Abstract

This paper examines the effect of natural disasters on US population movements over time. Do natural disasters affect population growth? Has the relationship between natural disasters and population growth changed over time? Using a data set of all sustained high wind speeds since 1850, earthquake magnitudes and volcanic eruptions since 1790, and all flood, fire, snow, and tornado disasters since 1973, as well as county populations from the US Census, I show that hurricane destruction has a significant impact on population growth in the US, particularly in earlier periods of the data and for hurricanes more intense than the county average. Earthquakes, volcanoes, and other disasters also have significant impacts.

"Before 1750 or even 1800, the march of progress could still be affected by un-expected events, even disasters" –Fernand Braudel (1973)

1 Introduction

Since ancient times, natural disasters have been implicated for city decline in popular lore. As an early example, the Greek historian Diodorus suggested that the decline of Sparta was sped by the earthquake of 465 BC, for which he reported 20,000 fatalities (which more recent estimates would place at over half the population). In South Asia, the decline of the Bronze Age Indus Valley civilization is traced to extensive and repeated flooding between 1900 and 1300 BC, induced by relatively minor changes in the environment and agricultural base that gradually diverted long-term river trajectories. In a recent archeological study of selected natural disasters for several thousand years, Me-Bar and Valdez (2004) show a convex correlation between the percent of total population lost to earthquakes and volcanoes and the number of years taken to recover to the pre-event population level-indicating that, past a certain point, it may be much more difficult to recover.

Although hurricanes affecting individual cities may have little impact on macroeconomic growth in a country as large as the United States[1], hurricanes may still significantly affect growth at the city level. U.S. Census Bureau data showed that nearly one in ten Louisiana residents fled the state following the 2005 hurricane season. Louisiana's population decreased from about 4,068,028 in January-August 2005 to 3,688,996 in September-December 2005, a loss of 9.3 percent of the state's population[2]. The 2010 decennial census indicates that, even four years later, Louisiana was one of the few US states to have declined in population in the last decade. Yet, within the state, the population decline has occurred in New Orleans counties directly affected by Hurricane Katrina, while nearby cities have experienced a population boom[3]. In contrast, other cities have re-built repeatedly from natural disasters. What separates declining cities from those that re-build? City-level data, and possibly spatial dependencies, are thus important to dissect aggregate population trends.

[1] See Strobl (2008)
[2] http://geography.about.com/od/obtainpopulationdata/a/postkatrina.htm
[3] http://www.2theadvocate.com/news/83186332.html

Despite literature on migration across the social sciences, relatively little work on natural disasters has focused on people who do not return to their pre-disaster homes (perhaps because of the difficulty of sampling migrants away from the case study locations). There is little consensus on how large migrations react to disaster events. Urban population changes in the face of disaster risk remain critical, not least because the geographic concentration of population itself affects the damages experienced in the event of disaster. Lall and Deichmann (2009) predict a rapidly increasing concentration of hazard risk in urban areas, due to the growth of population and economic assets. Globally, an estimated 9 percent of population lives within 100 km of a historically active volcano, for example, and many major coastal cities are exposed to cyclones. If people do not move away from disaster-prone areas, the populations in large cities exposed to hurricanes and earthquakes will vastly increase from 2010 to 2050.

2 Literature Review

This paper is related to the empirical literature on the extent to which temporary shocks have permanent effects on the location of economic activity, including Bleakley and Lin (2010), Brakman et al (2004), Davis and Weinsten (2002, 2008), Hanson (1996, 1997), Redding and Sturm (2008), and Redding et al (2010). It builds more broadly on the widespread literature on disaster recovery across the social sciences, but I focus here on how disaster shocks could be seen in the context of the economic geography literature.

The analysis of agglomerating and spreading forces that determines the stability of equilibria in Krugman (1991) and subsequent new economic geography models (NEG) is well known. In the basic "core periphery" model, two symmetric regions are in population equilibrium with shares S_1 and S_2, but asymmetric equilibria are possible. If the system is initially in symmetric equilibrium, a small shock does not shift S out of the local stability range of the symmetric equilibrium, so shares return to their initial values. Only with a shock exceeding some threshhold $\bar{b}$ does S converge to a new long-run equilibrium path, but even a small shock that exceeds a threshhold can have a large effect of equilibria.

In the real world, partial agglomeration seems to be the rule; multiple cities can exist that differ in size, and city size rank has been found to roughly follow Zipf's Law. Assuming that the economy is initially in a stable equilibrium, a shock to the labor force can have two theoretical implications for equilibrium in NEG models: either the shock is small enough that workers and firms return to their original equilibrium, or the shock is large enough to exceed the threshold of the nearest unstable equilibrium and the economy moves to another stable equilibrium.

Using data from Japan, Davis and Weinstein (2008) find no evidence of multiple equilibria in urban recovery from the shocks of wartime bombings, and furthermore conclude that cities have a very strong tendency to return to prior levels of both city size share and industry share. Davis and Weinstein (2002) supports the theory that cities form in certain locations based on "locational fundamentals," that is, some inherent advantages of the location that favor the presence of a city. Migrants might choose initial locations based on natural assets such as rivers for irrigating crops, or coastal conditions favorable for shipping. Yet there are numerous counter-examples to the theory that inherent geographic characteristics determine city location. Path dependence can mean that cities outlast their original reason for existence (Bleakley and Lin, 2010). As cities expand over wider geographies, marginal migrants may not experience the original benefits of the location choice. Nevertheless, migrants may join because of increasing returns to scale, benefits of agglomeration such as faster rates of matching, sharing, and learning from others in their social networks.

Despite location advantages, populations may still shift. The widespread migration from city centers to suburbs to escape crime, pollution, and other undesirable elements of agglomeration, shows that inherent location characteristics may either change, or be outweighed by other costs, over time, as discussed by Glaeser (1998). Furthermore, government or private incentives may encourage people to move, even to locations with little natural advantage. Helsey and Strange (1994) and Henderson and Venables (2009) introduce models of city formation in which government and private contractors are instrumental in supporting city development, based on their influence in the coordination problem and fixed cost investment in construction. Even if existing growth trends are not reversed by shocks, growth rates may be exacerbated.

If and when location advantages change, what should be the speed of population shifts? Glaeser and Gyourko (2001) ask why declining cities do not disappear faster, and they show evidence that durable housing keeps people in cities, even if non-durable goods are not cheaper. In their model, houses that decay are rebuilt if and only if the value of the unit (including its land value) exceeds its resale price. That is, people stay in declining cities as long as the cost of constructing a new house is more expensive than remaining in the old house while it depreciates in value. Although Glaeser and Gyourko do not discuss discrete disaster shocks, they do analyze gradual temperature changes and suggest a general trend that populations shift away from harsh climates over time. Furthermore, to explain increasing depreciation rates since the 1960s, they postulate that social problems in declining cities (such as arson and neglect) may have led to building collapse. This paper is motivated by the implication that a rise is extreme weather events also could have quickened depreciation.

