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Source: *The Review of Economics and Statistics*, May 2011, Vol. 93, No. 2 (May 2011), pp. 575-589

Published by: The MIT Press

Stable URL: https://www.jstor.org/stable/23015955

THE ECONOMIC GROWTH IMPACT OF HURRICANES: EVIDENCE FROM U.S. COASTAL COUNTIES

Eric Strobl*

Abstract—I estimate the impact of hurricane strikes on local economic growth rates. To this end, I assemble a panel data set of U.S. coastal counties' growth rates and construct a novel hurricane destruction index that is based on a monetary loss equation, local wind speed estimates derived from a physical wind field model, and local exposure characteristics. The econometric results suggest that a county's annual economic growth rate falls on average by 0.45 percentage points, 28% of it due to richer individuals moving away from affected counties. I also find that the impact of hurricanes is netted out in annual terms at the state level and does not affect national economic growth rates at all.

I. Introduction

GIVEN the potential havoc and destruction caused by hurricanes, the common fascination with these generally unpredictable events is not surprising. For instance, the unfolding destruction of Hurricane Katrina in 2005, estimated by Pielke et al. (2008) to have caused over $80 billion in damages in Louisiana and Mississippi alone, was followed on television by millions worldwide. A worry is that there appears to be an increasing trend in the number and strength of hurricanes, which some argue is linked to global warming.[1] Moreover, the U.S. coastal regions that are directly affected are those where a large and growing part of total economic activity is located and hence the regions that are also driving a substantial portion of national economic growth.[2] Thus, accurately assessing how economies are likely to be affected by hurricanes is of considerable importance to policymakers and academics alike.

The primary negative impact of hurricanes on affected regions involves the destruction of property in terms of housing, capital stock, and agricultural crops, where losses may lead to a disruption in production in many industries.[3] At the same time, however, disaster assistance, clean-up and recovery activity, and the production of replacement capital act a counterweights to any losses (see Horwich, 2000). Additionally, some of the losses may be insured, and payments in this regard may be coming from outside the affected region. Uncertainty regarding the exact interplay and relative size of these factors means that the net economic effect of hurricanes is not at all obvious. Moreover, even if the losses largely outweigh the boosts to local economic growth from recovery activity, it is not clear to what extent this may be reflected in more aggregate growth patterns, since hurricanes, like most other natural disasters, tend to be very localized.

To date, there is, to the best of our knowledge, no comprehensive study, for the United States or elsewhere, of how hurricanes may have affected local growth patterns and how any local impact translates into more aggregate levels of economic growth. More precisely, although a few papers have examined the local impact of hurricanes, these have either focused on particular types of microlevel responses or dealt with the impact on the local labor market. For instance, Evans, Yingyao, and Zhong (2010) discovered that fertility rates in the U.S. Atlantic and Gulf of Mexico regions change in response to hurricanes. Also, Belasen and Polacheck (2009) have shown that employment in Florida fell in response to hurricanes by between 1.5% and 5%. From a macroeconomic perspective, a handful of papers provide estimates of the growth impact of hurricanes. For example, Strobl's (2008) study of the the Central American and Caribbean region found that economic growth rates fell by 0.8 percentage points for an average destructive hurricane. However, it is not clear whether such results from developing county samples are relevant for an industrialized economy like the United States, given that it appears in the literature that economic losses due to natural disasters are negatively correlated with economic wealth.[4]

In this paper I thus set out to estimate the net growth impact of hurricanes on affected local economies, as well as to what extent such effects spill over into more aggregate economic growth patterns. To this end, I develop a hurricane destruction index based on a monetary loss equation, local wind speed estimates derived from a physical wind field model, and local exposure characteristics and estimate its impact on the growth rates of a panel of counties in the relevant U.S. coastal area. The econometric results suggest that in response to a average hurricane, a county's annual economic growth rate will fall by at least 0.45 percentage points, arguably a relatively large impact given that the average annual county-level growth rate is around 1.68%. I also find that nearly 28% of the growth effect is due to relatively richer people leaving a country as a consequence of the hurricane. At the state level, for which quarterly data are available, quarterly growth-reducing and recovery effects in annual terms are negligible. Hurricanes do not appear to be economically important enough to be reflected in national economic growth rates.

The remainder of the paper is organized as follows. The following section describes the nature of hurricanes and their destruction potential. Section III introduces the hurricane destruction proxy. Section IV describes the data. The

Received for publication August 13, 2008. Revision accepted for publication December 18, 2009.

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I am grateful for financing from La Chaire Développement Durable of the Ecole Polytechnique.

[1] See, for example, Emanuel (2005), Nordhaus (2006), and Elsner (2007).

[2] Rappaport and Sachs (2003).

[3] Although there may be some losses in life, these tend to be negligible in the United States.

[4] See, for instance, Kahn (2005) and Toya and Skidmore (2007).

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econometric analysis is contained in section V. Concluding remarks are given in the final section.

II. Some Basic Facts about Hurricanes and Their Destructive Power

Tropical cyclone is a meteorological term for a storm system characterized by a low-pressure system center and thunderstorms that produce strong wind and flooding rain, which generally first forms, and hence its name, in tropical regions of the world. Depending on their location and strength, these cyclones are referred to by various other names, such as *hurricane*, *typhoon*, *tropical storm*, *cyclonic storm*, and *tropical depression*. Tropical storms in the North Atlantic Basin are termed hurricanes if they are of sufficient strength.[5] Their season can start as early as the end of May and last until the end of November, although it generally spans July to October.

In terms of its structure, a hurricane generally harbors an area of sinking air at the center of circulation, known as the 'eye, weather in the eye is normally calm and free of clouds, a though if the hurricane is over the ocean, the sea under the eye may be extremely violent. Outside the eye, curved bands of clouds and thunderstorms, capable of producing heavy bursts of rain, wind, and tornadoes, move away from the eye wall in a spiral fashion. A hurricane affects a large area surrounding its eye and its structure is not symmetric. Hurricane-strength tropical cyclones are generally about 500 kilometers wide, although they can vary considerably. Hurricanes are typically categorized in terms of their wind speed on the Saffir-Simpson (SS) scale, where the scale ranges from 1 to 5,[6] although category 5 hurricanes are fairly rare in the North Atlantic Basin. Hurricanes generally lose their strength quickly as they move over land due to land friction and the lack of moisture and heat that the ocean provides.[7]

Physical damages due to hurricanes typically take a number of forms. First, the strong winds associated with the storm may cause considerable structural damage to buildings as well as crops. Second, the strong rainfall generally associated with a hurricane can result in extensive flooding and, in sloped areas, landslides. Finally, the high winds pushing on the ocean's surface can cause the water near the coast to rise higher than the ordinary sea level, and this effect, combined with the low pressure at the center of the weather system and the bathymetry of the body of water, results in storm surges. Generally these surges are the most damaging aspect of hurricanes. They can cause severe property damage, as well as destruction and salt contamination of agricultural areas. Such flooding may extend up to 40 kilometers or more from the coast for maximum-strength storms.

