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Weather-Related Hazards and Population Change: A Study of Hurricanes and Tropical Storms in the United States, 1980–2012

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Abstract

Environmental determinists predict that people move away from places experiencing frequent weather hazards, yet some of these areas have rapidly growing populations. This analysis examines the relationship between weather events and population change in all U.S. counties that experienced hurricanes and tropical storms between 1980 and 2012. Our database allows for more generalizable conclusions by accounting for heterogeneity in current and past hurricane events and losses and past population trends. We find that hurricanes and tropical storms affect future population growth only in counties with growing, high-density populations, which are only 2 percent of all counties. In those counties, current year hurricane events and related losses suppress future population growth, although cumulative hurricane-related losses actually elevate population growth. Low-density counties and counties with stable or declining populations experience no effect of these weather events. Our analysis provides a methodologically informed explanation for contradictory findings in prior studies.

Keywords

population; migration; hurricanes; weather; disaster events; losses

Scientific warnings that climate-related extremes will increasingly impact ecosystems and social systems have focused scholarly attention on social and demographic responses to weather-related hazards, particularly the migration response (IPCC 2014). Many have interpreted this to mean that any population living in an area susceptible to an extreme climate event will out-migrate (e.g., Myers 2002). In reaction, a burgeoning interdisciplinary literature seeks to move beyond environmental determinism to consider how weather, geography, and society produce adaptive responses that include, but are not limited to, migration (cf. Black et al. 2011; Morss et al. 2011). But there are more hypotheses about this complex relationship than there are data to test them. Further, most research occurs within disciplines despite the interdisciplinary nature of the research, and population scientists are among those least engaged in research on environmental drivers of population change (de Sherbinin et al. 2007; Gall, Nguyen, and Cutter 2015; Hunter, Luna, and Norton 2015).

For decades, demographers focused their attention on how migration affects environmental outcomes, viewing migration as a key factor influencing environmental degradation (de

Sherbinin et al. 2008; Hugo 2013). Recently, demographers reversed the causal order to ask how the environment drives migration (Hunter, Luna, and Norton 2015). They found heterogeneous effects of the environment on migration. For example, Gutmann and Field (2010) argue that catastrophes such as Hurricane Katrina or the 1930s Dust Bowl have relatively small impacts on population redistribution compared with the effects of environmental amenities (e.g., milder climates, proximity to water or mountains) or the management of environmental barriers (e.g., air conditioning, flood control, drainage, and irrigation). One example of migration to attractive but risky places is found in the growth of the population in coastal areas despite hurricane-related losses along the Atlantic hurricane coast (NOAA 2013). This is exactly the opposite of environmental determinists' prediction that people will move away from hazards.

Earlier demographers argued for modeling a dynamic relationship between population and environment, but data to do so were lacking (Bilsborrow 1992; Davis and Bernstam 1991). Our approach returns to this earlier articulation by building a dataset with sufficient temporal and spatial variability to model a reciprocal relationship between environment and population. To get at this dynamic relationship, we examine how past population trends, population density, current and cumulative weather events, and weather-related losses intersect at the county level to influence future population change. We hypothesize that the effect of weather hazards on future population growth is small compared with the effect of past population trends.

Weather Hazards and Population Change

Early research on weather hazards and population change in the United States concluded that there was no population impact of weather-related hazards on average (Wright et al. 1979). Since Hurricane Katrina struck the Gulf Coast in 2005, the question has been revisited, but findings are contradictory. For example, Pais and Elliott (2008) show that the four "billion dollar storms" of the early 1990s were associated with postevent population growth. Moving from hurricane-related losses to all hazard losses, Schultz and Elliott (2013) show that a county experiencing \$1 million in total property damage from hazards during the 1990s grew in population by an average of 3.2 percentage points more than a county experiencing no disaster-related property damage between 1995 and 2000. Pais and Elliott (2008) speculate that the repair of hazard damage and opportunities to improve disaster-affected areas create jobs and housing that attract new residents. This line of research indicates that hazards produce a churning of the population, with some sociodemographic groups increasing and others decreasing but typically resulting in a net population gain (Elliott 2014).

Other research shows that natural hazard exposure is associated with reduced growth. For example, Logan, Issar, and Xu (2016) found that between 1970 and 2005, Gulf Coast counties with higher levels of hurricane-related damage experienced reduced growth for up to three years after the hurricane event, especially in counties with low poverty rates. Similarly, Shumway, Otterstrom, and Glavac (2014) used county-to-county migration flow data from 2000 to 2010 to show that counties with high environmental hazard impacts lose residents through net out-migration, and those out-migrants tend to be higher income

residents who move to counties with lower cumulative hazard losses. These studies provide evidence that damage-related losses from hurricanes and other natural hazards suppress population growth when those who can afford to move to less hazardous places choose to do so and they are not replaced by in-migrants.

