



Did natural disasters affect population density growth in US counties?

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Abstract

This paper examines the long-run effects of natural disasters on population density growth across US counties during the period of 1960–2000. Detailed data for measuring the number and intensity of three types of major natural disasters (earthquake, tornado, and hurricane) are collected and incorporated into the empirical models. We do not find any significant adverse long-run growth effects of natural disasters. Weak evidence of minor tornadoes being positively correlated to growth is provided. Results also indicate that disasters have negligible indirect effects on county population density growth through impacting the county characteristics.

JEL Classification Q54 · R11

1 Introduction

Over the past decade, many countries around the world experienced the largest natural disasters in their history. A number of recent trends including growing population, development in coastal zones, the draining of wetlands, and changing climatic trends, such as global warming and weather anomalies, have increased the vulnerability of human beings to natural disasters. The combination of these factors increases the potential for loss of life and property in natural disasters-prone regions. As in many other countries, natural disasters afflict the USA every year, causing tremendous amount of economic damage and loss of life.

The main objective of the present paper is to investigate the long-run effects of natural disasters on population density growth in US counties during the period of 1960–2000. We assemble and analyze a detailed county-level dataset including data on three major types of natural disasters (earthquake, tornado, and hurricane) in the

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USA, complementing the literature in which most of the studies use country-level data. Spatial econometric models are used to account for spatial dependencies in the error term. Detailed data for measuring the number and intensity of three types of major natural disasters are incorporated into the models which allow us to further explore the effects of natural disasters. We try to control for mitigation and adaptation to the impacts of disasters in the post-disaster recovery. Our empirical models also consider those more indirect effects of natural disasters on growth through impacting the levels of human capital accumulation, age and ethnic composition of the population, and income inequality which are found to be correlated with regional population growth and income growth.

The present paper does not find any significant adverse long-run effects of natural disasters on population density growth in the US counties with the exception of minor tornadoes being positively correlated to growth. Results also indicate that disasters have negligible indirect effects through impacting the county characteristics. Adaptation to natural disasters is not a major driving force for post-disaster recovery.

The remainder of this paper proceeds as follows. The next section briefly reviews related literature. Section 3 proposes a simple framework which guides empirical analysis. Section 4 describes the data. Section 5 presents empirical results. The final section concludes.

2 Related literature

Natural disasters have gained increasing attention from economists in recent years. There is a growing body of literature on the effects of natural disasters on economic growth and welfare (Kahn 2005; Leiter et al. 2009; Skidmore and Toya 2002; Strobl 2011; Tavares 2004; Xiao 2011). The findings by the previous studies on the growth effects of natural disasters are far from conclusive, and even the signs of the net effects of natural disasters are not consistent. Using a panel data at the country level, Tavares (2004) finds some evidence that the occurrence of natural disasters has a negative and significant effect on per capita GDP growth rate. Noy (2009) also documents adverse impacts of disasters on macroeconomic output in the short run. However, Skidmore and Toya (2002) demonstrate that higher frequencies of climate disasters are correlated with higher rates of human capital accumulation, increases in total factor productivity, and long-run economic growth across countries. Rossi et al. (1978) find that there were no discernible net effects of natural disasters (floods, hurricanes, and tornadoes) on population growth trends in the period 1960–1970 in the USA. In a recent study, Xiao (2011) examines local economic impacts of the 1993 Midwest flood and finds that the flood's impacts on total employment are minimal. Also, long-run effects on personal income are negligible.

Another related literature is on man-made disasters. Though man-made disasters have many different types and causes (Loayza 2004), some interesting and useful papers focus on related topics. For example, Tavares (2004) finds that the cost to output of terrorist attacks is quantitatively small at the country level. Glaeser and Shapiro (2002) suggest that the costs of war and terrorism on cities are limited. Miguel and Roland (2011) find that the US bombing during the Vietnam War does not have negative

impacts on local poverty rates, consumption levels, literacy, or population density in Vietnam through 2002. Davis and Weinstein (2002) and Brakman et al. (2004) examine the effects of WWII on city growth in Japan and Germany, respectively. Both papers find evidence that it does not affect the relative growth of cities in the post-WWII period, although the evidence is somewhat limited for the case of Germany. In a later paper, Bosker et al. (2007) further find evidence for multiple equilibria in German city growth. However, the evidence is weaker when spatial interdependencies are not taken into account. Our results in the present paper basically indicate that natural disasters do not significantly affect relative growth in US counties with the exception of minor tornadoes.

The third related literature is on how natural disasters and weather anomalies may drive migration (Findley 1994; Marchiori et al. 2012; Saldaña-Zorrilla and Sandberg 2009). Per capita income growth in a region within a country may reflect increases in productivity or compensation for undesirable local quality of life. Thus, many previous papers in the literature of regional growth (Glaeser et al. 1995; Rappaport and Sachs 2003) argue that population growth is an appropriate measure of economic growth in the regional context because it represents good underlying fundamentals.¹ Population growth can be a result of increasing productivity and improving local quality of life. We focus on population density growth in this paper while also reporting some results on employment density change and per capita income growth.

The present paper is related to a recent paper by Strobl (2011) who constructs a novel hurricane destruction index and quantifies the short-run growth impacts of hurricanes in the USA. Strobl (2011) finds an overall net annual negligible impact of hurricanes in coastal states. The present paper mainly focuses on long-run population growth effects of earthquakes and tornadoes in addition to hurricanes. Also, we construct measures for disasters in a different way using the method used by Noy (2009) and some others. Our paper is also closely related to the study by Rossi et al. (1978) who estimate the effects on population growth across US counties. In contrast, our models not only control for correlated natural attributes, socioeconomic and demographic characteristics, and initial conditions which are found by the literature of regional and urban economics to be important for regional growth (Beeson et al. 2001; Glaeser et al. 1995; Higgins et al. 2006; Rappaport and Sachs 2003), but also take into account spatial interdependencies in the econometric model.

3 Estimation framework

To guide empirical analysis, we develop a very simple conceptual model which is an extension of the formulation proposed by Glaeser et al. (1995). The model presented here also draws from Rappaport and Sachs (2003). It explains the factors determining regional distribution of population and its growth over time. Natural disasters affect the levels of productivity and consumption amenities which thus have impacts on

¹ As our conceptual model in the appendix will show, it is based on the assumption that consumers are homogeneous and migration across regions is free and costless.

population distribution across counties. The appendix provides details for the simple conceptual model.

The econometric model on population density change is

$$\log\left(\frac{l_{i,t+1}}{l_{it}}\right) = \beta_0 + D'_{it}\beta_1 + C'_{it}\beta_2 + u_{i,t+1}, \quad (1)$$

where D_{it} is the vector of measures of natural disasters and C_{it} is the vector of some other natural, socioeconomic, and demographic characteristics of county i at time t . It suggests that the magnitude of net effect (and its sign) of natural disasters on population density growth in counties depends on the relative importance of their net amenity effects and net productivity effects. One of our major objectives of the present paper is to estimate the sum by using US county-level data. Before moving on to discuss our empirical strategy, we should note that our conceptual model is highly simplified. It does not explicitly model the role of labor demand (Greenwood 1975; Borjas 2010) in driving labor migration across regions. The issues of fertility are not considered in the model, either.

Spatial autocorrelation among the errors may occur when the model described by (1) omits certain independent variables that are spatially correlated themselves. Lagrange multiplier tests (Florax et al. 2003; LeSage and Pace 2009) are conducted to see if there is no spatial dependence in the population density change regressions due to spatial autoregressive errors. Test result rejects the hypothesis.² To account for the presence of autocorrelation, we further assume that,

$$u_{it} = \rho M_i u + \varepsilon_{it}, \quad (2)$$

where ε_{it} is an innovation term. Innovations are assumed to be totally independent. To compare the OLS model [Eq. (1)] and the spatial error model [Eqs. (1) and (2)], we perform a spatial Hausman test (LeSage and Pace 2009). The statistics strongly suggest that we reject the null hypothesis of equality of estimates from the two models. It indicates that the spatial error term is capturing the effect of omitted variables. See Table 11 (in Appendix) for the test statistics.