According to the model where people await house depreciation, natural disasters that render a portion of houses uninhabitable should speed the decline of already-shrinking cities, unless other forces such as government housing policy effectively reinforce re-construction. Belcher and Bates (1983), examining the determinants for permanent migrations after the Guatemalan earthquake of 1976 and Hurricane David in the Dominican Republic in 1979, find that the opportunities for personal betterment created by the disaster acted as a catalyst and accelerated the previously-existing trend of migration, regardless of whether or not the migrant had personally suffered losses.

Despite the assertion of Glaeser and Gyourko that negative shocks decrease housing prices more than they decrease population, Murphy and Strobl (2009) find that the typical hurricane strike *raises* real house prices for a number of years, with the maximum negative effect of 3 to 4 percent occurring three years after the hurricane. They allow for both a direct effect and an indirect effect via a fall in local incomes. This unresolved tension in the empirical literature between the supply shocks of housing destruction and depreciation, and demand shocks of income and future value expectations, may be further evidence that disaster-prone cities deserve special attention, as housing prices may fluctuate in different patterns from those observed in more stable cities, especially if structures are frequently bombarded by catastrophe.

City growth models predict that agent location choice, and thus city size, will be a function of transportation costs, housing costs, government policy, and agglomeration forces. We can think of natural disasters as shocks to physical capital or population share (in the case of major fatalities or evacuation). Furthermore, unlike with one-time events such as wartime bombing, observing a natural disaster occurrence may affect future expectations of natural disaster risk. Deryugina (2011) gives empirical evidence that individuals update their beliefs about climate change given weather observations, while Benhabib and Dave (2011) discuss the theoretical possibility that agents deviate from rational expectations equilibria following the occurrence of rare events. If we assume rational agents use a Bayesian updating process to learn about natural events, we could expect a change in location choice with updated knowledge about disaster risk.

3 Population Growth Models

The first population growth models were deterministic and could not allow for random fluctuations in population size. Throughout the twentieth century, population growth models developed to consider branching processes and random environments that could affect vital rates. Cumberland and Sykes (1982) propose that the natural starting point in modelling the crude vital rate of a human population is the first-order autoregressive process. We can think about population share with the following growth process:

$$S_{it} = \alpha S_{it-1} + \omega + \epsilon_{it} \tag{1}$$

where persistent shocks to population shares are modelled as

$$\epsilon_{it+1} = \epsilon_{it} + v_{it+1} \tag{2}$$

and if $\alpha < 1$ and $\epsilon_{it}\tilde{}WN(0, \sigma^2)$, it is an AR(1) process.

Considering time-dependent growth rates, Cumberland and Sykes (1982) show that the growth rate converges to the Ornstein-Uhlenbeck process (the continuous-time analogue of the discrete AR(1) process), which implies the log population change is normally distributed and over time tends to be mean-reverting. However, Dufresne (1989) mentions that the possibility that higher moments of ϵ_{it} do not exist is important in the context of "fat-tail" distributions, which are more appropriate for catastrophic risk associated with natural disasters. The possibility of spatial catastrophes is one of the most prominent features of the core periphery model. A theory of multiple equilibria relies on the existence of thresholds that separate distinct equilibria, for which an empirical test would require observing many shocks at various levels. In a two-period example, period t is the period containing the initial shock and period $t+1$ is the period of convergence from the initial shock to the new equilibrium. With a unique stable equilibrium, a negative shock to S in period t would be followed by an increased rate of growth in period $t+1$, as S converges back to its initial share. If multiple equilibria are possible, a negative shock in period t that is large enough to exceed the threshhold $\bar{b}$ would cause the growth rate in period $t+1$ to either be stable, as S reaches a new equlibrium, or even decreasing in the case of hysteresis.

4 Empirical Tests

Do people move away from disaster-prone areas over time? What separates cities that rebuild from those that do not? As outlined above, several theories interplay to explain the growth and decline of populations. In a "locational fundamentals" model of city formation, population growth rates immediately after a negative shock would accelerate to re-build previous population shares. In a "path dependence" model of city formation, population growth rates after a negative shock would decelerate, at least in the short term. According to the theory that population decline lags due to sunk costs in capital, we would also expect large physical capital destruction to particularly exacerbate negative growth rates. Natural disasters are exogenous shocks that represent deviations from population share, physical capital stock, or risk expectations. For example, due to property damages and evacuations, we expect a severe disaster event to cause an initial change in population level $(p_{t+1} - p_t)$. We are interested in whether the subsequent population growth rate $(\frac{p_{t+1}-p_t}{p_t})$ gives any evidence of an equilibrium shift.

4.1 Measuring Disaster Destructiveness

Measuring the physical destructiveness, rather than just the incidence, of disasters is important for empirically defining the shock v_{it+1}.

Hurricanes The following composite table shows the types of damage incurred by various wind speed categories, according to both the Fujita tornado scale and the Saffir-Simpson hurricane wind scale:

F-scale	Damage intensity	Wind speed (mph)	Types of windstorm damage
F-0	Light damage (Tropical storm)	40-72	Some damage to chimneys and TV antennae; pushes over shallow-rooted trees
F-1	Moderate damage (Saffir Simpson Category 1-2)	73-112	Peels surface off roofs; Windows broken; moving cars pushed off road
F-2	Considerable damage (Saffir-Simpson Category 3-4)	113-157	Roofs torn off frame houses, leaving strong upright walls; railroad cars pushed over; cars blown off highways
F-3	Severe damage (Saffir-Simpson Category 5)	158-206	Roofs and some walls torn off frame houses; rural buildings completely demolished; trains overturned; cars lifted off ground
F-4	Devastating damage	207-260	Whole frame houses leveled, leaving piles of debris; steel structures badly damaged; cars and trains thrown considerable distances
F-5	Incredible damage	261-318	Whole frame houses torn off foundations; steel-reinforced concrete structures badly damaged;

Although the highest observed hurricane wind speeds are not above $F3$, the most extreme tornadoes can attain wind speeds of more than 300 mph (480 kph)[4]

Emmanuel (2005) noted that the monetary losses and power dissipation of hurricanes tend to rise roughly to the cubic power of maximum observed wind speed[5]. He proposed an index of hurricane damages based on a simplified version

[4]Historical wind speeds are calibrated by the National Weather Service (NWS) to modern measurements. For example, in the Galveston Hurricane of 1900, the highest recorded wind speed was 100 mph before the anemometer blew away, but the NWS has since estimated winds at 145 mph for that storm, based on what is now known of the strong correlation between wind speed and categories of damage. Similarly, the lowest recorded barometric pressure in 1900 was 28.48 in Hg, considered at that time to be so low as to be obviously in error, but modern estimates subsequently adjusted the storm's official lowest measured central pressure to 27.63 in Hg.