We suspect that this apparent contradiction in the research on the population effects of hurricanes is due to long-term trends in population growth, which influence how residents of disaster-affected areas respond. We know of no research addressing this question explicitly. There is, however, one study that found that ninety-two U.S. communities that experienced tornados in which at least half of their structures suffered major damage between 1992 and 2008 and that were already experiencing declining populations before the disaster were more likely to experience large postdisaster population losses (Cross 2014). Much like case studies that focus on catastrophic events, this study selected only those places that suffered extensive damage to structures, limiting the generalizability of the conclusions.

By examining all counties affected by hazards and incorporating long-term population trends and hazard events and losses, we test the hypothesis that the effect of weather hazards on future population growth is small compared with the effect of past population trends. While we expect that our hypothesis will be supported, evidence inconsistent with our hypothesis may help to reconcile this contradiction in the existing research on how populations change after an environmental hazard event and which types of places are most likely to experience population change.

Data and Methods

Data

To obtain the spatial and temporal variability in population trends and weather hazard events and losses necessary to accomplish our research objectives, we integrated county-level annual population estimates from the U.S. Census Bureau (2016) with the Spatial Hazard Events and Losses Database for the United States (SHELDUS; HVRI 2015). For the measures of population change, we included annual, county-level estimates from 1970 through 2012. Intercensal estimates were used for the 1990s and 2000s, while postcensal techniques were used for the 1970s, 1980s, and 2010s. We did not include intercensal estimates for the 1960s because they were produced with methods that are inconsistent with later estimates. Our population change dataset treats county-year as the unit of analysis and measures annual population size for each county-year.

The SHELDUS dataset measures annual county-level fatalities, injuries, and property and crop losses associated with eighteen types of natural hazard events in the United States from January 1960 to December 2014. SHELDUS combines data from twenty-three sources, though most come from the National Centers for Environmental Information data products. The loss estimates are obtained from emergency managers, U.S. Geological Survey, U.S. Army Corps of Engineers, power utility companies, and newspaper articles. These amounts refer to losses associated with damage to private property, including structures, objects, and vegetation, as well as public infrastructure and facilities. Damages or loss amounts are distributed evenly between counties in a multicounty event. As in the population data, the

unit of analysis is a county-year. The population and hazard event data files were merged using ArcGIS geo-referenced county-year FIPS codes and county boundary files to produce a spatial-temporal database of county-years for each hazard type. We adjusted county boundaries to 2010 boundaries.¹ From the SHEL DUS database, we selected only weather-related hazards, which include avalanches, coastal storms, droughts, floods, fog, hail storms, heat waves, hurricanes/tropical storms, landslides, lightning storms, severe thunderstorms, tornados, wind, and winter weather. We focused on these because we expect to see more of these types of events as climate change progresses. This excludes wildfires, earthquakes, tsunamis/seiches, and volcanic eruptions, none of which are directly attributable to climate change: wildfires are typically started by human activity and geologic activity is not climate-related.

Our database provides an important corrective to previous approaches to how populations respond to hazard impacts. Analyses that focus on population impacts of a single hazard event in a specific place commit two errors that threaten the generalizability of their findings: (1) they select only the most damaging and costly events and thereby neglect the full range of events, and (2) they ignore the cumulative impacts of previous hazards, a source of unobserved heterogeneity. By using data from a long period of time and for the entire affected region and that include all weather hazard events, we address both concerns.

We addressed these sources of unobserved heterogeneity by measuring all hazard events and placing the effect of a single hazard event in the context of past hazard events, hazard-related losses, and past population growth. We observed hazard events and losses for the years 1970 to 2009 and population data from 1970 to 2012. We then constructed decadal measures of cumulative hazard events and losses. A decade is long enough to remove much of the random element of hazard occurrence and capture secular trends. The measures of cumulative hazard events and hazard losses sum those annual quantities over the previous 10 years. The past population trend is defined by a 10-year compound average population

growth rate: $CAPGR = \left(\frac{pop_t}{pop_{t-10}} \right)^{\left(\frac{1}{10} \right)} - 1$, where *pop* is the county population in a given county-year, and *t* is the reference year. Therefore, our analysis begins in 1980, the first year in which we have 10 years of past hazard and population data. We measure future population growth as a three-year compound average annual population growth rate:

$CAPGR = \left(\frac{pop_{t+3}}{pop_t} \right)^{\left(\frac{1}{4} \right)} - 1$ where *pop* is the county population in a county-year, *t*, and *t* is the reference year. We chose three years as a time frame because it allows for the possibility of population recovery and growth (or loss) after a hazard event. We also included a measure of county population density, defined as the population per square mile. Based on our

¹The spatial boundary files used for our mapping and modeling were generated from the 2010 TIGER/Line Shapefile. Historical SHEL DUS data have already been conflated to modern (2010) boundaries and thus require no boundary corrections over time. The population data used in our study, the U.S. Census Bureau county-level intercensal population estimates, are based on decadal boundaries that are anchored on boundary definitions at the end of the decade. In other words, we had to correct for boundary issues only in 1970, 1980, 1990, and 2000, not all individual years. Most county boundaries do not change. For those that have changed, we use the basic, but standard, process of areal weighting, or reassigning population counts based on the proportion of the county area that changed.

decision to measure future growth in three-year intervals and data availability, we end our analysis in 2012.