As counties differ greatly in land area, population, level of income, and other key variables, it is also reasonable to assume that the innovations, ε , in Eq. (2) are heteroskedastic. Our main estimation method for the growth regressions in the empirical section is borrowed from Kelejian and Prucha (2010). It is helpful to discuss the ways to construct the spatial weights matrices, M , in Eq. (2). Its element, M_{ij} , is set to be one if the counties i and j are geographic neighbors. Otherwise, $M_{ij} = 0$. All diagonal elements of M are set to be zero. This type of contiguity spatial weight matrix has been widely used in applied research. The spatial weight matrix is normalized such that each row sums to unity. Our results are robust to the selection of spatial weights

² Table 9 in the appendix reports the test statistics. For regressions on growth rates of population density, employment density, and per capita income, all statistics are greater than 372. Table 10 presents OLS results for population density growth for two 20-year periods.

matrices. Using the contiguity matrix or the distance-based matrix in the model, we find that the results are qualitatively the same.³

4 Data description

The dataset constructed for this paper consists of county-level data on population and employment, per capita money income, socioeconomic and demographic variables, natural attributes, and natural disasters. The year 1960 serves as the initial year for the analysis because it is the first year detailed and complete data on natural disasters are available. One of the important reasons for using county-level data in this study is that the occurrences of disaster events are reported at county level in many data sources such as those cited below. To keep county boundaries constant over time, we perform several minor adjustments⁴ and obtain 3077 counties in the contiguous USA.

The dataset includes three major types of natural disasters: earthquake, tornado, and hurricane. This paper considers measures that are exogenous—magnitudes and number of occurrence. Data on the number and magnitudes of earthquakes occurring between the years 1960 and 2000 are taken from Significant Earthquakes Database of National Oceanic and Atmospheric Administration (NOAA).⁵ The Richter scale is often used to report the magnitude of an earthquake where earthquakes at Richter 2.5 or below are not felt and those between 2.5 and 5.0 are often felt, but only cause minor damages. Our data sample includes all earthquakes with Richter 5.0 or higher which occurred between 1960 and 2000. Earthquakes between Richter 2.5 and 5.0 may also have potential effects on growth when people make location decisions and investment decisions. Unfortunately, data limitations on such small events prohibit their inclusion in this analysis, which will focus exclusively on larger earthquake events.

The second disaster type included in our analysis is tornado, one of the most destructive winds found on the earth's surface. The intensity of a tornado is often measured by Fujita Scale, which is based on wind speed and has a range from 0 to 5. If the wind speed is between 254 and 332 km/h, the tornado has a scale of F3 and results in severe damages. Causing even further damage are F5 tornadoes with wind speed greater than 419 km/h. Tornado data are collected from the National Climatic Data Center's Storm Event Database.⁶ For each tornado, information on its scale, location, and date of occurrence between 1960 and 2000 is recorded.

Finally, the third type of disaster is hurricane. Its force is measured on the Saffir/Simpson Scale, rating from 1 to 5 based on the hurricane's present intensity. As a hurricane reaches landfall, it has the potential to cause property damage and flooding

³ Later in this paper, we will report result from using a different spatial weight matrix.

⁴ Changes in county boundaries are documented by Bureau of Census. For more information, see <http://www.census.gov/geo/www/tiger/ctychng.html>. Most of such changes are that a county is split into two or more counties. We recombine such "split" counties so that counties in the data sample have constant boundaries in our sample.

⁵ The website is <http://www.ngdc.noaa.gov/nndc/struts/form?t=101650&s=1&d=1>. We also checked data available on the website <http://earthquake.usgs.gov/research/data/centennial.php>. Earthquakes from either source are included in our dataset.

⁶ It is available online at <http://www4.ncdc.noaa.gov/cgi-win/wwcgi.dll?wwEvent~Storms>.

Table 1 Number of counties/states afflicted by natural disasters

Disaster type	Time period						
	1960–1970	1970–1980	1980–1990	1990–2000	1960–1980	1980–2000	1960–2000
Earthquake	7/4	9/3	22/5	13/5	16/6	31/7	40/7
Tornado	2007/46	2287/48	2288/48	2479/48	2567/48	2743/48	2890/48
F0	738/43	1055/46	1326/47	1944/47	1372/47	2221/48	2420/48
F1	1260/46	1620/47	1599/48	1654/48	2018/47	2244/48	2583/48
F2	1186/46	1211/45	955/41	829/44	1745/46	1430/47	2139/47
F3	455/36	514/38	368/34	374/30	850/41	667/35	1225/43
F4	161/19	223/26	136/22	145/25	360/29	271/29	581/33
F5	23/9	34/9	6/3	14/5	57/13	20/7	74/15
Hurricane	112/16	48/10	119/17	69/12	127/18	142/17	167/18
C1	25/7	26/6	31/7	32/6	50/10	55/9	82/13
C2	42/5	13/4	28/7	30/10	52/7	44/12	78/13
C3	53/10	23/5	70/10	26/5	64/11	88/12	108/12
C4	15/2	0/0	3/1	1/1	15/2	4/2	18/3
C5	7/2	0/0	0/0	3/1	7/2	3/1	10/3

along the coast and the Saffir/Simpson Scale gives an estimate on the extent of this damage and flooding. Although all categories are dangerous, Categories 3, 4, and 5 are considered major hurricanes (Fitzpatrick 1999). Data on the number and category of hurricanes are collected from the NOAA Coastal Service Center. Our data sample includes all hurricanes that reached landfall between 1960 and 2000. Affected inland counties are impossible to be identified from our data sources.⁷

Total number of counties afflicted by each type of natural disasters is presented in Table 1. It documents that 167 coastal counties were hit by hurricanes during the 1960–2000 time period, while tornadoes affected a total of 2890 counties. Earthquakes, on the other hand, were much less widespread. Only 40 counties from 7 states experienced significant earthquakes with Richter 5.0 or higher during this period. Looking into the disasters data, we also observe that the juxtaposition of hazard events varies spatially in the USA (Figs. 1, 2, and 3). The Gulf and Atlantic coasts are much more prone to tropical storms, whereas the Pacific coastal states are much more susceptible to earthquakes and other types of tectonic hazards. The central portion of the USA is traditionally known as “Tornado Alley,” which covers the states from Texas northward to the Dakotas, claiming the highest annual average of tornadoes (Thomas and Mitchell 2001). Florida is also one with a very high frequency of tornadoes. On the other hand, the literature has also frequently noted the highly uneven distribution of

⁷ NOAA Coastal Services Center identifies coastal counties which are affected by hurricanes from 1900 through 2000; details are available online at <http://maps.csc.noaa.gov/hurricanes/pop.jsp> (accessed February 24, 2007) and http://www.aoml.noaa.gov/hrd/hurdat/Data_Storm.html. In a reply to the author’s query, Edward Rappaport at NOAA noted in an email that “we’re unaware of any study assessing the meteorological impact (e.g., category) for inland counties.” Missing information for affected inland counties in the dataset may bias our results as often the next county inland is hit just as badly as the coast.

economic activities across the USA, with an overwhelming concentration along the ocean and Great Lakes coasts (Rappaport and Sachs 2003) and denser populations within counties with more favorable climates (Beeson et al. 2001).