[5]Note that Nordhaus (2006) argues that the relationship of costs and wind speed is in fact not to the cubic, found by Emanuel (2005), but rather to the eighth power. More specifically, he regresses the log of the cost per hurricane normalized by US GDP on the logged maximum wind speed for a set of 20th century hurricanes and finds a coefficient of 7.6 on the wind speed. However, further investigation using his data demonstrates that this result is sensitive to the measure of cost he uses. In particular, arguably US GDP is unlikely to be a good normalization for costs, since hurricanes typically only affect areas close to the coast and not all of the US. Moreover, the relative local wealth that was affected is likely to have changed substantially over the period as coastal communities have grown in size and income. When one instead regresses the log of the normalized cost values calculated by Pielke et al (2005)-who normalize damages with regard to changes in inflation, population, and wealth of affected counties only-on the log of maximum observed wind speeds of the hurricanes in Nordhaus' data set, one finds that the resultant coefficient implies that costs rise instead to about the 3.6th power of wind speed, and thus much more in line with Emmanuel (2005). Murphy and Strobl (2009) find a 3.35 power coefficient for the years 1970-2005 and a 3.52 coefficient for 1900-2005.

of the power dissipation equation (PDI):

$$PDI = \int_0^{\tau} V^{\lambda} dt \tag{3}$$

where I is the wind speed measure, τ is the duration of the event, and λ is the power function relating maximum sustained wind speed to property value destroyed. Based on this established relationship between wind speed and property destruction, I use sustained wind speed as a proxy for hurricane intensity.

Earthquakes The Richter magnitude scale, or local magnitude (ML), is the most well-known measure of earthquake destructiveness still used today, but it saturates beyond 6.5 so is not appropriate for measuring large earthquakes. There are several alternate scales used for measuring earthquakes, including surface-wave magnitude (MS) and body-wave magnitude (MB), which are adjusted to measure larger earthquakes consistent with the ML scale but saturate at 8.0, and moment magnitude (MW), a more modern measure of the size of an earthquake, which does not saturate but is difficult to measure accurately. Hence, not all earthquakes can be compared on the same scale, but a rough normalization is provided in papers such as [Kanamori, 1982]. A rough indication is that physical property damage begins to occur around 5.0 and increases at an increasing rate with higher values.

Richter Magnitude Scale	Damage Effects
Less than 2.0	Not recorded
2.0-4.9	Shaking felt, but no significant damage
5.0-5.9	Significant damage to poorly constructed buildings, little damage to well-designed buildings
6.0-7.9	Serious damage in areas up to 100 miles (160 km) across
8.0-9.9	Serious damage in areas from several hundred to several thousand kilometres across
10+	Never recorded

4.2 Identification Strategy

The population level p is observed at interval t, which in this case represents the first year of every decade, as population data is observed reliably only in the decennial census. For any disaster event d that occurs in county c at or between population measurements, the post-event population growth rate will first be observed at the end of the disaster decade, at time $t+1$. The post-disaster population growth measurement is thus $Ln(\frac{p_{t+1}-p_t}{p_t})$, which we name $p_{c,t+1}$ or *Lnratepop*. The growth rate observed in the previous decade $Ln(\frac{p_t-p_{t-1}}{p_{t-1}})$ is named $p_{c,t}$ or *Lnprerate*.

We use wind speed as a proxy for hurricane damage and also control for storm speed. The data includes the natural log of maximum sustained wind speed $w_{c,t}$ observed in each unique county-time pair, as well as the log of storm speed $s_{c,t}$ and the log of maximum earthquake magnitude $e_{c,t}$. Because population data from the US census is taken every ten years, I also include the interactions between w and the dummy variables $Y_{c,t-i}$ to indicate the number of years i between the storm date and the next census. Missing observations for wind speed and storm speed (that is, counties in a decade that did not experience a severe storm) are included as zeros. Natural logs are taken by adding 1 to the variable to keep zero observations, and a dummy I_W or I_E is included to control for whether or not the observation is zero. The initial specification therefore takes the following form:

$$p_{c,t+1} = \alpha + \beta_w(w_{c,t}) + \beta_s(s_{c,t}) + \beta_1(W_{c,t}) + \sum_{i=1}^{9} \beta_{ti}(w_{c,t} * Y_{c,t-i}) + \phi_c + \phi_t + \epsilon_{c,t} \tag{4}$$

and ϕ_c and ϕ_t are fixed effects for county and time, with error term $\epsilon_{c,t}$.

The problem with including all counties in the US that do not experience hurricanes is that we have omitted other important physical capital destruction shocks that may have occured. The next specification adds the earthquake magnitude measure and controls for severe flood damage, fires, and volcanoes. With these, we are covering the main sources of catastrophic physical capital damage that have affected US counties since 1973.

To investigate whether, as discussed above, disaster destruction appears to hasten migration away from already-declining cities, I include population growth in the previous decade as a regressor and create an interaction term for the wind speed measure and population growth rate in the previous decade: $w * p_{c,t}$.

$$p_{c,t+1} = \alpha + \beta_p(p_{c,t}) + \beta_{p2}(w * p_{c,t}) + \beta_w(w_{c,t}) + \beta_s(s_{c,t}) + \beta_1(W_{c,t}) + \beta_{t*i}(w_{c,t} * Y_{c,t-i}) + \beta_e(e_{c,t}) + \beta_2(E_{c,t}) + \phi_c + \phi_t + \epsilon_{c,t} \tag{5}$$

According to Gibrat's Law, the proportionate growth process of cities gives rise to the lognormal distribution, rather than a Pareto distribution, so we expect that city sizes and growth rates are independent. Also, Zipf's Law indicates that city sizes will be inversely proportional to their size ranks, so that populations converge empirically to a size ranking following the Zipf distribution. Although population level, share, and density are certainly correlated, population growth is independent of share. I therefore estimate an alternate model using the log of the share of total population as the dependent variable.

There are several potential identification issues to be addressed. The measure of population growth rate changes in the decade of natural disaster may contain information, not only about the disaster shock, but also about historical growth rates, and thus be subject to serial correlation in the error term. I therefore test the model using a differenced dependent variable, for both population growth rate and share of total population, using lagged regressors, and using general method of moments (GMM).