[5] Generally at least 119 kilometers per hour. In order to be considered a tropical storm, the storm must have maximum wind speed of at least 55 kilometers per hour. To be upgraded to a hurricane, these speeds must reach at least 119 kilometers per hour.

[6] Scale definitions in terms of kilometers per hour are (1) 119–153, (2) 154–177, (3) 178–209, (4) 210–249, and (5) 250 and higher.

[7] See NOAA at http://www.aoml.noaa.gov/hrd/tcfaq/C2.html.

III. Hurricane Destruction Proxy

Previous studies of the local impact of hurricane destruction have used simple measures of hurricane incidence or their maximum observed SS scale category as the hurricane eye passes directly over locations as a proxy of their local destruction.[8] In reality hurricanes can have a destructive impact on spatially potentially very large areas, not just where the eye directly passes over. Moreover, the extent of this destruction is unlikely to be uniform across localities, although this depends on position relative to the eye, maximum wind speed, and local characteristics, among other things.

In order to take account of the complex nature of hurricanes, I use a proxy of local wind speed derived from a model of the spatial structure and movement of hurricanes, and hence of wind speeds experienced—directly along the track as well as locations around it. I then translate these local wind speeds into a proxy of local destruction. More precisely, Emanuel (2005) noted that both the monetary losses in hurricanes and the power dissipation of these storms are related to their maximum observed wind speed. Consequently, he proposed an index of hurricane damages based on a simplified version of a power dissipation equation:

$$\mathrm{PDI} = \int_0^{\tau} V^{\lambda} dt, \tag{1}$$

where V is the maximum sustained wind speed, τ is the lifetime of the storm accumulated over time intervals t, and λ is a parameter that relates local wind speed to the local level of damage. I modify this index to obtain a proxy of damages due to hurricanes at the county level i using census-tract-level j data. Thus, the total destruction due to the $r = 1,\ldots,k$ storms that affected county i at time t is assumed to be

$$\mathrm{HURR}_{i,t} = \sum_{j=1}^{m} \sum_{r=1}^{k} V_{i,j,r,t}^{\lambda} w_{i,j,t}, \tag{2}$$

where V is an estimate of the wind speed due to storm r observed in census tract j at time t. The w's are weights assigned according to characteristics of the affected census tracks intended to capture geographical differences within counties in terms of the potential exposure if a hurricane were to strike. With information on V, w, and λ, equation (2) provides a county-level proxy of hurricane damages for

[8] See, for instance, Belasen and Polacheck (2007).

FIGURE 1.—COASTAL COUNTIES IN THE NORTH ATLANTIC BASIN REGION

quantifying the impact of hurricane strikes on U.S. coastal counties' economic growth rates.

III. Data

A. Geographic Area of Study

Normally only a small proportion of the total geographic area of the United States, that relatively close to the coast, is affected by hurricanes since these quickly lose speed once they hit landfall. Moreover, storm surges generally cause most of the damages due to hurricanes, and this again is most relevant for coastal areas. I thus specifically focus this analysis on U.S. coastal counties in the North Atlantic Basin region. In terms of identifying coastal counties in this area, I rely on the list generated by the Strategic Environmental Assessments Division of the National Oceanic and Atmospheric Administration (NOAA). Accordingly, coastal counties are defined as those that have at least 15 percent of their land in the coastal watershed or that comprise at least 15 percent of a coastal cataloguing unit. Within the hurricane-relevant North Atlantic Basin region this constitutes 409 coastal counties located over nineteen states. These are shown in gray, in figure 1.

B. Economic Growth Data

To construct proxies of county-level per capita economic growth rates and per capita wealth, I turn to the Bureau of Economic Analysis's (BEA) Local Area Personal per Capita Income county-level estimates available since 1969. Personal income in the BEA data is defined as the income received by all persons from all sources and constitutes the sum of net earnings by place of residence, rental income of persons, personal dividend income, personal interest income, and personal current transfer receipts as taken from IRS tax returns. I convert these nominal values to constant 2005 dollars using the U.S. consumer price index. As can be seen from the summary statistics in table 1, the average annual county growth rate over the period 1975 to 2005 was 1.68. However, the high standard deviation relative to this mean indicates that it varies substantially over time and across space within the coastal community sample.

The BEA specifically discusses how natural disasters are likely to be accounted for in personal income estimates.[9] In particular they argue that natural disasters generally have two major effects on the data. First there will be destruction of property, where property losses net of the associated insurance claims will be incorporated as one-time effects. In this regard, damage to enterprise property will reduce owners' income and rental income by the amount of uninsured losses, measured by consumption fixed capital less business transfers. Damage to consumer goods will affect personal current transfer receipts net of the amount of insured losses of these goods. The second effect of natural disasters is likely to be a disruption of the flow of income in the economy as normal economic activity is interrupted. This is generally embedded within the data on which personal income estimates are based. For example, many industries in the directly affected area will experience a reduction in earnings as production is interrupted, while for others there may be an increase. Typically, however, these income flows are reduced in the short term (for example, a reduction in consumer spending) and rise later (for example, an increase in construction activity).

C. Data for the Hurricane Destruction Proxy

Weights w. The weights w in equation (2) allow me to control for local characteristics of affected areas. In this regard, as a benchmark I use the time-varying share of population of each individual census tract in its county at $t-1$, where the underlying argument is that of two equally affected (in terms of wind speed) areas, the one where more people live is likely to be more important in terms of adding to county-level damage incurred. The census-tract-level population shares (the w's) are derived from the decennial population censuses for 1970, 1980, 1990, and 2000, and is linearly interpolated to estimate annual values between these years. As can be seen from table 1 the average census tract has nearly 2% of total county-level population, albeit with considerable variation. I also experiment with using local income as weights. Like the population weights, these are derived from the decennial population censuses for 1970, 1980, 1990, and 2000, and their annual values for each census tract are then interpolated between these years. As with the population share, table 1 demonstrates that this variable is characterized by considerable variation.

Hurricane wind speed estimates of V. Since historical data on hurricanes normally provide wind speeds only at locations where the eye passes over, one needs to simulate these for areas surrounding the eye. Russell (1968) introduced the use of mathematical simulation methods to esti-

[9] http://www.bea.gov/katrina/index2.htm.