The primary dependent variable used in this study is population density growth. To offer more evidence, we also use growth rates of employment density and per capita income as dependent variables. Aside from natural disasters, additional explanatory variables include the following. Three variables (and their squares) are taken to measure weather: mean hours of sunlight for January, mean temperature for January and that for July, which are calculated as a land weight average of the temperature variables borrowed from McGranahan (2007); socioeconomic and demographic variables include educational attainment (percent of persons 25 years or older with 12 or more years of education in 1960, and percent of persons 25 years or older with 16 or more years of education in 1980), industrial composition (share of labor employment in manufacture), age and ethnic composition of the population (percent of population under 5 years old, percent of population 65 or more years old, and nonwhite population share), per capita income, and income inequality (percent of households with family income less than 3000 dollars in 1959, and percent of households with income less than 10,000 dollars in 1979), obtained from the *County and City Data Book* (1962, 1967, 1983, 1988, and 2000 editions). Computer files for the data books are found in Haines et al. (2005). These variables capture most of economic and social indicators shown to be associated with growth in regional literature (Beeson et al. 2001; Rappaport and Sachs 2003; Higgins et al. 2006; Wu and Gopinath 2008). Finally, we construct dummies for the 48 contiguous states and the District of Columbia and another dummy variable that takes a value of one if the associated county is a coastal county, as designated by the Strategic Environmental Assessments Division of the NOAA (NOAA 2006).

5 Empirical results

5.1 Natural disasters and population density growth: main results

This subsection focuses on the correlation between natural disasters and population density growth in the counties. As the effects of natural and socioeconomic characteristics may change over time with tastes and technology (Rappaport and Sachs 2003), the coefficients for related variables in our econometric models could be time-varying functions. Therefore, we split our data sample into two twenty-year periods: 1960–1980 and 1980–2000.

Before discussing the regression results, it is useful to describe the ways to construct disaster measures for the growth regressions. Tornadoes and hurricanes measures in this paper are calculated based on the intensity and the onset year. The Destruction Potential Index for tornadoes (Doswell et al. 2006; Thompson and Vescio 1998) provides basis for constructing our tornado measure for year k in a county. We define