Our treatment of hazard losses departs from much of the social science research on this topic. Most research tends to treat hazard losses as equivalent regardless of the hazard type producing the loss. We propose that losses are not equivalent; for example, damage to a home resulting in temporary or permanent loss of its use is different than damage to utility infrastructure that causes loss of access to electricity, gas, or water until services are restored. While the former displaces residents for prolonged periods, the latter does not. Differences in types of damage produced by hazard events means that they are unequally likely to produce population change even when monetized loss estimates are equivalent. Therefore, we consider hazards by type, and here we focus on hurricanes and tropical storms (hereafter, hurricanes) because they are among the most damaging weather events and are more likely to produce a migration response.

Methods

Our hypothesis is that the effect of a weather hazard in a given year on future population growth is small compared with the cumulative effects of weather hazards and past population trends. To test this, we estimate a random effects linear regression that takes a reduced form, evaluating the marginal impacts of hazards on future population change and controlling for past population trends. We assume that while political, social, and economic conditions and trends also influence future population growth, their influence is gauged by past population growth. Past population growth captures a large portion of this unobserved heterogeneity. To further address the issue of unobserved heterogeneity between counties, we analyze our county-year data with a random effects generalized least squares regression estimation model (STATA xtreg re):

$$y_{it} = x'_{it} (\beta_{it} + h_i) + (\alpha_{it} + u_i) + \varepsilon_{it}$$

This random effects estimator is a matrix-weighted average of the fixed-effects (within) and the between effects, where y_{it} is the outcome, the prospective three-year compound annual growth rate from time t , for every county i in year t ; x'_{it} is a vector of county-year factors that vary across time and counties; and β_{it} is the between-effects parameter.² The coefficients are interpreted as the average effect of a county-year factor on the future population growth rate, *ceteris paribus*.³ Since the data come from all U.S. counties that have experienced hurricanes between 1970 and 2012, our data constitute the entire population (not a sample) of county-years, and we report tests of statistical significance as

² h_i induces the variation of the parameters across individual counties; α_{it} is the constant; u_i is a group-specific random element, similar to ε_{it} except that for each group there is just a single draw that enters the regression identically in each period.

³There is considerable debate about the appropriate application of fixed and random effects models for estimating panel data results. A recent paper by Clark and Linzer (2015) sheds light on the debate, offers guidance on choice of models, and encourages practical and theoretical assessments. We do not estimate a fixed-effects model because we have theoretical and practical reasons to include county-level effects, and a fixed-effects model would make evaluating these effects impossible (Clark and Linzer 2015, 407). In this article, we present the results of our random effects estimation that corrects the standard errors. Furthermore, we evaluated models with a robust correction to control for heteroskedasticity.

an indication of the meaningfulness of the estimated coefficients (e.g., how different they are from zero).

In the analysis section, we explore the spatial and temporal variability of hazard-related losses to justify our focus on single hazard impacts, in this case, hurricanes. We follow this with a brief description of the spatial and temporal variability in population trends and provide a justification for evaluating our hypotheses on different county-year data subsets. Next, we discuss the descriptive statistics for our dataset. We then present the results of our regression analysis to test our hypothesis that the effect of a hurricane in a given year on future population growth is small compared with the cumulative effects of weather hazards and past population trends. In the final section, we summarize our findings and their implications for future research on weather-related hazards and population change.

Analysis

Spatial and temporal variability in hazard events

To illustrate the spatial and temporal variability in hazardous weather events, we use 2008 as our reference county-year, since this was a year in which total property and crop losses due to hazards was high (\$25.3 billion),⁴ but not extraordinary as in 2005 (\$122.3) or 1992 (\$56.1), when especially destructive hurricanes impacted large metropolitan areas.⁵ In 2008, spatial variability in hazard-related combined losses were mostly due to spring flooding in the Midwest and Hurricanes Ike and Gustav, which struck the Texas and Louisiana coasts and traveled inland (see Figure 1, Panel A). However, a current-year measure of hazard impact neglects the spatial variability in cumulative hazard losses over the prior decade (1998 to 2007), which is quite different (see Figure 1, Panel B). Observing cumulative hazard losses captures a spatial and temporal dimension of heterogeneity—the spatially unequal accumulation of hazard events and losses—unobserved in earlier studies that tends to focus on the effect of single events. Based on this observation, we expect that population responses to hazard events and losses in a single year will be different than population responses to the cumulative number of events and amount of losses.