TABLE 1.—SUMMARY STATISTICS OF MAIN COUNTY-LEVEL VARIABLES

Sample Period	Variable	Variable Description	Mean	S. d.
1970–2005	*GROWTH*	Personal income per capita growth rate	0.0168	0.0480
1970–2005	*INITIAL*	Logged lagged value of personal income per capita	9.3342	8.1381
1970–2005	*HURR*	Tract population weight. Hurricane measure ($\neq 0$) at 10^6 value	0.1031	0.1025
1970–2005	w_p	Census tract population share of county population	0.0234	0.1071
1970–2005	w_i	Census tract population share of county income	0.0225	0.0580
1970–2005	*SENIOR*	Share of persons above 65 in the population	0.1058	0.0399
1970–2005	*HD*	Dummy for whether hurricane passed over	0.0099	0.0991
1970–2005	*NHD*	Dummy for whether neighboring on where hurricane passed over	0.0224	0.1480
1983–2005	*IM*	Inward migration rate	0.0721	0.0316
1983–2005	*OM*	Outward migration rate	0.0676	0.0278
1992–2005	*GROWTH(O)*	Personal income per capita growth rate of outward migrants	0.0130	0.1697
1992–2005	*GROWTH(I)*	Personal income per capita growth rate of inward migrants	0.0113	0.1300

mate such local hurricane wind speeds and a large number of studies have since followed his proposed methodology.[10] The basic approach in all of these has essentially been to take site-specific statistics of key hurricane parameters, including the radius to maximum wind speed, heading, translation speed, and the coast-crossing position or the distance to the closest approach; implement a Monte Carlo simulation to sample from each distribution; use a mathematical representation of a hurricane along a straight path that satisfies the sampled path; and then record the simulated wind speeds. Here I use wind speed data generated from a new wind field model that is arguably superior to previous methods[11] and provides the underlying data for hurricane loss modeling in the well-known HAZUS software.[12] The full track of a hurricane is modeled beginning with its initiation over the ocean and ending with its dissipation. In essence it consists of two main components: (a) a mean flow wind model that describes upper-level winds and (b) a boundary-layer model that can be used to estimate wind speeds at the surface of the earth over a set of rectangular nested grids given the estimated upper-level wind speeds. The mean flow model, underlying the HAZUS data, developed by Vickery et al. (2000), solves the full nonlinear equations of motion of a translating hurricane and then parameterizes these for use in simulations. Compared to previous approaches, this allows a more accurate characterization of asymmetries in fast-moving hurricanes. The boundary-layer model used is that of Vickery et al. (2008), which is based on a combination of velocity profiles computed using dropsond data and a linear hurricane boundary-layer model. Its advantage, compared to earlier methods, lies in producing better estimates of the effect of the sea-land interface in reducing wind speeds and a more realistic representation of the wind speeds near the surface. Extensive verification through comparison with real hurricane wind speed data showed that this new wind speed model provides a good presentation of hurricane wind fields (see Federal Emergency Management Agency, 2007). In the most recent release of HAZUS (version MR3), this methodology was implemented at the census-tract level to generate maximum wind speeds if these were at least 50 miles per hour, using historical hurricane tracks of tropical storm that were at least of SS category 3 at the time of U.S. landfall over the period 1900 to 2005 as given in the HURDAT database.[13]

Of the 354 tropical storms that, according to the HURDAT database, traversed the Atlantic Basin for the benchmark period, 1970–2005, 21 hurricanes made the HAZUS cut-off criteria. The local wind field estimates are listed table 2. Their hurricane-strength tracks are shown in figure 2. Two points are noteworthy in this regard. First, various counties along the entire coastline were affected, although especially in Florida, Alabama, Mississippi, Louisiana, and Texas. Second, most hurricanes lose wind speeds fairly quickly once they leave the coastal area.

Estimation of λ. An important input variable in equation (2) is λ, the parameter that links wind speed to its level of destruction, as it is derived from equation (1). In this regard, Emanuel (2005) noted that the monetary damage figures from hurricanes tend to increase to the cubic power of the maximum observed wind speed; and hence, λ may be roughly equal to 3. However, his proposed cubic relationship between monetary damages and wind speed is based on only a few rudimentary calculations by Southern (1979) for Australia. In contrast, Nordhaus (2006) conducted a more comprehensive statistical analysis and showed that data for the United States suggest that the relationship between wind speed and damages is closer to the eighth power. More specifically, Nordhaus used data on total costs and maximum wind speeds for a set of twentieth-century hurricanes and regressed the log of the cost per hurricane

[10] See, for instance, Batts et al. (1980) and Vickery and Twisdale (1995).

[11] See FEMA (2007).

[12] HAZUS is a GIS-based natural hazard loss estimation software package developed and distributed without charge by FEMA.

[13] The HURDAT database consists of six-hourly positions and corresponding intensity estimates in terms of maximum wind speed of tropical cyclones in the North Atlantic Basin over the period 1851–2006 and is the most complete and reliable source of North Atlantic hurricanes.

TABLE 2.—HURRICANES IN THE SAMPLE

Name	Year	Maximum Wind Speed	States Affected in Coastal County Sample
Unnamed	1948	137	FL
Unnamed	1949	123	CT, DE, FL, GA, ME, MD, MA, NH, NJ, NY, PA, RI, SC, VA
Easy	1950	119	FL, GA
King	1950	125	FL
Carol	1954	131	CT, ME, MA, NH, NY, NC, RI
Edna	1954	127	CT, ME, MA, NH, NY, NC, NC, RI
Hazel	1954	134	CT, DE, MD, MA, NJ, NY, NC, PA, SC, VA
Connie	1955	106	DE, MD, NJ, NC, PA, VA
Ione	1955	115	NC, VA
Audrey	1957	127	LA, MD, TX, VA
Gracie	1959	125	GA, NC, SC
Donna	1960	144	CT, DE, FL, ME, MD, MA, NH, NJ, NY, NC, PA, RI, SC, VA
Carla	1961	137	TX
Dora	1964	105	FL, GA
Hilda	1964	111	AL, FL, LA, MS
Betsy	1965	151	AL, FL, LA, MS
Beulah	1967	133	TX
Camille	1969	161	AL, LA, MS
Celia	1970	126	TX
Carmen	1974	126	LA, TX
Eloise	1975	131	AL, FL
Frederic	1979	126	AL, FL, ME, MA, MS, NH, NY
Allen	1980	136	TX
Alicia	1983	105	LA, TX
Gloria	1985	119	CT, DE, ME, MD, MA, NH, NJ, NY, NC, PA, RI, VA
Elena	1985	120	AL, FL, LA, MS
Hugo	1989	136	NC, SC
Andrew	1992	157	FL, LA, MS
Opal	1995	100	AL, FL, GA
Fran	1996	98	NC, SC, VA
Bret	1999	111	TX
Jeanne	2004	109	FL, GA
Ivan	2004	109	AL, FL, LA, MS
Frances	2004	105	FL, GA
Charley	2004	147	FL
Wilma	2005	117	FL, SC, VA
Rita	2005	120	LA, MS, TX
Katrina	2005	135	AL, FL, LA, MS
Dennis	2005	114	AL, FL

normalized by U.S. GDP on the logged maximum wind speed and found a coefficient of around 8. However, arguably total U.S. GDP is unlikely to be a good normalization for costs, since hurricanes typically affect areas close to the coast, which constitutes only a small proportion of the United States. Moreover, the relative local wealth that was affected is likely to have changed substantially over the period as coastal communities have grown in size and income.[14] Given that many of the later hurricanes of the twentieth-century were particularly strong, neglecting these features is likely to bias his estimate of λ upward. For example, if one instead regresses the log of the normalized cost values calculated by Pielke et al. (2008), who normalized hurricane damages with regard to changes in inflation, population, and wealth of only the counties affected, on the log of maximum observed wind speeds of the hurricanes in Nordhaus's data set, one finds that the resultant coefficient implies that costs instead rise to the 3.8th, and not the 8th, power of wind speed.