$$F_k = \sum_{s=0}^5 n_{s,k}(s+1), \quad (3)$$

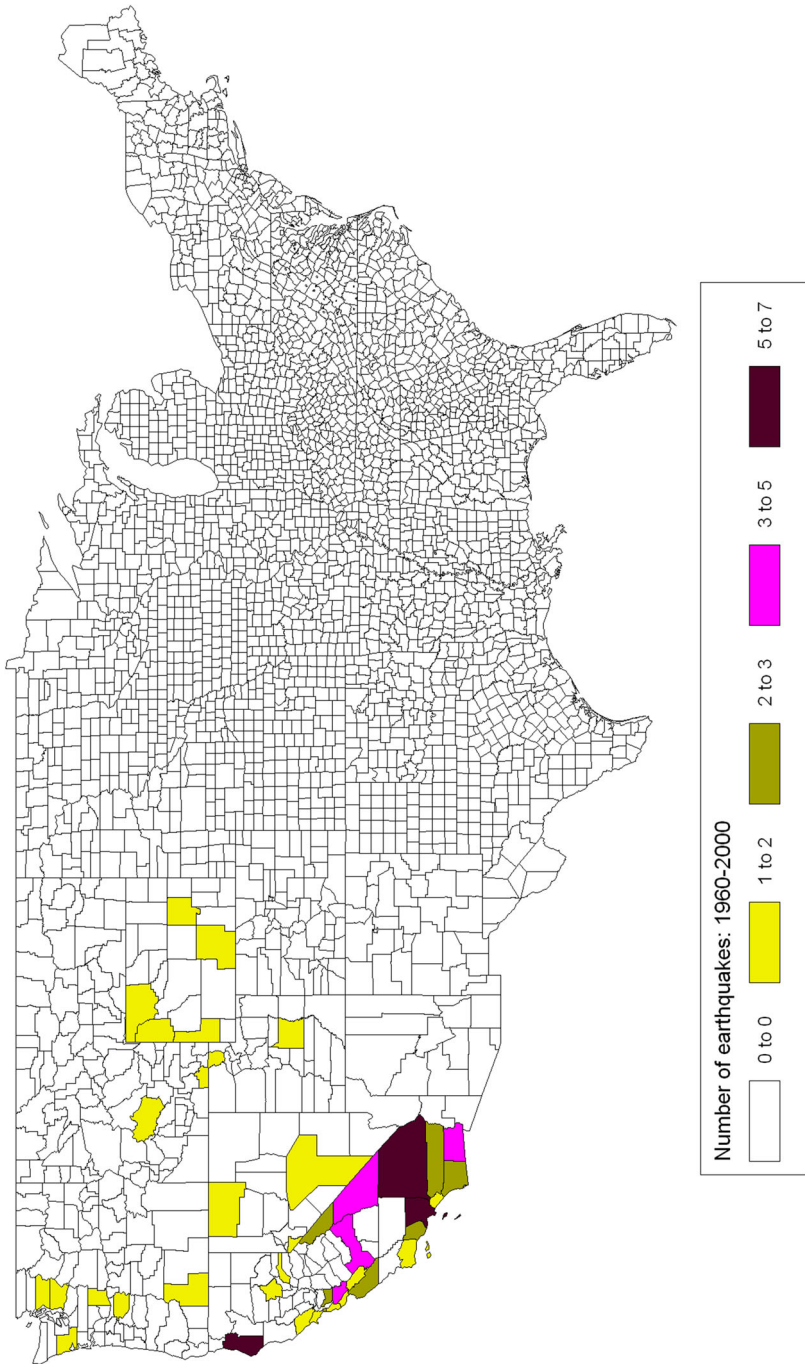


Fig. 1 The spatial distribution of earthquakes, 1960–2000

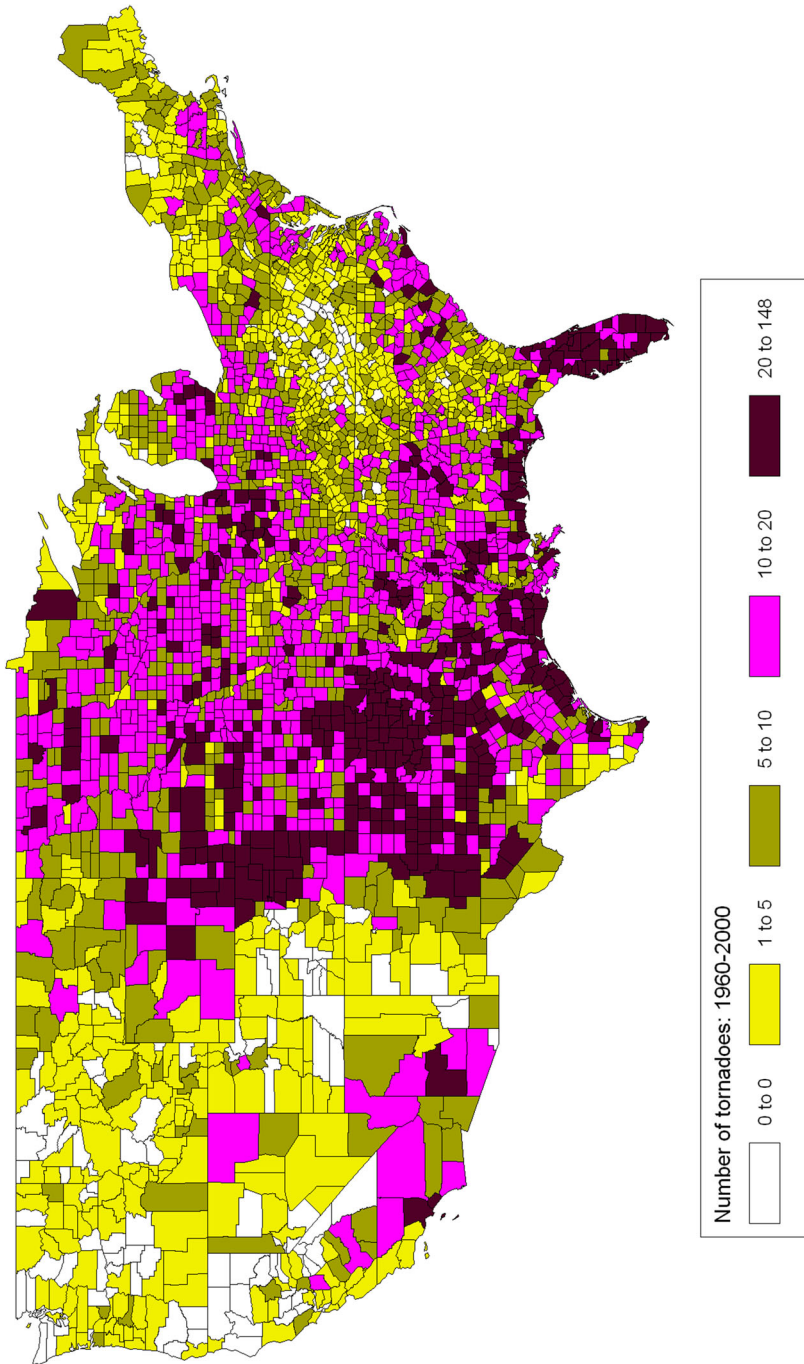


Fig. 2 The spatial distribution of tornadoes, 1960–2000

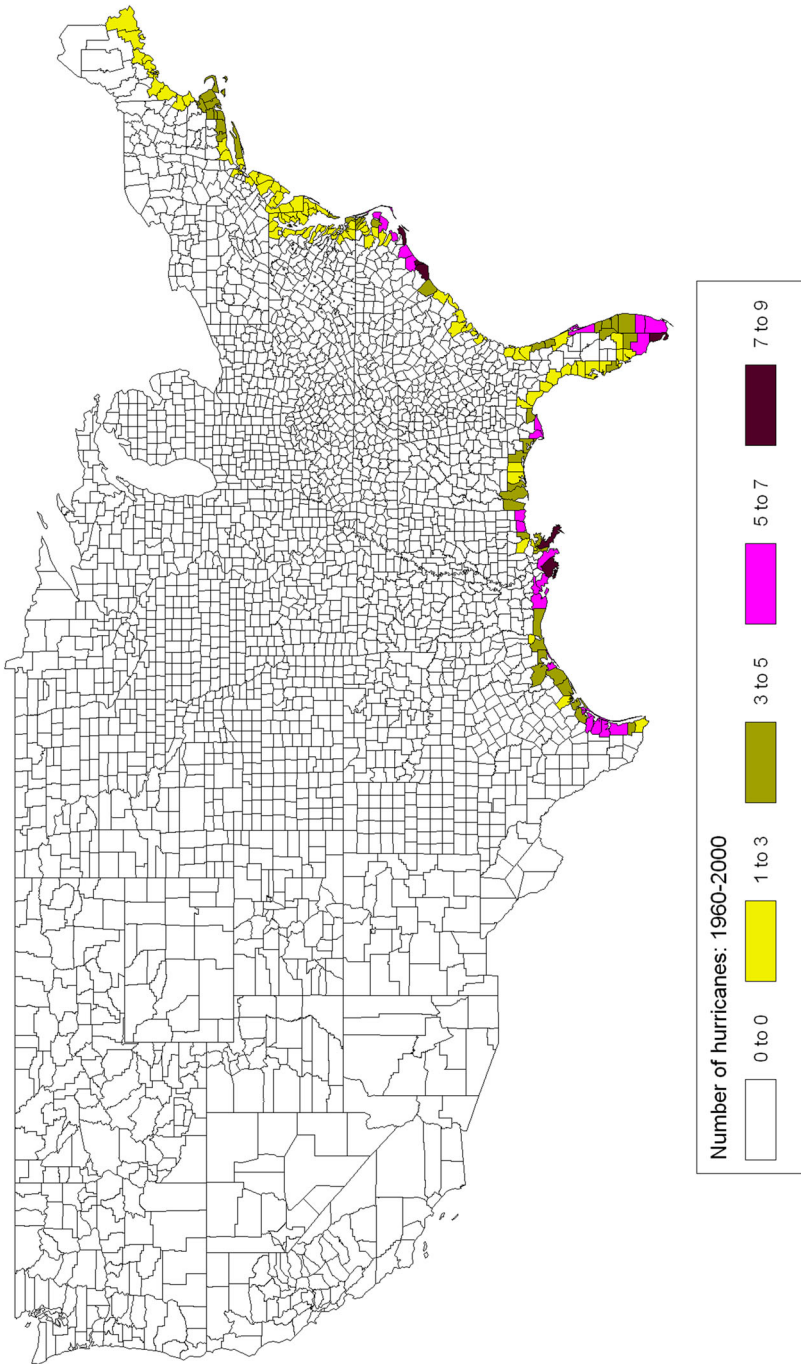


Fig. 3 The spatial distribution of hurricanes, 1960-2000

where $n_{s,k}$ is the number of tornadoes of Fujita scale s in year k . To aggregate disasters over years, we follow Noy (2009) and note that a disaster that occurred earlier will have a bigger impact on the economy.⁸ For the 20 years from 1960–1979, the tornado measure is calculated as

$$TM = \frac{1}{20} \sum_{k=0}^{19} (20 - k) F_{1960+k}. \quad (4)$$

Hurricane measure can be constructed in the same way where the measure for year k is equal to

$$H_k = n_{1,k} + n_{2,k} * 2 + n_{3,k} * 3 + n_{4,k} * 5 + n_{5,k} * 8, \quad (5)$$

where $n_{s,k}$ is the number of hurricane with Category s and the multiplier after it in the above equation is obtained by using results from previous studies (Emanuel 2005) on the relationship between wind speed and monetary loss from hurricanes. The above equation states that a Category 4 hurricane costs 5 times as much as a Category 1. The multiplier is obtained by calculating $(\frac{\text{median wind speed of Category } s}{\text{median wind speed of Category } 1})^3$ for $s = 4$ and rounding it up to the nearest integer, where the power 3 is suggested by Emanuel (2005) who actually suggests using maximum wind speed and considering the lifetime of the storm. Since we do not have information on wind speed for specific events, a same median speed is used for hurricanes of the same scale. Lifetime of the storm is ignored in the present paper due to data limitation. For the 20 years from 1960 to 1979, the hurricane measure is calculated as

$$HM = \frac{1}{20} \sum_{k=0}^{19} (20 - k) H_{1960+k}. \quad (6)$$

For earthquakes in a specific year, the number of events is counted and aggregated over the years. The measures for the 1980–2000 period regressions can be constructed in a similar way.

Column 1 of Table 2 presents a simple version of the spatial error model on population density changes between 1960 and 1980 as a function of the density at year 1960, weather, coastal and state dummies and the log of (1 + the disaster measures).⁹ It indicates that both tornadoes and hurricanes that occur over the 1960–1980 period are positively correlated with county population density growth in this time period. The estimated coefficient for earthquake is statistically insignificant.¹⁰

⁸ We also tried the measures which weight the number of disasters in the years equally. Qualitatively, the same results are obtained.

⁹ We use log of (1 + the disaster measures) in the model and add “1” because the disaster measures equal zero for many counties.

¹⁰ The focus of this paper is on the effects of natural disasters. It is noted that the regression results confirm the well-known facts that counties with nicer weather and western counties attract more people in the past decades. Estimated coefficients for those variables are also statistically significant in income and employment regressions. Results are available from the author upon request.