Prior research often uses total hazard-related losses to measure hazard impacts. However, by aggregating all hazards that have unequal probabilities of occurring across geography and are unequally likely to produce the same type of damage, total hazard losses are a noisy predictor of population change. For example, Figure 2 shows total cumulative combined losses due to hazards (Panel A), which amounted to \$266.2 billion (held constant to US \$2014) over 1998 to 2007, and hazard-specific cumulative combined losses in the other five panels. In each county, specific hazards account for different proportions of cumulative losses. Hurricanes, which account for nearly two-thirds of cumulative losses nationally, produce the greatest losses in coastal areas of the Gulf of Mexico and the Eastern seaboard, causing severe damage to private residential and business properties as well as built infrastructure and the environment (Panel B). Flooding losses—9.5 percent of cumulative losses—concentrate in parts of the Southwest, the South, the Midwest, and the Northeast

⁴All losses are standardized to \$2014 values.

⁵HVRI. 1960–2014 U.S. Hazard Losses; 2008 U.S. Hazard Losses. Available from <http://hvri.geog.sc.edu/SHELDUS/>.

and cause similar damages as hurricanes (which they often accompany) but over a smaller geographic area (Panel C). Losses from drought—6.5 percent—are concentrated in agricultural regions and principally destroy crops (Panel D). Tornado-related losses—4.9 percent—are spatially focused and dispersed through “tornado alley” in the Midwest and the Eastern seaboard, causing severe destruction over very defined areas (Panel E). Hail-related losses—4.4 percent—are spatially focused and widely dispersed, and may damage property but not as severely as the costlier hazards listed above (Panel F). Considering this variability in hazard geography and given our inference that associated losses are qualitatively different among hazard types, we chose to focus on total property and crop losses from one hazard type, hurricanes, which are spatially limited and costly.

Between 1970 and 2009, the years for which our data allow us to investigate hazards and population change in this analysis, virtually all of the hurricane-related losses occurred in the Gulf of Mexico and the Atlantic Coast. A few Pacific storms produced limited damage-related losses on the West Coast, Alaska, and Hawaii. By pairing the maps of cumulative hurricane-related losses with the maps of population change (growth and decline) over the same period, it is evident that many counties in Texas, Louisiana, Florida, and the Carolinas with the greatest cumulative losses also experienced sizable population growth (see Figure 3). This spatial correlation reflects two things. First, more densely populated counties have more assets exposed to hazards and therefore experience greater losses. Second, and important for our study, these areas continue to increase in population. On the surface, this would suggest that hurricanes do not discourage human settlement.

Spatial and temporal variability in population density and growth

To illustrate the spatial distributions of our population measures, we show population density, past population growth, and future population growth using 2008 as a reference year (see Figure 4). Population density (Panel A) shows densities are higher on average in the eastern United States and the West Coast compared with counties ranging from the western mountains through the arid Midwest. Panel B shows past population trends for county-year 2008, referencing the prior decade, 1998–2007. During this period, counties in the East and West grew the fastest, while many counties throughout the middle of the country declined, a few by more than 2 percent. Overall, most counties evince little change, registering less than 2 percent growth or decline. Panel C shows future population growth for county-year 2008, referencing change from 2008 to 2010. This shows that prospective population growth rates across U.S. counties are mostly inclining. Even for counties with declining past population growth rates, the forward projection appears to be one of little to slow growth with very few counties showing rates of decline greater than 2 percent.

Next, we complement our discussion of spatial variability in hazards and population with a discussion of temporal variability in population trends. We find that while past population growth rates and future population growth are relatively stable, variance around these annual means has been decreasing with each year. In contrast, means for population density have also been stable, but variance has been increasing with each year (analysis not shown). The mixed results of earlier studies may be due to these changes in variability with time and

across space, since results will vary depending on the counties chosen and the time frame evaluated.

Delving further into our investigation of differences between counties over time, we examined differences in future population growth between high- and low-density counties and counties with past inclining and declining growth rates (analysis not shown). We found that counties with declining past population trends, especially low-density counties, tend to have higher rates of future growth, especially when past declines were large. In contrast, counties with inclining past population trends, especially high-density counties, tend to have higher rates of future growth, especially when past inclines were large. Because these underlying population trends are so different, an analysis of the complete spatial-temporal database is likely to obscure the effects of hurricanes. To more cleanly expose population trends after a hurricane, we subset our data into four categories of counties: high (density $\geq 1,000$) and low (density $< 1,000$) density and inclining ($CAPGR > 0$) and declining ($CAPGR \leq 0$) past growth trends. We use these subsets in our multivariate random effects regression analysis in the next section.

Descriptive statistics for the spatial-temporal database and subsets

Distinguishing counties by past growth trends ($CAPGR$) and population density is a simple way to discern the heterogeneity of current year and cumulative hurricane events and losses (see Table 1). The vast majority (93 percent, or 36,480 of 39,314) of county-years were for counties with low population densities, and, of these, 80 percent (28,999 of 36,480) had declining past growth trends. Of the remaining county-years for counties with high population densities (7 percent, or 2,834 of 39,314), the majority (71 percent, or 2,010 of 2,834) had declining past growth. Only 2 percent (824 of 39,314) of all county-years were contributed by high-density counties with inclining past growth trends. These unequal group sizes mean the low-density, declining growth counties have an undue weight in any regression analysis, which is why we treat them separately in the regression analysis.