I can use disaster impact measures as instruments to test whether the change in population growth rate is persistent. The measures of disaster impact, such as the total number of injuries and the total damages in millions of dollars, are

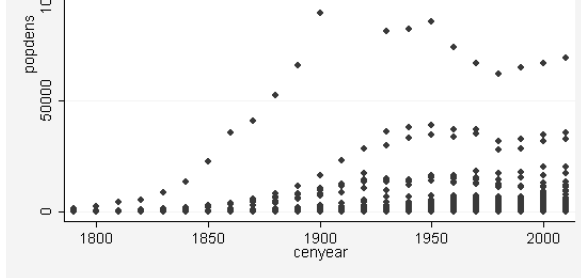

Figure 1: Population density in all US counties (1790-2010)

correlated with the disaster shocks but not with historical growth rates. In a separate specification not reported, I test storm speed, wind speed, barometric pressure, and earthquake magnitude as instruments correlated with disaster shocks, though I conclude they are poor instruments, as they could also be correlated with historic growth rates if there is serial autocorrelation in disaster events.

To address measurement error in the population variable, we would need an instrument that is correlated with historical population data but not with measurement error. For example, we could use modern (2010) population density, which could be correlated with historical population growth but likely not with historical measurement error in the Census.

County characteristics Given the Census data available by county, I can also estimate a model with more detailed county-level characteristics, to test whether certain traits cause populations to be more or less responsive to disaster shocks. For example, in the framework of location decisions based on house value depreciation and information sets about risk, we would expect counties with higher proportions of foreign-born residents, higher education per capita, or higher home ownership to be affected differently by disaster shocks. In the results below, I include a specification with county characteristics, using state fixed effects instead of county fixed effects.

4.3 Data Source and Descriptive Statistics

Our dataset contains population for all counties in the United States between 1790 and 2010, taken from the US Census Bureau. The 1790 census includes only the thirteen original colonies, but given the rapid growth of the country, most areas had begun settlement as either states or territories by 1820. By 1850, all major hurricane-prone and earthquake-prone areas were recorded by the census, with Florida and Texas becoming states in 1845, and California in 1850. The census dataset across the 150 years since 1850 is uniquely suited to examining population changes and weather shocks at the county-level in a newly-populated country.

Perhaps not surprisingly, population growth has been monotonic in many counties. Population density outliers are counties in New York, Philadelphia, and Los Angeles, with the most extreme being New York around the turn of the twentieth century.

The median population growth rate across all counties since 1790 has been

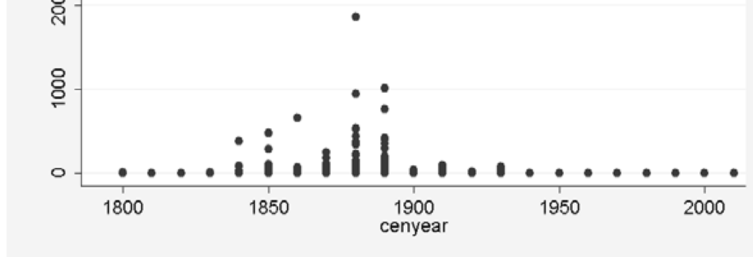

Figure 2: Population growth rate in all US counties (1800-2010)

7.7 percent. A few extreme outliers appear in the later half of the nineteenth century: most notably, three counties in Kansas, where the Atchison, Topeka, and Santa Fe railroad in 1879, had explosive growth in 1880 and 1890 that is unparalleled in any other county and decade. Population growth rates are negatively correlated with population densities, as well as with wind speed and earthquake magnitude.

The National Oceanographic and Atmospheric Administration (NOAA) provides measurements of sustained high winds (in miles per hour) since 1851 by longitude and latitude. Of the 3,143 counties and county equivalents[6] in the US, 1,912 (61 percent) have recorded high-speed wind measurements in the NOAA database. The average county recorded high winds 10 times over the period, with some counties recording high winds only once and others up to 47 times, for a total of 22,216 high wind speed observations at county-date level in the dataset and 16,714 observations at county-year level (as some counties reported more than once within a year). Of the 1,912 counties recording high speeds, 383 counties experienced hurricanes; 197 counties experienced at least a Category 2 hurricane; 118 experienced at least a Category 3 hurricane; 21 experienced at least a Category 4 hurricane; and 3 experienced a Category 5 hurricane.

Wind speeds varied across geography, as only 37 out of the 50 states measured extreme wind speeds. Some states had less than 20 reports over the whole time period, while 9 states (Georgia, Florida, Texas, North Carolina, Virginia, Mississippi, Alabama, Louisiana, and South Carolina) each had over 1,000 observations of sustained high winds over the 150-year period; these states comprise the hurricane-prone Atlantic coast. Because the dataset is specific to *sustained* high winds, it includes winds generated by storm systems such as tropical depressions, tropical storms, and hurricanes, but not tornadoes; this is appropriate given our theory of location choice based on the expected risks, since hurricane winds would have a more uniform affect on the whole geographic area the storm covers, whereas tornadoes are an idiosyncratic shock that would affect some households and skip others at random and without a predictable warning pattern. Therefore, the maximum sustained winds observed in our data are those of Hurricane Andrew, which reached 165 miles per hour in both Broward County and Dade County, two neighboring counties on the east coast of Florida, in 1992.

Among the 72,151 unique county-decade observations, 84 percent are zeros, which means the county did not experience a hurricane or other sustained high winds in that decade; that is, there are 11,669 county-decade observations of high sustained winds. In the larger data set of 117,657 unique event observations, however, there are 57,151 high wind speed observations, indicating that,

[6] Alaska is divided into boroughs and Louisiana into parishes, but these are considered "county equivalents" by the US government; all other states are divided into counties.

on average, affected counties reported multiple high wind speed event observations per decade. For robustness checks, I exploit the richness of this storm data in three ways: (1) using a data set with all unique high wind speed observations, (2) using a data set with only the maximum wind speed observation for each county-decade pair, and (3) using a data set with an index combining all high wind speed observations as a average for the decade, weighted by the years between the observation and the measurement of the dependent variable. The reported results use the second version of the data.

Storm speed (in miles per hour) is also reported for each sustained high wind speed measurement, and is directly related to the power of the storm and its "element of surprise" but may also be inversely related to the duration of the storm, depending on its diameter. In an earlier specification, I included both wind speed and storm speed, but with a data set of only maximum wind speeds, storm speed and wind speed have a correlation of 0.75 and the respective logs have a 0.97 correlation.

The National Geophysical Data Center (NGDC) provides data on earthquakes (above 4.0) and volcanic eruptions since before 1790. Earthquake magnitude is given on one of the five scales described above, by the epicenter longitude-latitude location. Volcanic eruptions are also given by longitude-latitude, along with the volcanic explosivity index (VEI) which is not used here because there are only a few major volcanoes reported at all during the time period in the US. Data can be matched to counties by longitude and latitude using the US Census using the Census Gazeteer.

4.4 Results

The tables below present the main findings. The standard errors are heteroskedasticity-robust and clustered by county. Except where noted, the specifications use county and decade fixed effects.