Table 2 The effects of natural disasters on population density growth: two time periods

Indep. var.	Dependent variable		Dependent variable	
	log(pop. density 1980)–log(pop. density 1960)		log(pop. density 2000)–log(pop. density 1980)	
	(1)	(2)	(3)	(4)
Earthquake	–0.018 (0.176)	0.034 (0.174)	–0.073 (0.069)	–0.063 (0.067)
Tornado	0.023*** (0.007)	0.013** (0.006)	0.016*** (0.006)	0.009 (0.006)
Hurricane	0.084** (0.039)	0.060* (0.035)	0.031 (0.027)	0.008 (0.024)
Income		–0.124* (0.065)		–0.428*** (0.071)
Education		0.006*** (0.001)		0.005*** (0.001)
Ethnic		–0.004*** (0.001)		–0.003*** (0.0005)
Manufacturing		0.002*** (0.001)		0.000 (0.001)
Population 5–		0.014** (0.006)		–0.026*** (0.006)
Population 65+		0.005 (0.004)		–0.008*** (0.002)
% poor households		–0.004*** (0.001)		–0.011*** (0.001)
Spatial AR	0.551*** (0.024)	0.549*** (0.023)	0.559*** (0.023)	0.520*** (0.024)
# of Obs.	3077	3064	3077	3077

1. Standard errors in parentheses. ***, **, * denote significant at 1%, 5%, and 10%, respectively; 2. All regressions control for initial level of population density, weather, state and coastal dummies, and a constant

Column 2 estimates the effects while controlling for additional socioeconomic and demographic characteristics of counties. The additional variables include levels of per capita income at year 1959, educational attainment, age composition, share of labor employment in manufacture, nonwhite population share, and a measure of income inequality within counties in the initial year.¹¹ After controlling for these factors, a similar picture emerges to the previous model: counties with larger tornado and hurricane measures experience faster long-run population density growth. However, the estimated coefficients are much smaller than those reported in Column 1. Again, earthquakes are not correlated with growth during this time period. The results pro-

¹¹ Data on income inequality in 1959 for several counties are missing, so we have a slightly smaller data sample in this round of regression exercises. We note that missing values for socioeconomic characteristics in year 1960 in several counties can bias the estimates if they are not random. However, we do not have information to evaluate it.

vide some evidence supporting Skidmore and Toya's (2002) hypothesis that climatic disasters promote growth.

For the second time period, 1980–2000, the first regression reported in Column 3 suggests that only tornadoes are positively correlated to county population density growth. We find positive correlation between the hurricane measure and population density growth during the 1980–2000 time period, but the estimates are not statistically significant. Column 4 controls additional socioeconomic and demographic characteristics. It finds qualitatively the same results. However, the estimated coefficient for the tornado variable is statistically insignificant at conventional levels.

The correlations between disasters and population density growth are possibly results from the impacts of disasters on changes in local productivity and consumption amenities. The empirical results indicate that tornadoes have smaller effects in the 1980–2000 period. The difference between sub-periods may come from the varying impacts on productivity and consumption amenities. The literature has tried to single out the positive impacts of coastal proximity on quality of life and production (Rappaport and Sachs 2003) and the two effects of human capital (Shapiro 2006) using additional variables.¹² It would be useful if we could conduct a similar analysis when more data and appropriate methods are available. That will help us understand the mechanism of the impacts of disasters including the effects on changes in local productivity and consumption amenities.

Disaster relief assistance can play an important role in the recovery process and growth performances of counties after the disaster. The different outcomes with respect to various disasters may be explained by differences in disaster assistance and the relief monies received by the affected counties. If the amount is significant enough, the assistance could then improve local production and consumption amenities so that economic activities and population density are increased.

There are no comprehensive data about actual disaster relief assistance available at the county level. However, data pertaining to presidential disaster declarations do exist and allow us to investigate this potential source of growth. We identify the presidential declarations related to each type of disasters in each county by looking at a dataset from the website of Federal Emergency Management Agency. Then, further regressions consider three additional variables about the declarations. Results indicate that the estimated coefficients for the declaration variables are statistically insignificant with the exception that the term of declared earthquakes has a significantly negative coefficient for the 1960–1980 period.¹³

¹² Rappaport and Sachs (2003) use coastal proximity measures (i.e., harbor proximity and the ratio of a county's shoreline to its total area) to distinguish the two effects. They find that the coastal concentration of economic activity "derives primarily from a productivity effect but also, increasingly, from a quality of life effect." Shapiro (2006) uses data on wages, rents, and house values to calibrate a model and find that "roughly 60% of employment growth effect of college graduates is due to enhanced productivity growth, the rest being caused by growth in the quality of life."

¹³ This result of presidential declaration having adverse impacts is contrary to our expectation. Possible reasons include that only those most costly events are declared. Another possibility is that the estimate could be biased. We should also note that the inclusion of presidential declarations in the regression with natural disaster can be potentially problematic because, among other reasons, it is not a perfect measure of relief efforts and there are various determinants of disaster payments (Garrett and Sobel 2003). The detailed results are available upon request from the author.

Table 3 The effects of natural disasters on population density growth: earthquakes, major and minor tornadoes, and major and minor hurricanes

Independent variable	Dependent variable			Dependent variable		
	log(pop. density 1980)–log(pop. density 1960)			log(pop. density 2000)–log(pop. density 1980)		
	(1)	(2)	(3)	(4)	(5)	(6)
Earthquake	0.003 (0.175)	–0.009 (0.174)	0.033 (0.174)	–0.063 (0.065)	–0.064 (0.066)	–0.063 (0.066)
Tornado						
Minor	0.027*** (0.007)	0.008 (0.006)	0.012* (0.007)	0.030*** (0.006)	0.013** (0.006)	0.013** (0.006)
Major	0.006 (0.006)	–0.002 (0.006)	0.001 (0.006)	–0.006 (0.005)	–0.005 (0.006)	–0.005 (0.004)
Hurricane						
Minor	0.067 (0.060)	0.054 (0.056)	0.049 (0.055)	0.014 (0.048)	–0.016 (0.047)	–0.016 (0.047)
Major	0.071 (0.041)	0.053 (0.043)	0.049 (0.042)	0.019 (0.034)	0.008 (0.029)	0.007 (0.029)
Initial density	No	No	Yes	No	No	Yes
Socioeconomic and demographic variables	No	Yes	Yes	No	Yes	Yes
# of observations	3077	3064	3064	3077	3077	3077

1. Standard errors in parentheses. ***, **, * denote significant at 1%, 5%, and 10%, respectively; 2. All regressions control for weather, state and coastal dummies, and a constant

5.2 Robustness checks

One grand disaster measure for tornadoes and one for hurricanes might not be able to capture the possibility that major events could have much more profound and lasting effects on regional growth than minor ones. To address such concern, we assign tornadoes into two groups: F0–F2 tornadoes as minor tornadoes and F3–F5 as major ones. Each hurricane is also assigned into either of two groups: major hurricanes include C3–C5 and minor hurricanes include C1–C2 hurricanes.

We perform regressions with these redefined groups and report the results in Table 3. Results for both time periods from different model specifications show that only minor tornadoes are positively correlated to long-run population density growth, while major tornadoes do not contribute to the growth. Other types of natural disasters are not statistically significantly correlated to growth. The findings are consistent for the two periods.

Using employment density change and per capita income growth as dependent variables, Table 4 re-estimates the models. Because population growth and employment growth are highly correlated, it is not surprising to see that employment density change regressions show results which are similar as those from the population density regressions. Tornadoes have positive impacts on employment density growth. The

Table 4 The effects of natural disasters on employment density growth and per capita income growth

	$\Delta \log(\text{employment density})$		$\Delta \log(\text{per capita income})$	
	1980–1960	2000–1980	1980–1960	2000–1980
Earthquake	0.157 (0.173)	-0.065 (0.078)	0.007 (0.053)	0.028 (0.037)
Tornado	0.021*** (0.007)	0.016** (0.007)	0.009*** (0.003)	0.000 (0.003)
Hurricane	0.060* (0.035)	0.038 (0.027)	0.016* (0.009)	0.017* (0.010)

1. Standard errors in parentheses. ***, **, * denote significant at 1%, 5%, and 10%, respectively; 2. All regressions control for weather, state and coastal dummies, socioeconomic and demographic characteristics, initial value of the associated dependent variable and a constant

table also suggests that the disasters do not have adverse effects on income growth, either. Hurricanes are found to be positively correlated with income growth in both periods. The estimates are statistically significant at the level of 10%. Tornadoes were also positively correlated with income growth in the 1960–1980 period. Mellinger et al. (2000) use income density (i.e., income per square mile) as an indicator of economic development when examining the impacts of geography and climate. We also tried its growth rate and found quite similar results as those for income growth.