Counties with declining 10-year growth trends tend to experience growth in the next three years, regardless of population density. Counties with inclining 10-year growth trends tend to experience population loss in the next three years, regardless of population density. There are fewer differences between county-types in hurricane events and losses in both current year and the past decade. Counties that ever experienced a hurricane between 1970 and 2009 experienced at least one hurricane on average in 9.1 out of every hundred county-years, with large variability between counties (mean = 0.091; $SD = 0.287$). The total amount of property and crop losses in the current year adjusted to 2014 U.S. dollars and presented as millions per capita provides a measure of losses relative to the number of people at risk.⁶ In the average county-year, these losses amount to \$120 per capita (mean = 0.00012; $SD = 0.002$). In general, per capita losses are greater in low-density than high-density county-years. The accumulated hurricane-related losses are the total amount of property and crop losses summed for each of the 10 years prior to the current year adjusted to 2014 U.S. dollars and presented as millions per capita. In an average county-year, the cumulative losses amount to

⁶A better measure would be losses relative to the value of the property and crops at risk, but such a measure is not easily obtained. See Ash, Cutter, and Emrich (2013) for a measure of the relative loss ratio using SHEL DUS and other county-level data.

\$981 per capita (mean = 0.000981; $SD = 0.008$). The cumulative count of hurricanes is a sum of hurricane and tropical storm for the previous 10 years. In an average county-year, the county had experienced 1.272 ($SD = 1.979$) hurricanes in the previous 10 years. We use these measures in our multivariate analysis to examine differences in hurricane effects between county-years.

Multivariate random effects regression analysis

To test our hypothesis that the effect of hurricanes on future population growth is small compared with past population trends, we estimate regression models for each subset of the data. In Table 2, we focus on low- and high-density county-years with declining population growth trends, and in Table 3, we focus on low- and high-density county-years with inclining population growth trends. Each panel of the two tables includes three models: model 1 includes only the population variables, past CAPGR, and population density; model 2 includes the four hurricane variables, current year and past decade hazard losses and events; and model 3 includes both the population and hazard variables. This allows us to evaluate the relative contribution of each set of variables to explaining variance in future population growth. We fully interpret the analysis of county-years with declining past population trends and low population densities (see Table 2, Panel A), and summarize findings for the remaining panels in Tables 2 and 3.

Among county-years in which past growth is negative and population density is low, we confirm the fluctuation in growth rates that we discerned in our investigation of means and variance. In model 1, the coefficient for past population growth has a negative value (-0.291). Since all the values of this variable in this data subset are negative by design, this coefficient is always multiplied by a negative value, so that a 1-unit decline in the past population growth rate yields a 0.291-unit increase in the future population growth rate. In other words, on average, a county with a pattern of past population decline experiences a lower future rate of decline, or possibly slightly positive growth. This interpretation applies only to this variable in county-years with declining populations (see Table 2). Model 1 also shows that population density has a trivial negative effect on future population growth: each additional person per square mile reduces the future population growth rate by 0.000004 units in counties with population densities less than 1,000 people per square mile. These two population measures explain about two-thirds of the variability in future population growth between counties ($R\text{-square} = 0.655$) but very little of the within-county variability in future population growth ($R\text{-square} = 0.013$).

Models 2 and 3 of Table 2 show the effects of hurricane losses and events on future growth, on their own and in combination with the population variables, and formally test our hypothesis. In model 2, the effects of current year and accumulated hurricane losses are both negative, as expected, and small. Each additional \$1 million per capita loss in a particular year reduces the future growth rate by 0.2 units. The effect of each additional \$1 million per capita in losses accumulated over 10 years reduces the population growth rate by 0.079 units. Given that hurricane loss amounts per capita are far below \$1 million in any county-year, these impacts are small. Counties that experience at least one hurricane in a year experience a very slight ($b = 0.0006$) incline in the future population growth rate. However,

this may be negated if there were recent hurricanes, since each additional hurricane event in the past decade is associated with a decline in the population growth rate ($b = -0.0005$). Consistent with our expectation that population trends are more important than hurricanes, hurricane events and losses do not explain much variability in future population growth, either between (R -square = 0.009) or within (R -square = 0.016) these lower density counties with declining rates of population growth.

The coefficients are relatively unchanged in model 3, which includes both population and hurricane variables. Model fit improves negligibly in model 3 relative to model 1 but is an improvement over model 2. Overall, population trends in low-density counties with declining growth rates are more important in predicting future population growth than hurricane events and losses. This confirms our hypothesis for this set of county-years.

