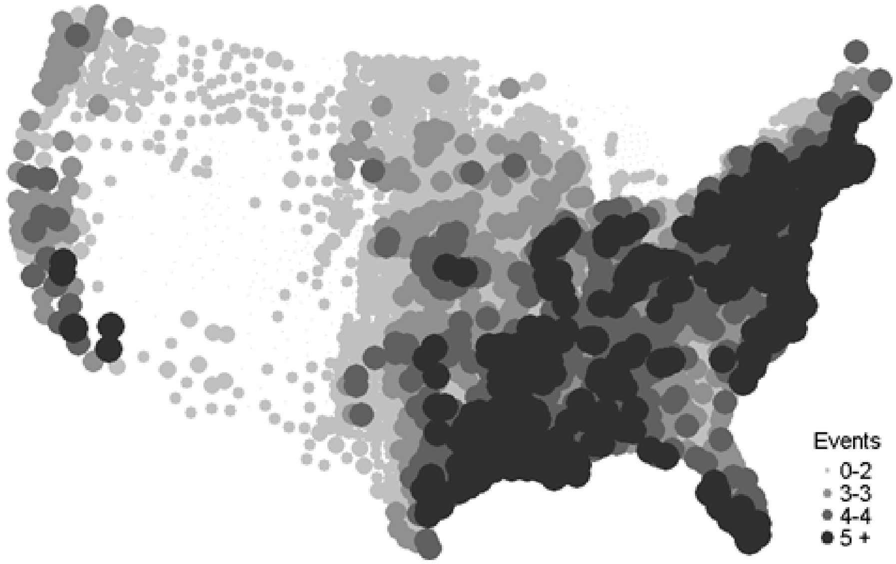
This graph plots the summation of county-level disaster counts by year and source. Note that this measure will treat a given natural event that occurred in two separate counties as two different disaster events. Disaster count is truncated at 3000.

Figure 2: Disaster count by county, 1930-2010



This map plots disaster counts within each county for the whole period 1930-2010. Marker size is strictly increasing in number of events, while color represents quartiles [max=87].

Figure 3: Count of decades with a severe disaster event by county, 1930-2010



This map shows the number of decades with severe events per county in the period 1930-2010. Severe events are disasters associated to 10 or more deaths. Marker size is strictly increasing in number of events, while color represents quartiles [max=8].

Figure 4: Count of decades with a super-severe disaster event by county, 1930-2010

This map shows the number of decades with super-severe events per county in the period 1930-2010. Super-severe events are disasters associated to 100 or more deaths. Marker size is strictly increasing in number of events, while color represents quartiles [max=6].