In addition to the analysis on two equal sub-periods of 20 years, decade-by-decade growth regressions are also examined. Results show that only minor tornadoes are positively correlated to growth. In another check, we use frequencies of each type of disasters as the disaster measures in the regressions and obtain qualitatively the same results. We also apply a spatial error model to the constructed panel data and find that tornadoes are positively correlated to population density growth and earthquakes are negatively correlated to growth.

In the above regressions, we use a spatial weight matrix which is defined on whether two counties are geographic neighbors. However, there are other alternative definitions. As a robustness check, we define a new spatial weight matrix in which a element, M_{ij} , is set to be one if the counties i and j are from the same metropolitan statistical area. This is used to model the idea that the two counties are close in the sense of economic distance. It is a possible reason for spatial correlation in the error term of Eq. (2) as our main regression model does not explicitly control for such links among counties in the same area. Using the new spatial weight matrix, Table 5 reports the regression results. A general finding is that climatic disasters are positively correlated to county growth. However, the tornado estimates from the population growth regressions with the new spatial weight matrix become insignificant statistically. They are still significant for the employment regressions.

Table 5 The effects of natural disasters on population density growth: a different spatial weight matrix

	$\Delta\log(\text{population density})$		$\Delta\log(\text{employment density})$		$\Delta\log(\text{per capita income})$	
	1980–1960	2000–1980	1980–1960	2000–1980	1979–1959	1999–1979
Earthquake	–0.089 (0.174)	–0.071 (0.068)	0.050 (0.180)	–0.076 (0.068)	0.003 (0.062)	0.038 (0.038)
Tornado	0.006 (0.006)	0.006 (0.005)	0.014** (0.007)	0.012* (0.007)	0.010*** (0.003)	–0.000 (0.003)
Hurricane	0.066** (0.029)	0.016 (0.022)	0.065** (0.030)	0.045* (0.026)	0.019** (0.009)	0.018* (0.010)
# of observations	3064	3077	3064	3077	3064	3077

1. Spatial weight matrix for the regressions is defined on whether two counties are from the same metropolitan statistical area. 2. Standard errors in parentheses. ***, **, * denote significant at 1%, 5%, and 10%, respectively; 3. All regressions control for weather, state and coastal dummies, socioeconomic and demographic characteristics, initial value of the associated dependent variable, and a constant

Table 6 The effects of natural disasters on population density growth: excluding outliers

	$\Delta\log(\text{population density})$		$\Delta\log(\text{employment density})$		$\Delta\log(\text{per capita income})$	
	1980–1960	2000–1980	1980–1960	2000–1980	1979–1959	1999–1979
Earthquake	0.001 (0.225)	–0.067 (0.068)	0.147 (0.227)	–0.086 (0.081)	0.075 (0.048)	0.047 (0.036)
Tornado	0.007 (0.006)	0.009* (0.005)	0.014** (0.007)	0.012* (0.006)	0.009*** (0.003)	–0.001 (0.003)
Hurricane	0.057* (0.033)	0.023 (0.023)	0.074** (0.035)	0.053** (0.027)	0.015 (0.010)	0.024** (0.010)
# of observations	3005	3015	3006	3015	3008	3015

1. Standard errors in parentheses. ***, **, * denote significant at 1%, 5%, and 10%, respectively; 2. All regressions control for weather, state and coastal dummies, socioeconomic and demographic characteristics, initial value of the associated dependent variable, and a constant

Some forms of measurement error may bias the estimates. One particular form is recording errors that create extreme outliers in the sample. We check the robustness of our results with a sample without outliers. For the population density growth regression reported in Table 6, an observation is deleted from the data sample if it is for a county whose (1) population growth rate is larger than the 99.5 percentile or smaller than the 0.5 percentile, or (2) value of the constructed tornado measure is larger than the 99.5 percentile or smaller than the 0.5 percentile, or (3) earthquake measure (or the hurricane measure) is positive and takes the highest or lowest value.¹⁴ The deletions leave us with a slightly smaller sample. The regression results are again qualitatively the same as those reported earlier. We find that tornado is positively correlated to growth in most of the regressions, while the estimates for earthquakes are not significant.

¹⁴ As the number of counties hit by earthquake or hurricane is very small, we exclude only those affected counties with the highest or lowest measures for the two disasters.

5.3 Controlling for forecasts about future occurrences of disasters

In addition to historical and current county characteristics, public forecasts about future occurrences of disasters in counties are also considered by individuals when making their location and investment decisions (Bernknopf et al. 1990). They may consider the fact that some counties in the USA are often hit by tornadoes or earthquakes. Our estimates on the impact of disasters on growth from the previous regressions without variables on forecasts might be biased if the forecasts do in fact matter. To address such concerns, we need to re-estimate the growth effects while controlling for forecasts. One challenge to incorporating this variable is that there are no data on forecasts. In lieu of this information, we try different ways to capture people's expectations of future disasters.

Columns 1–2 in Table 7 estimate the regressions for the 1980–2000 period while controlling for a series of dummies for disaster-prone areas. The dummy E-prone1 (H-prone1) equals to one if a county ever experienced earthquakes (hurricanes) from 1960 to 1980, zero otherwise. T-prone1 equals one if the county has been hitting by 2 or more F2–F5 tornadoes over the 1960–1980 period, zero otherwise. Columns 3–4 in Table 7 control for another set of dummy variables on disaster-prone areas which have stricter definitions. E-prone2 (H-prone2) equals to one if the number of earthquakes (hurricanes) from 1960 to 1980 is not less than the median number of earthquakes (hurricanes) in counties being hit by this type of disaster, zero otherwise. Following the findings from Concannon et al. (2000), we focus on the states of Texas, Oklahoma, Kansas, Nebraska, South Dakota, and Colorado to define T-prone2 which is equal to one if a county is in these states and the number of F2–F5 tornadoes in the county is not less than the median number of F2–F5 tornadoes among all counties in these states. The area identified by T-prone2 and the conventionally defined core of tornado alley are much more similar.

None of the estimated coefficients for the disaster-prone areas are statistically significant with the exception of the estimates for tornadoes. Overall, the results imply that tornadoes have insignificant impacts in tornado alley, while they are positively correlated to growth in those counties outside the alley. The results also suggest that “predictions” regarding future earthquake and hurricane events almost have no effect on county population growth. There are two possible explanations for the insignificant effect of the forecasted future occurrences of natural disasters. First, prior to a low-probability disaster, it is not uncommon for individuals to deny that such an event will occur, so they behave as though the likelihood of a disaster causing damage to their property is zero. Those at risk often do not even seek out information on probabilities when making their decisions on low-probability events (Camerer and Kunreuther 1989; Kunreuther and Pauly 2006; Magat et al. 1987). Second, individuals believe that the government will respond with disaster assistance following the disasters events in the future.