For Table 2, panel B, high-density counties with declining population trends, the patterns are very similar to low-density counties with declining population trends (Panel A). Therefore, we focus only on model 3 in panel B. This model indicates that high-density counties undergoing past population declines experience slowing rates of population decline ($b = -0.265$) and population density exerts a trivial effect ($b = 0.00000005$) on future growth. Unlike counties in Panel A, current year hurricane-related losses ($b = 0.80$) and accumulated hurricane losses ($b = 0.88$) positively impact future population growth. However, given that hurricane loss amounts per capita are far below \$1 million in any county-year, these impacts are quite small. Like counties in panel A, current year ($b = -0.0001$) and cumulative ($b = -0.0004$) hurricane events exert very small negative effects on future population growth. The model fit statistics are also similar, indicating that population differences between these high-density counties with declining populations are more important in predicting future population growth than hurricane events and losses, again confirming our hypothesis for this set of county-years.

Turning to Table 3, in which we estimate models for low- and high-density counties with past inclining growth rates, we again focus on model 3 coefficients. In panel A, with model estimates for low-density counties, past population growth leads to increased ($b = 0.214$) future population growth, while population density has a trivial effect on future population growth. Hurricane losses have minor impacts on future growth: hurricane-related losses in a given year slightly decrease ($b = -0.033$) future population growth, and losses over the previous decade slightly increase ($b = 0.055$) future population growth. Hurricane events also have minor effects: county-years in which at least one hurricane struck experience a 0.001-unit decrease in future population growth rates, and each additional hurricane over the previous decade produces a very slight ($b = -0.0002$) reduction in future population growth. None of the models is particularly powerful in explaining the variance in population growth, either within or between county-years. In other words, low-density counties with inclining population growth rates are growing in response to factors other than past population trends and hurricane events and losses.

In contrast, Table 3, panel B, model 3, explains more of the variation in future population growth for high-density counties with inclining population growth trends. For these counties, higher past population growth rates yield positive effects ($b = 0.312$) on future population

growth rates, although population density impacts ($b = 0.000003$) are trivial. As in low-density counties (Panel A), hurricane losses suffered in a particular year negatively affect future population growth, but the effect is larger: for each one million dollars of losses per capita in a given year, the future population growth rate is reduced by -2.38 units. However, higher amounts of per capita loss accumulated over the previous decade compensate for this and yield a 2.46 -unit higher future population growth rate. The effects of a hurricane strike in the current year ($b = -0.0022$) and in the past decade ($b = -0.0017$) both tend to suppress future population growth. Notably, the coefficient for past population growth declines by 61 percent between model 1 and model 3, indicating that hurricane events and losses dampen the effect of past growth on future growth. In other words, unlike what we hypothesized, the effect of past growth on future growth depends to a degree on both current and cumulative hurricane events and losses. Specifically, current and cumulative hurricane events and current year losses tend to suppress future growth, while cumulative losses tend to increase it. The model fit statistics suggest that both population and hurricanes explain within-county variance, although neither contributes much to between-county variance in the full model. From this set of models for all four county-year types, we can conclude that it is mainly these higher density counties with inclining population growth rates that experience population impacts of hurricane events and losses.

The findings of our regression analysis are more clearly displayed in Figure 5, which shows predicted future growth rates for each subset of county-years for each of the six variables of interest while holding all other variables at their mean. The six panels include four groups (county-year subsets) of three bars: the first bar is the predicted future growth with the variable of interest held at its mean value, and the second and third, respectively, are the predicted future growth with the variable held at the mean value plus or minus one standard deviation, or in the cases where the mean value minus one standard deviation falls into the negative range, we substitute zero. When the difference in height between bars is small for a subset of county-years, the effect of the variable on future growth is small; when the difference in bar heights is large, the effect is more meaningful.

Our hypothesis that the effects of hurricanes on future population growth is small compared with that of past population growth is clearly supported because the size of the effect of past population growth on future population growth is greater than the effect of any of the other variables shown here, with only a few notable exceptions (Figure 5). Panel A shows that within each subset of counties, the effects of past population growth on future population growth is sizable, especially in comparison to the effects of the hurricane variables (Panels C through F). The effects of past growth are especially large in the subsets of county-years with declining population trends: the greater the rate of past decline, the greater the rate of future growth. More modest effects are evident for the subsets of county-years with inclining past growth, where higher than average past growth is associated with higher future growth, on average. Population density (Panel B) shows small effects on future growth, which we do not discuss because the effects are statistically insignificant.

Among the hurricane-related variables, both current year and cumulative hurricane events and losses have relatively small effects on future growth in most county-year subsets (Figure 5, Panels C through F). These effects are trivial for county-years with declining population

trends, regardless of population density, as is evident from the similarity in bar heights. Differences are also small and close to zero for county-years with inclining growth and low population density.

The notable exception to the pattern of small effects of hurricanes relative to past population trends is found for county-years with inclining past population trends and high population densities. These county-years show sizable effects of hurricanes on future growth (the last set of bars). For these county-years, future growth is suppressed by a hurricane in the current year (Panel C), a higher than mean number of hurricanes in the past decade (Panel D), and higher current-year hurricane-related losses (Panel E). However, higher cumulative losses over the past decade strongly increase future population growth (Panel F). This suggests that there is a dynamic relationship between cumulative hurricane losses and population growth in these high-density, growing counties that merits further investigation.