[14] See Rappaport and Sachs (2003).

Given the arguable shortcomings of both Emanuel's (2005) and Nordhaus's (2006) estimates, here I use detailed information in the HAZUS data on what counties were affected by what wind speeds at the census-tract level to generate an arguably more accurate estimate of λ. In this regard, I face, as did Nordhaus (2006), the restriction that the official damage figures of a hurricane are available only in the aggregate, limiting me to estimating the relationship between the average monetary damages per census tract affected and the average wind speed experienced by these. More precisely, I estimate a log-linearized stochastic version of this relationship as

$$log(DAMAGES_{r,t}/N_{r,t}) = \lambda log(\bar{V}_{r,t}) + \varepsilon_{r,t} \quad where \quad \bar{V} = \sum_{j=1}^{N_r} V_{j,r,t} s_{j,t}, \tag{3}$$

where *DAMAGES* are the total monetary hurricane damages, *N* are the census tracts affected, *V* are the local wind speed estimates, *s* is the share of total affected popula-

FIGURE 2.—RELEVANT HURRICANE-STRENGTH TRACKS

tion that is resident in affected county j, ε is a standard error term, λ is the parameter of interest, and the subscript r refers to a particular storm. In estimating equation (3), I used hurricane damage figures from Pielke et al. (2008)—information on which census tracts were affected and the corresponding wind speed estimates from the HAZUS data, and the local population of these as calculated from interpolated census data. For the period 1970 to 2005, this produced a statistically significant coefficient of 3.17 for λ. Using income instead of population shares to calculate the average wind speed of a hurricane resulted in a marginally higher coefficient of 3.18. In order to investigate whether my low value of λ, relative to Nordhaus (2006), is due to my shorter time horizon, I also reestimated equation (3) for the period 1900 to 2005, although, given the sparse information on population size at the census-tract level prior to 1960, this limited me to using a county-level version of the equation. This produced a somewhat higher coefficient of 3.70. Re-running county-level versions of equation (3) separately for the subperiods 1900 to 1969 and 1970 to 2005 resulted in estimates of 3.49 and 4.22, respectively, roughly suggesting that the larger value of λ for 1900 to 2005 than 1970 to 2005 is likely due to the bias of using a census, rather than a tract, level of analysis.

For the remainder of the paper, I thus use 3.17 as the benchmark value for λ. Using a value of λ greater than unity implicitly assumes that local damages increase more than proportionally with the wind experienced. For instance, for $\lambda = 3.17$, if there are two regions with a single inhabitant, then the one exposed to winds of 240 kilometers per hour (equal to level 4 on the SS scale) is assumed to experience almost fourteen times as much damage from the one subjected to winds of only 120 kilometers per hour (equal to 1 on the SS scale).

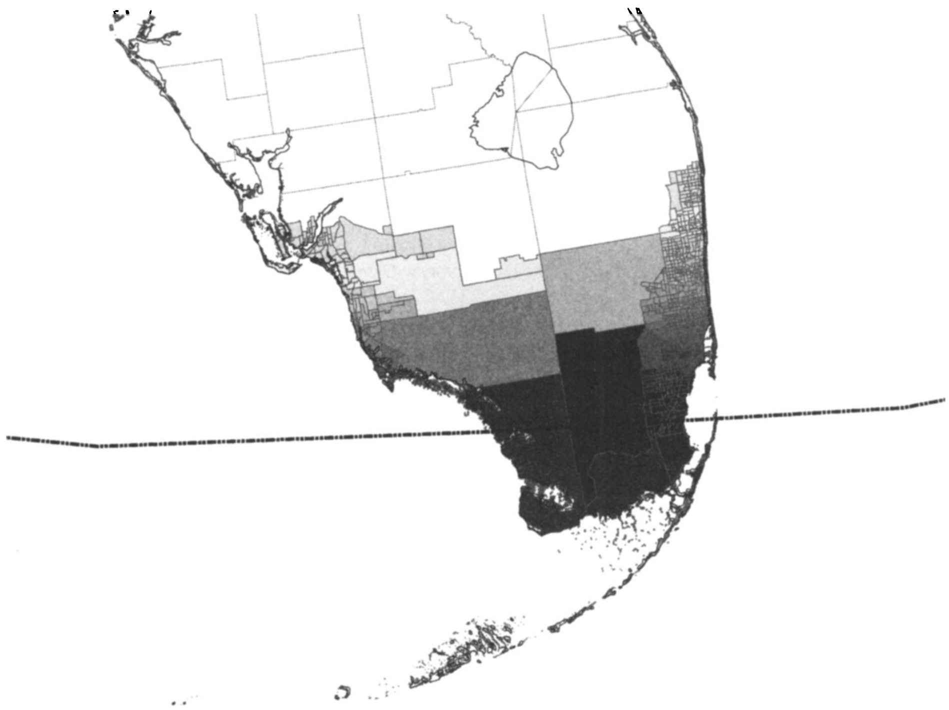
D. *Some Graphical Illustrations of the Hurricane Destruction Proxy*

The data described in Section C provide all the input variables needed to make equation (2) operational. To demonstrate the role of the individual components of V and w in the hurricane damage proxy, *HURR*, I turn to the example of Hurricane Andrew. Andrew first made landfall in Miami–Dade County in Florida on August 24, 1992, and then later crossed into southwest Louisiana. It is considered the second-most-destructive hurricane in U.S. history, and the last of three category 5 hurricanes that made U.S. landfall during the twentieth century (see Landsea et al., 2004). Wind speeds during its landfall reached over 115 miles per hour, and storm surges were as high as 5.2 meters in southern Florida. In terms of damage, Andrew caused around \$26.5 billion worth (\$38.1 billion in 2006 dollars), with most of that damage cost in southern Florida.