The results indicate that the prediction about future tornado events does matter for growth, while the forecasts about the other two types of disasters do not. Compared to earthquake and hurricane, a county has a much higher probability of tornado occurrence. Even though relatively small areas are affected, tornadoes might be more

Table 7 The effects of natural disasters on population growth: controlling for “expectations”

	Dependent variable log(pop. density 2000)–log(pop. density 1980)			
	(1)	(2)	(3)	(4)
Earthquake	– 0.027 (0.043)	– 0.025 (0.042)	– 0.039 (0.051)	– 0.037 (0.051)
Tornado	0.011** (0.005)	0.012*** (0.005)	0.010** (0.005)	0.012** (0.005)
Hurricane	– 0.005 (0.021)	– 0.007 (0.021)	– 0.005 (0.025)	– 0.008 (0.025)
E-prone1	– 0.025 (0.050)	– 0.021 (0.049)		
T-prone1	– 0.016** (0.007)	– 0.013* (0.007)		
H-prone1	0.024 (0.043)	0.027 (0.043)		
E-prone2			– 0.024 (0.050)	– 0.020 (0.049)
T-prone2			– 0.014* (0.007)	– 0.011 (0.007)
H-prone2			0.024 (0.042)	0.027 (0.042)
Initial density	No	Yes	No	Yes
# of Obs.	3077	3077	3077	3077

1. Standard errors in parentheses. ***, **, * denote significant at 1%, 5%, and 10%, respectively; 2. All regressions control for weather, state and coastal dummies, socioeconomic and demographic characteristics, and a constant. 3. E-prone1 (H-prone1) equals to one if the county ever experienced earthquakes (hurricanes) from 1960 to 1980, zero otherwise. T-prone1 equals one if the county has been hitting by 2 or more F2–F5 tornadoes over the 1960–1980 period, zero otherwise. For the second set of dummy variables on disaster-prone areas: E-prone2 (H-prone2) equals to one if the number of earthquakes (hurricanes) from 1960 to 1980 is not less than the median number of earthquakes (hurricanes) in counties being hit by this type of disaster, zero otherwise. T-prone2 is equal to one if a county is in the states of Texas, Oklahoma, Kansas, Nebraska, South Dakota, and Colorado, and the number of F2–F5 tornadoes in the county is not less than the median number of F2–F5 tornadoes among all counties in these states. E60–80 is equal to $1/20 * \log(1 + \text{number of earthquakes occurring over the period of 1960–1980})$, T60–80 and H60–80 are, respectively, defined similarly for (intensity-adjusted) tornadoes and hurricanes

important because they make people constantly aware of the danger, which might be less the case with the rare big earthquake and hurricane events. The results in Table 7 also confirm previous findings presented in Tables 4, 5, and 6 which show that most of the disasters have no statistically significant effects on growth with the exception of tornadoes.

5.4 Natural disasters and socioeconomic and demographic characteristics

The regressions performed in Tables 2, 3, 4, 5, and 6 confirm the findings by many previous studies in the regional literature that initial levels of educational attainment, age and ethnic composition of population, industrial composition, and income inequality have significant effects on growth (Beeson et al. 2001; Rappaport and Sachs 2003; Higgins et al. 2006; Wu and Gopinath 2008). Most of these correlations are statistically significant over the whole period and two sub-periods.

Given the results, our next set of regressions seeks to determine if natural disasters contribute to changes in these socioeconomic and demographic characteristics. If such a linkage does exist, then natural disasters may have indirect effects on growth through affecting the associated variables for socioeconomic and demographic characteristics. Related possible linkages between natural disasters and community and regional characteristics are discussed in the studies of sociology, demography, and economics, but prior studies find different effects.

In regard to human capital accumulation, the regional and urban economics literature provides evidence supporting the notion that locations with higher levels of amenities attract a larger number of highly educated immigrants and migrants (Cullen and Levitt 1999; Kahn 2000). Thus, a link between natural disasters and human capital accumulation may exist because of the amenity effects of natural disasters. Studies also document that locations with higher level of amenities attract a greater number of retirees, implying a possible connection between natural disasters and the age composition of population. Demographic research suggests that fertility rates response to natural disasters (Jones 1987; Rogers et al. 2005). Natural disasters do not affect all social groups equally as poorer individuals bear a disproportionate share of losses and the elderly are over-represented among the dead and the injured (Cochrane 1975). Thus, disasters could deepen existing income inequalities and change the age composition of population.

To test those possible links in our data, we perform several regressions of county characteristics in 1980 on the variables for natural disasters and other controls. The level, not growth rate, of the associated socioeconomic and demographic characteristics is used as dependent variable. Regression 1 of Table 8 examines the effects of natural disasters which occurred between 1960 and 1980 on the share of population 25 years and older with 16 or more years of schooling in 1980. Results indicate that natural disasters have no statistically significant effects on the measure of human capital stock with the exception of tornadoes having positive effect. The estimate is significantly different from zero at 10% level.

Regression 2 presents the effects on the share of nonwhite population. It finds an insignificance of disaster measures. The effects on the age structure of population are presented in Columns 3 and 4, showing that only hurricanes have statistically significant effects on percent of population with 65 years or older. The estimated positive correlation between hurricane and the proportion might just be driven by the fact that a large amount of retirees moved to Florida counties which have high frequencies of hurricanes. Column 5 reports the regression on income inequality and finds no effect of any type of natural disasters with the exception of tornadoes lowering

Table 8 The effects of natural disasters on socioeconomic characteristics in 1980

	% Persons 25+ w 16+ years schooling (1)	% Nonwhite population (2)	% Population 5 years and younger (3)	% Population 65 years and older (4)	% households w/income <\$10,000 (5)
Earthquake	2.957 (3.555)	3.043 (2.897)	0.151 (0.592)	- 1.141 (1.220)	- 1.128 (3.006)
Tornado	0.264* (0.148)	- 0.047 (0.133)	- 0.004 (0.027)	- 0.055 (0.059)	- 0.320** (0.136)
Hurricane	0.283 (0.609)	- 0.603 (0.612)	- 0.142 (0.091)	0.663*** (0.237)	- 0.238 (0.473)

1. Standard errors in parentheses. ***, **, * denote significant at 1%, 5%, and 10%, respectively; 2. All regressions control for socioeconomic characteristics in 1960, weather, state and coastal dummies, and a constant

inequality. We try a few other different specifications of regressions of Table 8 (e.g., just keeping the initial level of interested characteristics as the independent socioeconomic condition). From such exercises, we obtain similar results regarding the effects of natural disasters on the characteristics although the level of the estimated coefficient for some variables changes a little bit.

Overall, there are negligible effects of natural disasters on socioeconomic and demographic characteristics of counties. This implies that the impacts of disasters on growth through those correlated variables are minimal.

It should be noted that the present paper presents many estimates about the correlation between natural disasters and regional growth. The period of analysis is relatively short, and the effect of these disasters shocks might already be internalized in economic behavior.¹⁵ These estimates are not necessarily casual impacts. For future work, it is interesting to explore the causality by using different techniques such as synthetic control model by Cavallo et al. (2013). We used disaster counts and intensities and constructed the disaster measures in the present paper. It will also be interesting in the future to explore other alternatives and make more suitable choices.

6 Conclusions

This paper continues a limited number of empirical studies on the effects of natural disasters on regional growth. Specifically, it investigates the effects of earthquakes, tornadoes, and hurricanes on long-run population density growth across US counties. The paper complements the literature of disaster effects in which most of the studies use country-level data.

We employ a simple model to guide the econometric analysis. It considers that disasters may have impacts on changes in local productivity and consumption amenities. Then, the changes drive population density changes across counties. Results from estimating the spatial econometric models find no significant adverse effects of the

¹⁵ I thank a reviewer for pointing it out.

disasters on long-run population density growth in the counties over the period of 1960–2000. Weak evidence of minor tornadoes being positively correlated to growth is provided. The results also indicate that natural disasters have negligible indirect effects through county characteristics on growth.

Our results differ substantially from those in some previous studies which use country-level data and find significant effects of natural disasters on economic growth. This difference between our results and those from cross-county analysis could also possibly be explained by the scope and level of mitigation activities following disaster events. The shock of a disaster event might be shared by regions within a country through resource transfer between regions, whereas a country must take the risk and consequences almost alone. Moreover, the USA, as a developed and wealthy country, responds to disaster events effectively and efficiently.