Conclusion

The existing demographic literature on weather hazards and population change in the United States is sparse and unsystematic. To analyze this relationship, we constructed a spatial-temporal database of U.S. counties from 1980 to 2012 with measures of population, weather events, and weather-related losses. We explored this spatial-temporal database to refine our approach to this problem. We concluded that the best way to model the problem is separately by hazard, recognizing that weather events are variable in their spatial and temporal distribution, mode of impact, and the value of associated losses. We focused on hurricanes and tropical storms because of their destructive power and their potential to displace people from their homes and communities. We differentiated between long- and short-term effects to estimate more precisely how hurricanes influence future population trends. We differentiated the counties according to past population growth trends and population density, and used a reduced form, random effects linear regression model to test our hypothesis that the effects of weather hazards on future population growth are very small compared with the effect of past population trends.

We find support for our hypothesis in counties with past population declines regardless of their population density. These are the majority of hurricane-affected U.S. counties, and in these places, hurricanes hardly affect future population; past population trends are far more predictive of future population trends. Similarly, hurricanes hardly impact population dynamics in growing, low-density counties.

We find evidence that is inconsistent with our hypothesis in high-density, growing counties. In these counties, hurricane events and related losses in the current year and a greater number of hurricanes in the past decade suppress future population growth. However, when hurricanes in the past decade have been very costly, future population growth tends to be greater. In other words, while hurricane events and losses tend to suppress population growth in counties with growing, high-density populations, this effect may be reversed when substantial hurricane-related monetary losses over the past decade have promoted investment in those places, consistent with the “recovery machine” thesis (Pais and Elliott 2008). These results begin to reconcile the inconsistencies in the sparse literature on hurricane and hazard

impacts on population, but further research is needed to understand where and when these effects promote or suppress population growth. For now, we conclude that hurricanes are heterogeneous in their population impacts, and that past population trends and cumulative hurricane events and losses contribute to this heterogeneity.

Our results provide an important corrective to previous investigations into the effects of hurricanes on future growth, which have selected only places with extreme hurricane impacts or have failed to control for the effects of long-term population and hazard event trends. In general, the impact of a single hurricane should be assessed relative to past population trends to discern its net effect on future growth. Further, the impact of a single hurricane should be considered together with the cumulative impacts of past hurricanes and relative to counties that have not experienced hurricanes. This quasi-experimental approach leads to generalizable conclusions about the impacts of hurricanes and tropical storms and can be applied to the study of other types of hazards.

Our analysis has several limitations. First, measures of county-level demographic, economic, and environmental characteristics would have been preferable to a simple measure of past population trends and population density, but they were not consistently available in all county-years. During this period, county boundaries changed, and counties' demographic, economic, and political characteristics have changed in ways that were difficult to measure consistently across time and space. To make the project tractable and demonstrate the value of proceeding in this line of inquiry, we used simple metrics and a model that takes into account this unobserved heterogeneity. Second, our multivariate analysis did not take account of the spatial relationships between counties. While a spatial regression analysis is planned, in this analysis we sought to explore new measures and their use in a multivariate regression framework. Nevertheless, our systematic approach to spatial-temporal data shows that hurricanes have heterogeneous impacts on counties, and that their impact depends on past population change and population density, thereby explaining some of the inconsistencies in the growing field of research on weather-related hazards and population change.

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FIGURE 1.
Total Property and Crop Losses Due to All Weather-Related Hazards in 2008 (A) and the
Previous Decade (1998–2007; B), Both Adjusted to 2014 Dollars

FIGURE 2.

Total Cumulative Property and Crop Losses in a Decade (1998–2007) Due to All Weather-Related Hazards (A) and the Five Costliest Hazards (B–F)

FIGURE 3.
Comparison of County-Level Hurricane and Tropical Storm Property and Crop Losses (A)
and Population Change (B) from 1970 to 2009

FIGURE 4.
 Variability in Population Density (A), Historic Population Trends (B), and Future Growth
 for Counties in Reference Year 2008 (C)

FIGURE 5.
Prediction of Future Population Growth Given Covariate Values Based on Results from Regression Models

Population Trends and Hazard Exposures for All Counties Ever Experiencing a Hurricane