Hurricane Andrew's hurricane strength track, taken from HURDAT, is shown in figure 3. Andrew maintained hurricane strengths even as it made a second landfall in Louisiana. The wind speeds generated from the HAZUS wind field model for Florida by census tract, along with the actual hurricane tract, are shown in figure 4, where darker shading indicates stronger wind speed. Accordingly, while the highest wind speeds were experienced along the track of the hurricane, even census tracts over 180 kilometers away from the actual track of the hurricane eye were subject to potential wind damage.

FIGURE 3.—PATH OF HURRICANE ANDREW, 1992

FIGURE 4.—HURRICANE ANDREW SPEED DISTRIBUTION IN FLORIDA



In terms of assessing how the local exposure to potential damages may vary by census tract with regard to its county-level importance (the *w's*), I depict the census-tract-level population share (of a county) in figure 5, where darker shading again indicates higher values. These weight components are not evenly distributed across southern Florida census tracts within counties. More specifically, it is clear that census tracts on the west coast tend to have a greater share of a county's population than those on the east coast due to fact that there are fewer census tracts within counties in the former area.

The derived coastal values of *HURR* for Andrew using our proxies V and w in equation (2) are depicted in figure 6, where darker shading indicates higher values. Again it is obvious that while most of the damage is found along the hurricane's path, other counties, both neighboring and farther away were also affected. Essentially all of the southern tip of Florida was affected; in Louisiana, large parts of the state were subject to damaging wind speeds. Additionally, a small area of Mississippi was affected when Andrew entered the state.

FIGURE 5.—HURRICANE ANDREW POPULATION SHARE (*POP_SHARE*) DISTRIBUTION IN FLORIDA

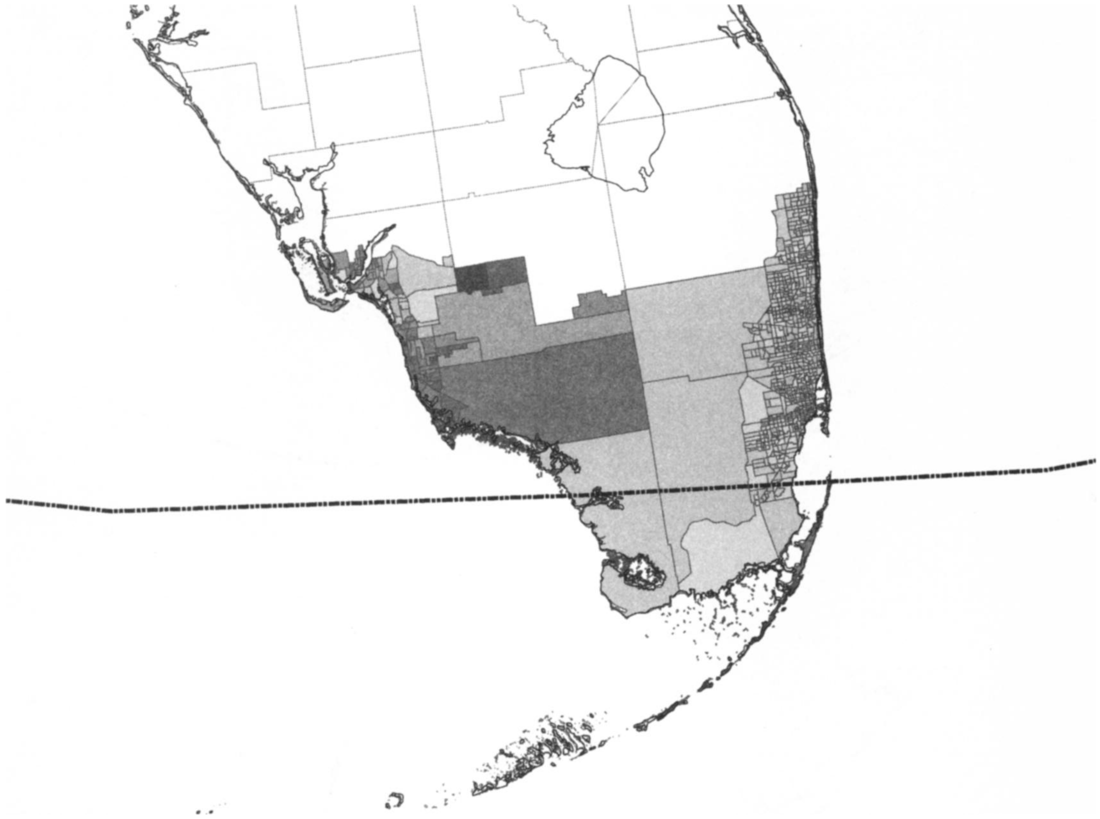


FIGURE 6.—HURRICANE ANDREW DESTRUCTION

Finally, the mean value of *HURR* for all coastal counties over the sample period 1970 to 2005 is shown in figure 7. Accordingly, almost all counties have been affected at least once since the 1970s, with most destruction suffered in Florida, Alabama, Mississippi, Louisiana, and Texas.

FIGURE 7.—MEAN VALUE OF *HURR*, OVER 1970–2005

IV. Econometric Estimation and Results

A. Econometric Specification

The main econometric task in this paper is to investigate the economic growth impact of hurricane strikes at the county level using my index of destruction. To this end, I assume a standard neoclassical growth model as the underlying framework, where a hurricane strike can be considered a negative shock to the capital stock, such as through property destruction, and will temporarily move an economy away from its equilibrium growth path. In this regard, since hurricanes are assumed to entail asymmetric destruction, that is, they leave human capital stock largely intact, they will raise the marginal product of physical capital and hence spur investment so that recovery should be relatively fast (Barro & Sala-i-Martin, 2003). My empirical specification of a county's growth process consists of a standard conditional convergence growth equation:

$$GROWTH_{i,t-1\rightarrow t} = \alpha + \beta_1 log(INITIAL_{i,t-1}) + \beta_2 HURR_{i,t} + \pi_t + \mu_i + \varepsilon_{i,t}, \quad (4)$$

where *GROWTH* is the per capita economic growth rate in county i over $t-1$ to t, *INTIAL* is the initial wealth per capita in county i at time $t-1$, *HURR* is the county-level destruction proxy, summed over all hurricanes r and all census tracts within counties i at time t, π are a set of time dummies, μ is an unobserved county-specific fixed effect, and ε is an error term.