The incidence of hurricanes, earthquakes, and volcanoes have significant negative relationships with population growth rates. Wind speed has a significant non-linear relationship with population growth, which is consistent in all specifications. While the binary incidence of sustained wind speed is positively related to population growth, the log intensity of wind speed has a strong negative relationship with population growth, indicating there is a threshhold beyond which wind speeds have a negative impact on population growth. Interpretation of the coefficients suggests that, although the presence of sustained wind speed (a jump from zero to 10 miles per hour) doubles the population growth rate, a doubling of wind speed reduces the population growth rate by 25 percent. This is confirmed by including dummies for hurricane categories according to the Saffir-Simpson Scale, which show that hurricanes at threshholds of 74, 110, and 155 miles per hour have a significant negative impact on population growth relative to lower wind speeds. Storm speed has little relationship with population growth.

Not surprisingly, when using the change in population growth rate as the dependent variable, there is a similar nonlinear relationship with wind speed. The presence of sustained wind speeds corresponds to an increasing growth rate, but the doubling of wind speeds decreases population growth by 13 percent. Coefficients for category 5 hurricanes and volcanoes remain significant. In contrast, there is little relationship between the change in population shares and disasters.

When the first lag of population growth rate is included as a regressor, it is significantly positive, and hurricanes, earthquakes, and volcanoes remain significantly negative. Interestingly, the negative coefficient on the wind interaction term indicates that counties with higher previous growth rates experience a more negative impact of wind speeds on growth rates, although the significance of the interaction term disappears when dummies for hurricane categories are included, suggesting previous growth rates are not as important in the face of serious hurricanes.

Including lags of wind speed and earthquakes suggests that there are persistent effects in the second decade following a high wind speed event but reversed trends following an earthquake. For wind speeds, we reject the F-test null hypothesis that the wind lag coefficients are zero, so there is evidence of Granger causality from wind speeds to population growth, whereas for earthquakes, there appears no evidence of Granger-causing population growth.

There is also evidence that the relationship between natural disasters and population growth has changed over time. In the spline regressions presented, wind speed is important only in earlier years (before 1935), while earthquakes are important only in later years. (The major volcano recorded during this time period erupted in 1980 so is not included in earlier data.)

Finally, I proxy for expectations by including interaction terms of event magnitude with the mean, median, quantity, and interquartile range of all events in each county during the 150-year period[7] The significant positive coefficient on the mean of wind speed indicates that counties that have experienced a higher average wind speed over time react less negatively to shocks.

4.5 Robustness Checks

In states that experienced both hurricanes and earthquakes, the incidence of earthquakes is negatively significant but hurricanes are not, while hurricanes are significant in Gulf Coast states.

In a smaller dataset using all Federal Emergency Management Agency (FEMA) disaster declarations, available only since 1973, I test whether the backdrop of other disasters affects the impact of earthquakes and volcanoes. (Wind speeds are also included but were previously found to have less impact in the post-1935 period.) Earthquake and volcano coefficients remain negative, while fire and snow are significantly negative, and flood and tornado are not significant.

[7] A better proxy would be taking the distribution only for events that have occurred up to the time of each event.

Keeping in mind the limitations of the shorter time frame, it is possible that various types of disasters have different effects (for example, wildfires may cause more widespread loss of physical capital than tornadoes, which hit only a small percentage of houses in a given area) or future expectations of risk. The negative effects of snow disasters might capture a historical migration away from cold climates, as described by Glaeser (1998).

An alternate specification shows the interactions of hurricane intensity with the number of years between the event and the next census measurement. Although events happening two and three years before the census seem to have a significantly more negative effect, the pattern is not monotonic across later years. Indeed, the identification of annual disaster effects on population is difficult, given that the effects of natural disaster on population are likely to happen in a multi-year timeframe; for example, in the immediate aftermath of large disasters, there may be an influx of emergency relief and construction workers, and there may be some short-term migration for refugees, but this does not necessarily indicate long-term population shifts.

I include county characteristics of average rural area, tertiary education levels, house vacancy, house owner occupancy, and percent of population foreign born, and their interactions with wind speed intensity and earthquake magnitude, to examine whether certain types of counties react more strongly than others to hurricanes and earthquakes. Because the county characteristics are time-invariant based on the 2000 census, I include spline regressions for post-1960 only.

Additional tables present results excluding outliers, which do not change the core results. Based on the Breusch-Pagan Langrangian multiplier test for random effects, I reject the null that variances across counties is zero and conclude that a random effects model may be suitable, so the results with random effects are also presented.

4.6 Discussion

The results indicate that there is a significant relationship between disaster events, particularly hurricanes, and population growth. In contrast to the "locational fundamentals" theory in economic geography, natural disaster shocks can have persistent effects on city formation. However, the effects appear weaker in more recent years and in certain types of counties, including those that have more experience with disasters on average.

In modern markets, perceived disaster risk is affected by both government safety nets and insurance availability; in historical markets pre-dating government and private insurance programs, perceived risk may have been less informed or based on other factors. The development of government disaster relief in the 1930s and the Federal Emergency Management Agency (FEMA) in the 1970s, as well as the differences in insurance regulation and subsidies by state, may explain the differential responses to disaster events seen in the data.

The results are consistent with a Bayesian updating process proposed by the behavioral economics literature, and which could only be observed over a long-term horizon, since the low probability of catastrophe risk means information sets will be updated very slowly. This updating process, and the ability of human populations to adapt behaviors by incorporating new information about the environment remains a key question in the face of rapidly increasing exposure of human populations to natural disaster risk, which many believe will be exacerbated by climate change. Further analysis is needed to understand the microfoundations of behavioral response to natural disaster and its persistence.

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On population growth rate, with county and decade fixed effects (1850-2010)

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratepop	(4) lnratepop	(5) lnratepop
magdummy			-2.056	-0.200**	-0.191**
			(1.361)	(0.0955)	(0.0953)
volcdummy				-0.672**	-0.684***
				(0.264)	(0.264)
hurr1					-0.165***
					(0.0502)
hurr2					-0.0102
					(0.0839)
hurr3					-0.234**
					(0.116)
hurr4					0.0521
					(0.259)
hurr5					-1.195***
					(0.0864)
lnmphwind	-0.254***	-0.265***	-0.255***	-0.254***	
	(0.0358)	(0.0366)	(0.0358)	(0.0358)	
winddummy	1.011***	0.939***	1.018***	1.013***	
	(0.135)	(0.143)	(0.134)	(0.135)	
lnmag			0.977		
			(0.711)		
lnmphspeed		0.0421			
		(0.0280)			
Constant	-0.800***	-0.798***	-0.800***	-0.800***	-0.808***
	(0.0415)	(0.0416)	(0.0416)	(0.0416)	(0.0416)
Observations	30,664	30,664	30,664	30,664	30,664
R-squared	0.190	0.190	0.190	0.190	0.189
Number of fipscode	3,115	3,115	3,115	3,115	3,115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Comparing different dependent variables, with county and decade fixed effects (1850-2010)