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Appendix

Conceptual framework

Consider an economy composed of a set of counties $i \in \{1, 2, \dots, I\}$. Suppose that population in county i at time t is represented by L_{it} . Following Ciccone and Hall (1996), we assume that the aggregate production function for county i is given by

$$Y_{it} = A_{it} L_{it}^{\gamma} S_{it}^{1-\gamma}, \quad (\text{A1})$$

where A_{it} denotes the level of productivity. S_{it} denotes total land area. Wage rate for an individual in this county, R_{it} , is the marginal product of labor, thus

$$R_{it} = \gamma A_{it} L_{it}^{\gamma-1} S_{it}^{1-\gamma}. \quad (\text{A2})$$

A representative individual in county i at time t derives utility, V_{it} , from local quality of life and wage rate she received:

$$V_{it} = \left[Q_{it} \left(\frac{L_{it}}{S_{it}} \right)^{-\alpha} \right] R_{it}, \quad (\text{A3})$$

where $Q_{it} \left(\frac{L_{it}}{S_{it}} \right)^{-\alpha}$ is an index of local quality of life in which Q_{it} denotes exogenous environmental amenities such as weather; $\left(\frac{L_{it}}{S_{it}} \right)^{-\alpha}$ represents congestion effects in this county with $\alpha > 0$. This is linked to previous studies, suggesting that amenities play an important role with respect to migration destinations (Knapp and Graves 1989).

Let $l_{it} \equiv \frac{L_{it}}{S_{it}}$ denote population density.¹⁶ Combining (A2) and (A3) gives that

$$V_t = \gamma Q_{it} A_{it} (l_{it})^{\gamma-1-\alpha}. \quad (\text{A4})$$

Assume that migration across counties is free and costless. In equilibrium, utility levels across counties are equal. Let V_t denote equilibrium level of utility at time period t , then $V_t \equiv V_{it}$ for any county i . Thus, Eq. (A4) implies that,

$$\log l_{it} = \frac{1}{\gamma - 1 - \alpha} [\log V_t - \log \gamma - \log Q_{it} - \log A_{it}].$$

Growth rate in population density between 2 years can be expressed as

$$\log\left(\frac{l_{i,t+1}}{l_{it}}\right) = \frac{1}{\gamma - 1 - \alpha} \left[\log\left(\frac{V_{i,t+1}}{V_{it}}\right) - \log\left(\frac{Q_{i,t+1}}{Q_{it}}\right) - \log\left(\frac{A_{i,t+1}}{A_{it}}\right) \right]. \quad (\text{A5})$$

Natural disasters may contribute to the growth of local productivity, A_{it} , by encouraging the adoption of new production technologies by firms through replacing the damaged machines and equipment in the afflicted regions (Tol and Leek 1999). Affected locations also benefit from higher growth of total assets in firms (Leiter et al. 2009) and a massive inflow of capital for rebuilding, and from technological innovations in the construction sector (Albala-Bertrand 1993). On the other hand, disasters could have adverse productivity effects through destroying physical capital stock, lowering marginal product of labor. Thus, the net effects of natural disasters on local productivity growth are not clear in theory.

In addition to productivity effects, the occurrences of natural disaster events also change the level of quality of life, Q_{it} , by directly destroying amenity structures, damaging transportation system, and causing inconvenience to daily life for people in the affected regions. However, some case studies find that natural disasters improve local quality of life through promoting and reinforcing a sense of regional identity among population in the affected region (Geipel 1982). Thus, the net effects on quality of life are also ambiguous.

To describe the dynamics of productivity and quality of life, A_{it} and Q_{it} are assumed to change over time and are functions of natural disaster events and other characteristics of the associated county (Glaeser et al. 1995). Formally,

$$\log\left(\frac{A_{i,t+1}}{A_{it}}\right) = D'_{it}\delta_A + C'_{it}\pi_A + v_{i,t+1}, \quad (\text{A6})$$

and

$$\log\left(\frac{Q_{i,t+1}}{Q_{it}}\right) = D'_{it}\delta_Q + C'_{it}\pi_Q + \mu_{i,t+1}, \quad (\text{A7})$$

¹⁶ In the empirical analysis, we focus on population density growth, but not population growth. The main reason is that land areas for some counties in our sample have changed slightly even when we make the county boundaries consistent over the years. Note that change in population density is equal to change in population when the land area is constant between 2 years. In that case, our model is the same as the one developed by Glaeser et al. (1995) and many others in the regional literature.

where D_{it} is the vector of measures of natural disasters and C_{it} is the vector of some other natural, socioeconomic, and demographic characteristics of the associated county. The error terms in the two processes are represented by $v_{i,t+1}$ and $\mu_{i,t+1}$, respectively. Neither of the two error terms is correlated with natural disasters or county characteristics. It is well documented in the regional literature that locational fundamentals such as weather and coastal proximity have impacts on regional growth. The growth literature also finds substantial evidence on the importance of human capital, political and social characteristics, industrial composition, and many other factors for population growth. Those related variables are grouped in C_{it} . Combining (A5), (A6), and (A7) yields the expression for population density change between two periods:

$$\log\left(\frac{l_{i,t+1}}{l_{it}}\right) = \frac{1}{1 + \alpha - \gamma} D'_{it}(\delta_A + \delta_Q) + \frac{1}{1 + \alpha - \gamma} C'_{it}(\pi_A + \pi_Q) + u_{i,t+1}, \quad (A8)$$

where $u_{i,t+1} = \frac{1}{1+\alpha-\gamma}[-\log(\frac{V_{i,t+1}}{V_{it}}) + v_{i,t+1} + \mu_{i,t+1}]$.

Appendix tables

Table 9 Lagrange multiplier test statistics

	$\Delta\log(\text{population density})$	$\Delta\log(\text{employment density})$	$\Delta\log(\text{per capita income})$
1960–1980	727.88	637.70	495.67
1980–2000	673.36	458.73	372.20

To calculate the statistics, all regressions control for weather, state and coastal dummies, socioeconomic and demographic characteristics, initial value of the associated dependent variable, and a constant. Contiguity-based spatial weight matrix is used for calculating the LM statistics

Table 10 The effects of natural disasters on population density growth: OLS results

Indep. var.	Dependent variable $\log(\text{pop. density 1980})-\log(\text{pop. density 1960})$	Dependent variable $\log(\text{pop. density 2000})-\log(\text{pop. density 1980})$
Earthquake	-0.068 (0.166)	-0.052 (0.056)
Tornado	0.009 (0.006)	0.007 (0.005)
Hurricane	0.063*** (0.019)	0.009 (0.018)

Table 10 continued

Indep. var.	Dependent variable log(pop. density 1980)–log(pop. density 1960)	Dependent variable log(pop. density 2000)–log(pop. density 1980)
Income	– 0.133** (0.054)	– 0.558*** (0.056)
Education	0.006*** (0.001)	0.005*** (0.001)
Ethnic	– 0.003*** (0.0005)	– 0.003*** (0.0005)
Manufacturing	0.003*** (0.001)	0.000 (0.0004)
Population 5–	0.012** (0.005)	– 0.036*** (0.005)
Population 65+	0.005 (0.004)	– 0.008*** (0.002)
% poor households	– 0.004*** (0.001)	– 0.012*** (0.001)
# of obs.	3064	3077

1. Standard errors in parentheses. ***, **, * denote significant at 1%, 5%, and 10%, respectively; 2. All regressions control for initial level of population density, weather, state and coastal dummies, and a constant

Table 11 Spatial Hausman test statistics: OLS versus SEM

	$\Delta\log(\text{population density})$	$\Delta\log(\text{employment density})$	$\Delta\log(\text{per capita income})$
1960–1980	216.40	234.31	252.56
1980–2000	290.19	288.02	247.28

To calculate the statistics, all regressions control for weather, state and coastal dummies, socioeconomic and demographic characteristics, initial value of the associated dependent variable, and a constant. Contiguity-based spatial weight matrix is used for the spatial error model

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