In order to take account of the county-level unobserved fixed effect μ that may be correlated with initial wealth per capita or other regressors, I could simply use a standard panel fixed-effects estimator. However, a worry with equation (4) is that there may be spatial dependence between counties' growth rates that are geographically near. As Anselin (1988), noted depending on the nature of the spatial dependence, failure to take this into account may result in biased or inefficiently estimated coefficients. To investigate whether spatial correlation exists across economic growth rates of counties, I conducted Moran's test for each year of data using a contiguity spatial weighting matrix[15] and found that the null hypothesis of no spatial correlation could be decisively rejected for all but one year, strongly suggesting that spatial correlation is indeed a problem. Commonly, such spatial correlation is modeled either using a spatially autoregressive error term (SEM) or including a spatially lagged dependent variable (SAR). In order to identify which is the more appropriate model for the data, I conducted fixed-effects Lagrange multiplier tests of the presence of a spatial AR error process and the presence of spatially lagged dependent variable (see Elhorst, 2010). Since the significant test statistic was higher for the latter than the former, I followed a suggestion by Florax, Folmer, Rey (2003) and modeled equation (4) as a fixed-effects SEM using a contiguity matrix as the spatial weighting matrix.[16] More precisely, the error term ε in equation (4) is modeled as

$$\varepsilon_{it} = \theta W \varepsilon_{it} + \eta_{it}, \quad (5)$$

where W is the spatial contiguity weighting matrix and θ is the (to be estimated) coefficient of spatial autocorrelation.

Another worry in estimating equation (4) may arise from the fact that *HURR* is by construction only a proxy of actual hurricane damages and hence subject to measurement error. This may result in attenuation bias if the measurement error

[15] A contiguity matrix gives a weight of 1 to each neighboring county and 0 otherwise.

[16] Alternatively I could have also used a spatial decay function weighting matrix where one arbitrarily chooses some distance cut-off point. I experimented doing so using 500 kilometers as the cut-off point and a geometric distance decay function. However, qualitatively this produced essentially the same and quantitatively similar results.

TABLE 3.—COUNTY-LEVEL GROWTH REGRESSIONS

	1	2	3	4	5	6	7	8	9
$HURR_t$		−0.0451*	−0.0439*	−0.0450*	−0.0958**	526.509			−0.0492**
		(−2.509)	(−2.440)	(−2.527)	(−4.647)	(1.698)			(−2.723)
$HURR_{t-1}$			−0.0244						
			(−1.332)						
HD							−0.0164**		
							(−3.407)		
NHD							0.0073		
							(1.901)		
HD(1–3)								−0.0211**	
								(−3.235)	
HD(4–5)								−0.0087	
								(−1.277)	
NHD(1–3)								0.0139*	
								(2.748)	
NHD(4–5)								0.0019	
								(0.344)	
SENIOR									−0.0542**
									(−3.234)
$log(INITIAL)_{t-1}$	−0.0529**	−0.0523**	−0.0523**	−0.0523**	−0.0521**	−0.0534**	−0.0528**	−.0529**	−0.0513**
	(−29.139)	(−28.640)	(−28.578)	(−28.643)	(−28.611)	(−29.048)	(−28.923)	(−28.924)	(−27.578)
θ	0.4870**	0.4859**	0.4870**	0.4829**	0.4840**	0.4889**	0.4869**	0.4829**	0.4890**
	(60.322)	(60.126)	(60.320)	(59.550)	(59.744)	(60.710)	(60.320)	(59.549)	(60.708)
Number of counties:	409	409	409	409	409	409	409	409	409
Observations	14,724	14,724	14,724	14,724	14,724	14,724	14,724	14,724	14,724
HURR:	—	*Tr.Pop.W*	*Tr.Pop.W.*	*Tr.Inc.W.*	*Un.W.*	$\lambda = 1$	—	—	*Tr.Pop.W.*
Period:	*1970–2005*	*1970–2005*	*1970–2005*	*1970–2005*	*1970–2005*	*1970–2005*	*1970–2005*	*1970–2005*	*1970–2005*

** and * denote 1% and 5% significance levels, respectively. Asymptotic t-statistic in parentheses. Tr.Pop.W: Tract-level population weighted; Un.W.: Unweighted. Time dummies included.

is correlated with the true value of hurricane damages, hence biasing the estimated coefficients toward zero (see Wooldridge, 2001). Such a bias will be lower where the mismeasured variable is uncorrelated with the other regressors, as is likely the case in equation (3). Moreover, any correlation between the error term and the true value of damages is likely to be relatively low here given that the error in measurement is most likely to occur for data points where HURR takes on a nonzero value.[17]

B. Econometric Results for Counties

Overall the combined data provide a balanced panel of 409 counties over the period 1970 to 2005. The results of estimating equation (4) on these data first with only including *INITIAL* are shown in the first column of table 3. The spatial autoregressive error term is highly significant, providing further support for modeling spatial correlation of counties' growth rates. The negative and significant coefficient on *INITIAL* suggests a conditional convergence rate of about 5.2%. The implied convergence parameter is not out of line with recent growth studies using county-level data. More specifically, using a cross-sectional variant of Evans's (1997) 3SLS approach, Higgins, Levy, and Young (2006) find for all U.S. counties an average annual convergence rate of between 6% and 8% over the period 1970 to 1998.

For the hurricane destruction index, *HURR*, the resultant coefficient shown in column 2, is negative and significant, indicating that a hurricane strike will cause a county's annual growth rate to fall. Results from using the estimated coefficient and the mean annual value of destruction due to a hurricane shock (the mean of nonzero values) suggest that in a year in which a county is struck by an average hurricane, its growth rate will fall on average by 0.45 percentage points. A year in which hurricane destruction was about a standard deviation above the mean would reduce the growth rate by 0.93 percentage points, while the most destruction viewed in any year in any county in the sample would cause the growth in per capita wealth to fall by at least 3.04 percentage points. These effects are, given that the average county growth rate lies around 1.68%, arguably relatively large.

I also investigated whether there are more long-term effects of hurricanes on county-level growth rates by including a $t-1$ lagged value of *HURR*. The results, shown in column 3, suggest that there is no longer a significant impact after the year in which the hurricane struck. Moreover, although not reported here, further lags also proved to be insignificant.[18] Thus, as suggested by the neoclassical growth model, the effect of a negative shock to the capital stock of a county's economy is relatively short-lived.

An important component of the destruction proxy is the weighting scheme, which is intended to take account of differences in tract-level potential destruction, as benchmark proxied by the distribution of population within a county.

[17] See, for instance, the parallel example on the impact of days of marijuana smoking on wages given by Wooldridge (2001).

[18] From here on, unless otherwise indicated, any further lags always proved to be insignificant and hence are not supported.

However, there may be considerable income inequality even among two equally populated areas. In this regard, wealthier areas are likely to experience greater losses because there is a greater value of property to be potentially destroyed. But it may be that wealthier individuals can afford higher spending on disaster mitigation. I thus investigated whether using income rather than population share weights as w's in equation (2) would affect the estimated coefficient on *HURR*. However, the estimate is virtually identical (see column 4 in table 3).