	(1)	(2)	(3)	(4)
VARIABLES	lnratediff	lnratediff	lnsharediff	lnsharediff
hurr1		-0.00903		-0.107
		(0.0779)		(0.0956)
hurr2		0.198*		0.131
		(0.119)		(0.134)
hurr3		-0.0989		-0.443*
		(0.190)		(0.238)
hurr4		-0.284		-0.128
		(0.630)		(0.380)
hurr5		-2.224***		-0.160
		(0.322)		(0.418)
magdummy	-0.269	-0.257	-0.0958	-0.0978
	(0.169)	(0.169)	(0.193)	(0.192)
volcdummy	-0.730***	-0.736***	1.000***	0.993***
	(0.0723)	(0.0723)	(0.0630)	(0.0633)
lnmphwind	-0.133**		-0.167**	
	(0.0529)		(0.0665)	
winddummy	0.494**		0.679***	
	(0.194)		(0.245)	
Constant	-1.612***	-1.622***	-9.570***	-9.576***
	(0.0630)	(0.0631)	(0.0571)	(0.0570)
Observations	19,404	19,404	14,324	14,324
R-squared	0.120	0.120	0.096	0.096
Number of fipscode	3,080	3,080	2,937	2,937

Robust standard errors in parentheses

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

Including lagged dependent variable (1850-2010)

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratepop	(4) ins: housing2000	(5) ins: injuries damages
lnprerate	0.259***	0.333***	0.266***	0.414***	0.259***
	(0.00842)	(0.0379)	(0.00999)	(0.00553)	(0.00641)
mwind_prerate		-0.0738**	-0.00656		
		(0.0371)	(0.00554)		
hurr1			-0.0968*		
			(0.0511)		
hurr2			0.0165		
			(0.0990)		
hurr3			-0.178		
			(0.108)		
hurr4			0.0519		
			(0.203)		
hurr5			-1.205***		
			(0.315)		
magdummy	-0.190*	-0.190*	-0.188*	0.118	-0.190*
	(0.103)	(0.103)	(0.103)	(0.0951)	(0.102)
volcdummy	-0.466**	-0.466**	-0.469**	-0.120	-0.466
	(0.192)	(0.192)	(0.191)	(0.386)	(0.391)
lnmphwind	-0.0738**			0.144***	-0.0738*
	(0.0371)			(0.0322)	(0.0385)
winddummy	0.245*	0.245*		-0.538***	0.245*
	(0.138)	(0.138)		(0.123)	(0.143)
Constant	-0.907***	-0.907***	-0.909***	-0.957***	-0.907***
	(0.0394)	(0.0394)	(0.0393)	(0.0358)	(0.0359)
Observations	23,203	23,203	23,203	23,203	23,203
R-squared	0.212	0.212	0.212		
Number of fipscode	3,009	3,009	3,009	3,009	3,009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Including wind and earthquake lags (1850-2010)

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratediff	(4) lnratediff	(5) lnsharediff
lnprerate	0.238***	0.340***	0.0572***	0.164**	0.440***
	(0.00857)	(0.0385)	(0.0150)	(0.0830)	(0.0712)
lnmphwind	-0.102***		-0.107		
	(0.0379)		(0.0818)		
lagwind	-0.161***	-0.161***	-0.187**	-0.187**	-0.0234
	(0.0409)	(0.0409)	(0.0725)	(0.0725)	(0.0693)
winddummy	0.339**	0.339**	0.389	0.389	0.605**
	(0.140)	(0.140)	(0.302)	(0.302)	(0.255)
lagwinddummy	0.624***	0.624***	0.740***	0.740***	0.0508
	(0.152)	(0.152)	(0.270)	(0.270)	(0.257)
lnmag	1.389*	1.389*	-0.258	-0.258	-0.605
	(0.718)	(0.718)	(1.432)	(1.432)	(0.950)
lagmag	-1.107*	-1.107*	0.708	0.708	-1.413
	(0.638)	(0.638)	(1.557)	(1.557)	(1.259)
magdummy	-2.820**	-2.820**	0.228	0.228	1.146
	(1.365)	(1.365)	(2.784)	(2.784)	(1.854)
lagmagdummy	2.095*	2.095*	-1.385	-1.385	2.579
	(1.203)	(1.203)	(2.976)	(2.976)	(2.402)
mwind_prerate		-0.102***		-0.107	-0.152**
		(0.0379)		(0.0818)	(0.0704)
Constant	-1.244***	-1.244***	-2.101***	-2.101***	-10.15***
	(0.0357)	(0.0357)	(0.100)	(0.100)	(0.0799)
Observations	22,244	22,244	9,515	9,515	10,812
R-squared	0.199	0.199	0.090	0.090	0.102
Number of fipscode	3,008	3,008	2,727	2,727	2,679

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

On population growth rate, spline time periods

VARIABLES	(1) Pre-1935	(2) Pre-1975	(3) Post-1900	(4) Post-1935	(5) Post-1975
lnmphwind	-0.266***	-0.259***	-0.146***	-0.0621	0.0493
	(0.0708)	(0.0491)	(0.0402)	(0.0414)	(0.0488)
winddummy	1.155***	1.067***	0.515***	0.222	-0.256
	(0.274)	(0.187)	(0.146)	(0.149)	(0.172)
lnmag	0.134	-0.185	0.995	1.376	2.776***
	(0.797)	(0.788)	(0.707)	(0.846)	(0.954)
magdummy	-0.239	0.222	-2.094	-2.783*	-5.248***
	(1.561)	(1.523)	(1.366)	(1.597)	(1.781)
volcdummy			-0.481**	-0.307**	-0.289**
			(0.209)	(0.148)	(0.147)
Constant	-0.629***	-0.750***	-1.705***	-2.506***	-1.843***
	(0.0379)	(0.0396)	(0.0311)	(0.0249)	(0.0168)
Observations	15,089	21,979	21,144	15,575	8,685
R-squared	0.219	0.198	0.078	0.097	0.257
Number of fipscode	2,967	3,049	3,095	2,974	2,829

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Using mean, median, count, and interquartile range of wind speed observations