TABLE 1

All County- Years 1980–2009, among Counties Ever Exposed to Hurricanes between 1970–2009; means (SD)						
	All Counties	Counties with Declining 10-Year Population Trend		Counties with Inclining 10-Year Population Trend		
		Pop density < 1,000 people/ square mile	Pop density 1,000 people/ square mile	Pop density < 1,000 people/ square mile	Pop density 1,000 people/ square mile	Pop density < 1,000 people/ square mile
<i>N</i>	39,314	28,999	2,010	7,481		824
Population variables						
Compound annual pop growth rate from year = t to $t + 3$	.0061 (0.019)	.00821 (.012)	.007 (.008)	-.002 (.010)		-.001 (.012)
Compound annual pop growth rate from year = $t - 11$ to t	-.00898 (0.0129)	-.01307 (.012)	-.01 (.009)	.005 (.006)		.005 (.006)
Population density (people per square mile) in year t	418.785 (2503.25)	129.085 (172.023)	4156.024 (8907.199)	71.272 (137.926)		4652.892 (6951.653)
Hazard variables (hurricanes)						
\$ losses (million)/capita (USD 2014) in past decade	.000981 (0.008)	.00085 (.005)	.0001 (.0001)	.002 (.014)		.0003 (.003)
\$ losses (million)/capita (USD 2014) in a county-year	.00012 (.002)	.00012 (.002)	.00001 (.0002)	.0001 (.002)		.00004 (.001)
# of hurricanes in past decade	1.272 (1.979)	1.296 (2.005)	1.326 (2.007)	1.111 (1.768)		1.742 (2.601)
Any hurricane in a county-year	.091 (.287)	.094 (.292)	.105 (.307)	.073 (.260)		.101 (.301)

TABLE 2

Random Effects Linear Regression for Three-Year Prospective Population Growth Rate among Counties with Declining Population Growth Trends (County-Years 1980–2009 Ever Exposed to Hurricanes Between 1970–2009); coefficient (SE)

PANEL A (< 1,000 pop/square mile)	Model 1	Model 2	Model 3
Historic compound annual pop growth rate	–.291 (.007) ***		–.285 (.007) ***
Population density	–3.90E–06 (7.20E–07) ***		–3.60E–06 (7.10E–07) ***
\$ losses (million)/capita (USD 2014) in past decade		–.079 (.013) ***	–.073 (.012) ***
\$ losses (million)/capita (USD 2014) in county-year		–.201 (.019) ***	–.213 (.021) ***
# of hurricanes in past decade		–.0005 (.00004) ***	–.0003 (.00004) ***
Any hurricane in a county-year		.0006 (.0002) ***	.0009 (.0002) ***
Constant	.004 (.0002) ***	.007 (.0003) ***	.004 (.0002) ***
R-square within (R-square between)	.013 (.655)	.016 (.009)	.022 (.646)
PANEL B (1000 pop/square mile)	Model 1	Model 3	Model 4
Historic compound annual pop growth rate	–.272 (.024) ***		–.265 (.024) ***
Population density	–4.65E–08 (4.46E–08)		–4.80E–08 (4.38E–08)
\$ losses (million)/capita (USD 2014) in past decade		1.028 (.322) ***	.884 (.301) **
\$ losses (million)/capita (USD 2014) in county-year		.829 (.701)	.802 (.702)
# of hurricanes in past decade		–.0004 (.0001) ***	–.0002 (.0001)
Any hurricane in a county-year		–.0001 (.0004)	–.0001 (.0004)
Constant	.004 (.001) ***	.007 (.0006) ***	.004 (.0005) ***
R-square within (R-square between)	.017 (.623)	.014 (.0006)	.0234 (.6204)

* $p < .01$.

** $p < .005$.

*** $p < .001$.

TABLE 3

Random Effects Linear Regression for Three-Year Prospective Population Growth Rate among Counties with Inclining Population Growth Trends (County-Years 1980–2009 Ever Exposed to Hurricanes Between 1970–2009); coefficient (SE)

PANEL A (< 1,000 pop/square mile)	Model 1	Model 2	Model 3
Historic compound annual pop growth rate	.270 (.022) ***		.214 (.023) ***
Population density	2.72E–06 (2.03E–06)		3.41E–06 (1.74E–06)
\$ losses (million)/capita (USD 2014) in past decade		.08 (.009) ***	.055 (.001) ***
\$ losses (million)/capita (USD 2014) in county-year		–.022 (.045)	–.033 (.045)
# of hurricanes in past decade		–.0002 (.00009) **	–.0002 (.00009)
Any hurricane in a county-year		–.001 (.0004) *	–.001 (.0004) **
Constant	.0008 (.0004)	.0007 (.0003)	–.0006 (.0003)
<i>R</i> -square within (<i>R</i> -square between)	.027 (.009)	.0007 (.0598)	.0287 (.0003)
PANEL B (1,000 pop/square mile)	Model 1	Model 3	Model 4
Historic compound annual pop growth rate	.816 (.077) ***		.312 (.090) ***
Population density	8.66E–09 (7.32E–08)		4.71E–08 (6.92E–08)
\$ losses (million)/capita (USD 2014) in past decade		2.953 (.218) ***	2.463 (.253) ***
\$ losses (million)/capita (USD 2014) in county-year		–2.324 (.465) ***	–2.379 (.464) ***
# of hurricanes in past decade		–.0019 (.0003) ***	–.0017 (.0003) ***
Any hurricane in a county-year		–.0023 (.0012)	–.0022 (.001)
Constant	–.003 (.001) ***	.003 (.0008) ***	.001 (.0009)
<i>R</i> -square within (<i>R</i> -square between)	.206 (.196)	.289 (.0062)	.318 (.0053)

*
 $p < .01$.

**
 $p < .005$.

 $p < .001$.