I also experimented with not controlling for local differences by recalculating *HURR* using an unweighted average of wind speed in equation (2). This gives equal weight to maximum wind experienced across all census tracts. Moreover, it does not allow for counties to change their importance in terms of potential destruction exposure over time. The use of this alternative proxy, as shown in column 5, produces a coefficient over double the size of the weighted one, suggesting that, assuming that local weighting is an important component of *HURR*, failure to take account of local differences in the census tracts affected produces an upwardly biased coefficient. In column 6, I also investigated how assuming a simple linear relationship between wind speed and damages (setting λ equal to 1) would affect the estimated economic growth impact of hurricane strikes. The resulting insignificant coefficient, however, highlights the importance of allowing damages to rise exponentially with the local exposure to wind during a hurricane.

Previous studies of the county-level effects of hurricanes have relied on using simple incidence dummies. For example, Belasen and Polacheck (2009) examined the impact of county-level employment and earnings by using dummies to identify counties where a hurricane directly passed over and neighboring counties. This abstracts from differences in winds experienced and restricts the impact to go no farther than one county off a hurricane's path. The results of using such pass-over and neighboring dummies, *HD* and *NHD*, respectively, are shown in column 7. The hurricane pass-over dummy also produces a statistically significant negative coefficient, but the size of the coefficient suggests that hurricanes reduce county-level growth rates by only 0.02 percentage points. Belasen and Polacheck (2009) decompose their two dummies according to hurricane wind speed at the time of landfall into those of less than 4 and those with at least 4 on the SS scale. Including similar dummies in the specification, depicted in column 8, suggests implausibly that only lower-wind-speed hurricanes reduce growth, as well as that counties neighboring to such hurricanes will experience a boost to their economy.

One of the potential problems with using the BEA county personal income estimates to proxy county-level economic growth rates is that the data represent the income of residents of a county from all sources, regardless of where the income was generated, since it is based solely on the residence of the income tax return filer. Within the context of a hurricane strike, there thus could hypothetically be a situation where negative losses within a county are taken account of in other counties' personal income figures if some of the affected residents file their returns elsewhere. If this measurement error is systematically more likely in counties where hurricane strikes are more probable and of a time-varying nature, then this may produce a biased coefficient on *HURR* in equation (4). Unfortunately I have no information on what role such cross-county tax declarations may play in this context. One possible culprit, however, may be coastal counties with a high incidence of hurricanes but where there are also many recently moved retirees who may still file their tax returns in their county of origin. For example, this could be the case of many counties in Florida popular with retirees. In order to roughly assess the possible role of this example, I include the share of those over the age of 64 in total county population, *SENIOR*, generated from annually interpolating information from the decennial population censuses, as an additional control in equation (4). As can be seen from column 9 in table 3, counties with a greater share of senior citizens experience lower county-level growth rates. More important, including this variable increases the coefficient on *HURR* by about 10%. Of course, it should be kept in mind that the share of senior citizens may be capturing many other factors besides greater cross-county tax filing.

The simple specification in equation (4) abstracts from cross-county heterogeneity that might lead some counties to respond in net growth terms differently from others. Two obvious ones are differences across counties in terms of disaster relief and disaster preparedness. For example, with regard to the latter, Garrett and Sobel (2003) showed that at the state-level the president's disaster declarations are in part determined by whether states are politically important and have congressional representation on FEMA oversight committees. Although not reported here, I did investigate whether such political factors at the county level could induce heterogeneity in the response of county's net growth rates to hurricane strikes and found that having political influence at both the county and state levels, and hence a greater likelihood of receiving disaster assistance, can significantly dampen the effect of hurricanes. In terms of disaster preparedness, I also examined whether participation in the National Flood Insurance Program, which requires a minimum standard of flood preparation for entry, can reduce the effect of hurricanes and found that its role was substantial. (For further details on these extensions, see Strobl, 2009.)

C. *Endogenous Migration*

Given that the distribution of population is unlikely to be static over time, a bias in the estimated coefficient on the hurricane destruction proxy due to population movements may occur through selective inward and outward migration flows that take place immediately in response to a hurri-

TABLE 4.—ENDOGENOUS MIGRATION REGRESSIONS

	1	2	3	4	5	6	7
Dependent Variable:	*OM*	*IM*	*GROWTH*	*GROWTH*	*GROWTH(IM)*	*GROWTH(OM)*	*GROWTH(ADJ)*
$HURR_t$	0.082**	0.093**	−0.061**	−0.070**	−0.108	0.234**	−0.044**
	(5.589)	(5.953)	(−3.257)	(−3.132)	(−1.648)	(2.862)	(−2.322)
OM_t				0.169**			
				(8.230)			
IM_t				0.104**			
				(5.361)			
$OM_t \times HURR_t$				9.144**			
				(7.014)			
$IM_t \times HURR_t$				−8.787**			
				(−7.017)			
$log(INITIAL)_{t-1}$			−0.027**	−0.027**	−0.386**	−0.508**	−0.028**
			(−11.68)	(−11.62)	(−39.172)	(−44.470)	(−11.670)
θ	0.576**	0.551**	0.573**	0.576**	0.187**	0.176**	0.574**
	(61.49)	(64.12)	(69.05)	(69.72)	(11.376)	(10.647)	(69.050)
Number of counties	409	409	409	409	409	409	409
Observations	9,407	9,407	9,407	9,407	5,726	5,726	9,407
Period	*1983–2005*	*1983–2005*	*1983–2005*	*1983–2005*	*1992–2005*	*1992–2005*	*1983–2005*

** and * denote 1% and 5% significance levels, respectively. Asymptotic *t*-statistic in parentheses. Time dummies included.

cane.[19] More specifically, some people may choose to locate elsewhere because of the current destruction experienced and its immediate economic consequences. In this regard, there may also be some inward migration if any recovery effect involves the influx of inhabitants, such as those coming to engage in construction or relief activity. If there is sample selection in the nature of inward or outward migrants in terms of income or property, then the estimated effect of hurricanes on local growth rates may potentially be biased.

To investigate the role of migration, I resorted to the only comprehensive source of information of geographical annual migration flows: IRS County-to-County Migration Data, which are constructed from IRS tax returns and available from 1983 onward.[20] Inward (outward) migration flows are constructed based on year-to-year changes in the addresses entered on income tax returns filed by individual taxpayers and the number of individuals listed on their returns as exemptions. I use these data to construct annual inflow and outflow migration rates (relative to the previous year's number of returns and exemptions) for each county. To assess what role hurricane strikes might play in migration movements, I first regressed each of the two rates on the destruction proxy in the first two columns of table 4 for the period 1983 to 2005. Hurricanes increase both the inflow and outflow rates of migrants (*IM* and *OM*), and the estimated impact is fairly identical for both. Their coefficients suggest that for an averaged-size county, an average hurricane strike induces about 1600 persons to enter and leave.