	(1)	(2)	(3)	(4)
VARIABLES	lnratepop	lnratepop	lnratepop	lnratepop
lnmphwind	-0.300***	-0.273***	-0.279***	-0.289***
	(0.0463)	(0.0409)	(0.0433)	(0.0431)
wind_mean	0.000818*			
	(0.000481)			
wind0dum	-1.133***	-1.071***	-1.075***	-1.102***
	(0.156)	(0.148)	(0.148)	(0.148)
magdummy	-0.200**	-0.200**	-0.200**	-0.201**
	(0.0956)	(0.0956)	(0.0956)	(0.0956)
volcdummy	-0.672**	-0.672**	-0.672**	-0.672**
	(0.264)	(0.264)	(0.264)	(0.264)
wind_med		0.000360		
		(0.000333)		
wind_iqr			0.000327	
			(0.000308)	
wind_count				0.000912
				(0.000562)
Constant	0.329**	0.268*	0.274*	0.298*
	(0.162)	(0.154)	(0.155)	(0.155)
Observations	30,664	30,664	30,664	30,664
R-squared	0.190	0.190	0.190	0.190
Number of fipscode	3,115	3,115	3,115	3,115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Only Gulf coast states: AL, GA, TX, LA, MS, SC, NC

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratepop	(4) lnratediff
lnmphwind	-0.262***	-0.262***		
	(0.0511)	(0.0511)		
wind0dum	-0.967***	-0.967***	-0.709***	-1.195***
	(0.194)	(0.194)	(0.197)	(0.430)
lnmag	0.0638		-0.00135	
	(0.237)		(0.247)	
magdummy		0.110		
		(0.409)		
lnprerate			0.416***	0.332***
			(0.0561)	(0.117)
mwind_prerate			-0.207***	-0.316***
			(0.0528)	(0.114)
Constant	-0.0559	-0.0559	-0.517**	-0.674
	(0.214)	(0.214)	(0.219)	(0.471)
Observations	8,076	8,076	6,140	2,717
R-squared	0.175	0.175	0.176	0.119
Number of fipscode	772	772	765	735

Robust standard errors in parentheses

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

Only states with both earthquakes and storms: AL, DE, IL, IN, KY, MD, MO, PA, SC

	(1)	(2)	(3)	(4)
VARIABLES	lnratepop	lnratepop	lnratepop	lnratediff
lnprerate			0.170**	-0.0704
			(0.0805)	(0.153)
mwind_prerate			0.0981	0.125
			(0.0789)	(0.152)
wind0dum	0.0756	0.0913	0.264	0.309
	(0.281)	(0.283)	(0.286)	(0.542)
lnmag	6.445*		7.278**	
	(3.385)		(3.437)	
magdummy	-11.49*	-0.343	-13.16**	-1.052
	(5.934)	(0.214)	(6.050)	(0.642)
lnmphwind	0.0561	0.0605		
	(0.0773)	(0.0777)		
Constant	-1.122***	-1.138***	-1.134***	-2.245***
	(0.286)	(0.288)	(0.291)	(0.570)
Observations	6,772	6,772	5,301	2,264
R-squared	0.213	0.212	0.238	0.084
Number of fipscode	634	634	629	603

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Including all disasters (1973-2010)

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratediff
lnmphwind	-0.00115		
	(0.0466)		
winddummy	-0.0528	0.0113	-0.359
	(0.163)	(0.163)	(0.514)
lnmag	2.228**		
	(0.967)		
magdummy	-4.229**	-0.0939	-0.0626
	(1.815)	(0.114)	(0.454)
volcdummy	-0.315**	-0.338**	-0.967***
	(0.148)	(0.140)	(0.145)
flood	0.0256	0.00579	0.00640
	(0.0232)	(0.0246)	(0.0653)
fire	-0.180***	-0.224***	-0.339***
	(0.0414)	(0.0430)	(0.129)
tornado	0.0532	0.0133	-0.219**
	(0.0336)	(0.0340)	(0.0876)
snow	-0.142***	-0.125***	0.120*
	(0.0283)	(0.0308)	(0.0729)
lnprerate		-0.00553	-0.329**
		(0.0477)	(0.145)
mwind_prerate		-0.0275	0.100
		(0.0461)	(0.143)
Constant	-2.426***	-2.091***	-3.550***
	(0.0260)	(0.0431)	(0.118)
Observations	10,404	7,916	3,485
R-squared	0.195	0.223	0.166
Number of fipscode	2,862	2,308	1,929

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Including interactions with years since the event

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratepop
lnmphwind	-0.290***	-0.289***	
	(0.0400)	(0.0400)	
wind0dum	-0.983***	-0.980***	-0.155*
	(0.143)	(0.143)	(0.0868)
lnmphspeed	0.0374	0.0377	-0.00391
	(0.0280)	(0.0280)	(0.0275)
lnmag	1.004		
	(0.715)		
magdummy	-2.104	-0.205**	-0.198**
	(1.369)	(0.0957)	(0.0955)
volcdummy	-0.645**	-0.666**	-0.681***
	(0.265)	(0.264)	(0.264)
yrs1_wind	0.0231	0.0232	-0.0120
	(0.0169)	(0.0169)	(0.0161)
yrs2_wind	-0.00483	-0.00468	-0.0398**
	(0.0171)	(0.0171)	(0.0164)
yrs3_wind	-0.00772	-0.00762	-0.0391**
	(0.0189)	(0.0189)	(0.0184)
yrs4_wind	0.0157	0.0157	-0.0253
	(0.0180)	(0.0180)	(0.0170)
yrs5_wind	0.0348**	0.0347**	0.00249
	(0.0163)	(0.0163)	(0.0156)
yrs6_wind	0.0722***	0.0720***	0.0344**
	(0.0171)	(0.0171)	(0.0164)
yrs7_wind	0.00647	0.00659	-0.0351*
	(0.0194)	(0.0194)	(0.0184)
yrs8_wind	-0.00681	-0.00715	-0.0408**
	(0.0177)	(0.0177)	(0.0170)
yrs9_wind	0.00653	0.00656	-0.0272
	(0.0178)	(0.0178)	(0.0172)
Constant	0.182	0.179	-0.661***
	(0.151)	(0.151)	(0.0956)
Observations	30,664	30,664	30,664
R-squared	0.192	0.191	0.190
Number of fipscode	3,115	3,115	3,115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Including county characteristics, with state and decade fixed effects

VARIABLES	(1) lnratepop	(2) lnshare	(3) lnratepop post-1960	(4) lnshare post-1960	(5) lnratepop	(6) lnshare
lnprerate	0.346***	0.0577***	0.166***	0.0545***	0.347***	0.0577***
	(0.0164)	(0.00944)	(0.0160)	(0.00563)	(0.0165)	(0.00943)
lnmphwind	-0.174*	0.148***	-0.0289	-0.153***		
	(0.102)	(0.0467)	(0.121)	(0.0498)		
winddummy	0.159	-0.151	-0.0650	0.0425		
	(0.206)	(0.136)	(0.241)	(0.0716)		
pcrural	-0.320***	-1.450***	0.157	-2.385***	-0.293***	-1.484***
	(0.0604)	(0.109)	(0.120)	(0.102)	(0.0536)	(0.105)
rural_lnwind	0.00764	-0.0360*	0.00765	0.0200**		
	(0.0363)	(0.0206)	(0.0483)	(0.00975)		
pctertiary	0.841***	0.289	3.252***	1.645***	1.029***	0.293
	(0.140)	(0.244)	(0.301)	(0.263)	(0.111)	(0.263)
educ_lnwind	0.156**	-0.0287	0.223***	0.113***		
	(0.0651)	(0.0279)	(0.0798)	(0.0232)		
pcvacant	0.566***	-2.728***	0.106	-2.704***	0.408***	-2.658***
	(0.166)	(0.400)	(0.359)	(0.514)	(0.147)	(0.375)
vac_lnwind	-0.157**	-0.000852	-0.117	-0.0623**		
	(0.0653)	(0.0356)	(0.115)	(0.0258)		
pcowneroccupied	0.719***	-0.605	3.222***	0.149	0.789***	-0.735*
	(0.189)	(0.442)	(0.304)	(0.428)	(0.144)	(0.427)
occ_lnwind	0.0819	-0.106**	-0.0680	0.114*		
	(0.0765)	(0.0464)	(0.0956)	(0.0610)		
pcforeignborn	1.313***	0.496	2.855***	2.206**	1.584***	0.485
	(0.273)	(1.218)	(0.436)	(0.894)	(0.216)	(1.062)
for_lnwind	0.165***	-0.0166	-0.0643	0.132***		
	(0.0632)	(0.130)	(0.199)	(0.0475)		
waterpc	-0.0282	0.129	-0.351*	0.128		
	(0.0646)	(0.206)	(0.188)	(0.261)		
magdummy					-0.857	0.215
					(0.985)	(1.107)
rural_lnmag					-0.321	-0.553
					(0.264)	(0.416)
educ_lnmag					-0.315	0.0890
					(0.422)	(0.934)
vac_lnmag					1.424**	1.139*
					(0.683)	(0.610)
occ_lnmag					0.709	-0.0659
					(0.502)	(0.234)
for_lnmag					0.248	0.257
					(0.736)	(0.470)
Constant	-2.487***	-8.296***	-5.688***	-8.731***	-2.619***	-8.190***
	(0.157)	(0.293)	(0.305)	(0.323)	(0.116)	(0.289)
Observations	23,203	29,753	7,916	9,895	23,203	29,753
Number of fipscode	3,009	3,074	2,308	2,846	3,009	3,074

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

County and decade fixed effects, dropping population growth outliers

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratepop	(4) lnratepop	(5) lnratepop
lnmphwind	-0.252***	-0.264***	-0.254***	-0.253***	-0.254***
	(0.0358)	(0.0366)	(0.0358)	(0.0358)	(0.0358)
winddummy	1.006***	0.934***	1.012***	1.008***	1.011***
	(0.135)	(0.143)	(0.134)	(0.135)	(0.134)
lnmag			0.977		0.942
			(0.711)		(0.713)
magdummy			-2.056	-0.200**	-1.981
			(1.361)	(0.0955)	(1.366)
lnmphspeed		0.0420			
		(0.0280)			
volcdummy				-0.672**	-0.653**
				(0.264)	(0.265)
Constant	-0.802***	-0.800***	-0.801***	-0.801***	-0.801***
	(0.0415)	(0.0416)	(0.0416)	(0.0415)	(0.0416)
Observations	30,660	30,660	30,660	30,660	30,660
R-squared	0.190	0.190	0.190	0.190	0.190
Number of fipscode	3,115	3,115	3,115	3,115	3,115

Robust standard errors in parentheses

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

Including interactions with years since the event, dropping outliers

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratepop
lnmphwind	-0.280***	-0.279***	
	(0.0399)	(0.0399)	
wind0dum	-0.946***	-0.943***	-0.146*
	(0.143)	(0.143)	(0.0865)
lnmphspeed	0.0362	0.0364	-0.00376
	(0.0279)	(0.0279)	(0.0274)
lnmag	1.009		
	(0.714)		
magdummy	-2.113	-0.205**	-0.199**
	(1.368)	(0.0957)	(0.0955)
volcdummy	-0.648**	-0.668**	-0.683***
	(0.265)	(0.264)	(0.264)
yrs1_wind	0.0234	0.0236	-0.0104
	(0.0169)	(0.0169)	(0.0160)
yrs2_wind	-0.00438	-0.00422	-0.0382**
	(0.0171)	(0.0171)	(0.0163)
yrs3_wind	-0.00643	-0.00633	-0.0368**
	(0.0189)	(0.0189)	(0.0184)
yrs4_wind	0.0139	0.0140	-0.0257
	(0.0180)	(0.0180)	(0.0170)
yrs5_wind	0.0342**	0.0341**	0.00302
	(0.0163)	(0.0163)	(0.0155)
yrs6_wind	0.0722***	0.0719***	0.0356**
	(0.0171)	(0.0171)	(0.0164)
yrs7_wind	0.00501	0.00512	-0.0352*
	(0.0193)	(0.0193)	(0.0184)
yrs8_wind	-0.00654	-0.00688	-0.0394**
	(0.0177)	(0.0177)	(0.0170)
yrs9_wind	0.00655	0.00657	-0.0261
	(0.0178)	(0.0178)	(0.0172)
Constant	0.132	0.128	-0.683***
	(0.150)	(0.151)	(0.0952)
Observations	30,636	30,636	30,636
R-squared	0.191	0.190	0.189
Number of fipscode	3,115	3,115	3,115

Robust standard errors in parentheses

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

Random Effects GLS

VARIABLES	(1) lnratepop	(2) lnratepop	(3) lnratepop	(4) lnratepop	(5) lnratepop	(6) lnratepop
lnmphwind	-0.106***	-0.0871**	-0.107***	-0.106***	-0.107***	-0.121***
	(0.0355)	(0.0359)	(0.0354)	(0.0355)	(0.0354)	(0.0355)
wind0dum	-0.379***	-0.525***	-0.384***	-0.376***	-0.383***	-0.432***
	(0.133)	(0.141)	(0.132)	(0.133)	(0.132)	(0.133)
lnmag			1.707**		1.683**	1.655**
			(0.688)		(0.691)	(0.688)
magdummy			-3.265**	-0.0236	-3.213**	-3.169**
			(1.327)	(0.0853)	(1.331)	(1.326)
lnmphspeed		-0.0815***				
		(0.0268)				
volcdummy				-0.499*	-0.465*	-0.460*
				(0.255)	(0.256)	(0.256)
waterpc						0.326***
						(0.0963)
Constant	-0.548***	-0.409***	-0.544***	-0.551***	-0.545***	-0.512***
	(0.141)	(0.148)	(0.140)	(0.141)	(0.140)	(0.140)
Observations	30,664	30,664	30,664	30,664	30,664	30,664
Number of fipscode	3,115	3,115	3,115	3,115	3,115	3,115

Robust standard errors in parentheses

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