I next proceeded to reestimate equation (4) for the shorter time period for which migration flow data are available, depicted in column 3. Accordingly, hurricane strikes still have a negative impact on county growth rates, although at a somewhat higher rate than for the entire sample period. I then include the migration inflow and outflow migration rates to control for the direct effect of migration flows, as well as their interaction terms with *HURR* to allow for compositional changes in the flows due to hurricane strikes. As seen in column 4, all of these variables are significant, and their inclusion leads to a higher coefficient on *HURR*, suggesting that not taking account of migration flows may lead to a biased estimate of a hurricane's impact.[21]

Characterizing compositional changes in migrants (that is, selective migration) induced by hurricanes is arguably of interest in and of itself. In this regard, while the IRS migration data do not allow one to explicitly link individuals' incomes over time, they do, from 1993 onward, provide the total personal income of inflowing and outflowing migrants, as declared in their county of destination. The raw data suggest that the per capita income of incoming and exiting migrants is roughly similar in coastal counties—about 90% of those who are incumbent to a county in any year. I use these data to estimate inward and outward migrants' total personal income per capita (that is, per number of total returns and exemptions) in growth versions of equation (4), as depicted in columns 5 and 6 of table 4. Accordingly, greater hurricane destruction has no impact on the growth in incomes of incoming migrants but increases the average

[19] A more long-term channel through which endogenous population movements may occur is through changing return probabilities. In other words, if these are changing over time and are perceived as doing so, then over the longer term there may be a shift of population away from areas with higher return probabilities. I investigate this in a previous version of the paper by including measures of return probabilities in the specification. This indicated that such anticipation shifts may result in an underestimation of the negative effect of hurricanes of up to 26% see Strobl (2009).

[20] For a description of the data, see http://www.irs.gov/taxstats/article/0,,id=212695,00.html. The tax returns are believed to cover around 90% of the population (Gober, Jeffery, & McHugh, 1996).

[21] It is difficult to read too much into the coefficients on the migration terms and their interaction terms as these are highly correlated with each other.

TABLE 5.—STATE, AND NATIONAL-LEVEL GROWTH REGRESSIONS

	1	2	3	4	5	6	7
$HURR_t$	−0.960**	−1.157**	−1.203**	27.915	4.282	36.704	35.651
	(3.244)	(−12.45)	(−15.18)	(657.437)	(232.706)	(597.118)	(176.247)
$HURR_{t-1}$	1.963**	1.764**	1.757**	−274.645	−299.026	28.087	−96.129
	(6.625)	(18.45)	(21.52)	(465.129)	(198.574)	(359.310)	(646.920)
$HURR_{t-2}$	−0.717*	−0.460**	−0.309**	−374.140	−333.918	53.807	22.765
	(−2.386)	(−3.934)	(−3.073)	(774.694)	(430.844)	(494.539)	(263.320)
$HURR_{t-3}$	0.320	0.186	0.056	−128.477	−142.968	−2.859	−16.299
	(1.062)	(1.592)	(0.566)	(951.247)	(282.065)	(416.968)	(239.476)
$log(INITIAL)_{t-1}$	−0.023**	−0.022**	−0.007**	−0.132**	−0.149**	−0.104**	−0.107**
	(−5.949)	(−5.963)	(−5.037)	(0.030)	(0.028)	(0.031)	(0.024)
θ	0.304**	0.358**	0.344**	—	—	—	—
	(17.16)	(21.06)	(25.34)				
Constant	—	—	—	1.363**	1.399**	1.095**	0.996**
				(0.312)	(0.260)	(0.329)	(0.225)
Number of states	*19*	*19*	*19*	—	—	—	—
Observations	*2,603*	*2,603*	*4,370*	*36*	*58*	*36*	*58*
HURR	*Ct.Pop.W.*	*Tr.Pop.W.*	*Ct.Pop.W.*	*Ct.Pop.W.*	*Ct.Pop.W.*	*Ct.Pop.W.*	*Ct.Pop.W.*
Level	*State*	*State*	*State*	*National*	*National*	*National*	*National*
Period	*1970–2005*	*1970–2005*	*1948–2005*	*1970–2005*	*1948–2005*	*1970–2005*	*1948–2005*
Frequency	*Quarterly*	*Quarterly*	*Quarterly*	*Quarterly*	*Quarterly*	*Quarterly*	*Quarterly*
Method	*Sp. SEM FE*	*Sp. SEM FE*	*Sp. SEM FE*	*OLS*	*OLS*	*OLS*	*OLS*
Growth variation	*PI*	*PI*	*PI*	*PI*	*PI*	*GDP*	*GDP*

** and * are 1% and 5% significance levels. Asymptotic *t*-statistic in parentheses. Time and quarter dummies included in all regressions. Ct.Pop.W: country population weight; Tr.Pop.W: tract population weight; Sp. SEM FE: spatially auto regressive error term fixed effects model.

income of outgoing flows. For the latter the estimated coefficient would suggest that the income of outflowing migrants is about 2% higher during an average hurricane. These our results on migrants' income, in conjunction with the finding that both outward and inward migration rise to the same extent during hurricane years, would suggest a likely positive bias in neglecting endogenous migration in estimating equation (4). In other words, because richer people, and more of them, leave as consequence of a hurricane, the actual negative impact on income is overestimated. This stands in contrast to what I found using migration rates and their interaction terms, and hence these may be poor proxies to account for such a bias.

Given that the average income in a county is about \$14,000 and that migrants earn about 10% less than those who remain, the coefficient from column 6 indicates that outflowing migrants during an average hurricane have a higher per capita income of about \$250. To get a rough idea of how large the effect of hurricanes might be if this compositional effect did not occur, I readjusted the BEA per capita income series to include an estimate of the additional income leaving a county during hurricanes due to outward migration. To do so, I first estimated the additional earnings of outflowing migrants during hurricane years using the estimated coefficient in column 6, the value of *HURR*, the average income of outflowing migrants during nonhurricane years (\$12,600), and the number of outflowing migrants. In nonhurricane years, the additional earnings were set equal to 0. I then added this series to the total income in a county and divided this by its population to arrive at an adjusted per capita income series. The results of estimating equation (4) using this adjusted series is shown in the last column of table 4. The resultant coefficient is substantially lower, where the estimate suggests that the exit of relatively richer people during hurricanes can account for about 28% of the observed negative growth impact.

D. *State and National Effects*

It is also of interest to examine how the net negative growth impact of hurricanes in coastal counties translates into state-level growth patterns, given that a large portion of counties within a state may be only indirectly affected. Additionally, moving to the state and national levels allows us to investigate the effect of hurricanes at quarterly rather than annual frequency due to greater data availability. The destruction index in equation (2) can be easily altered to derive quarterly state-level measures by using the quarterly census tract share of state-level population as weights.[22] Given that the effect at the county level was only within the year of the hurricane, I include the contemporaneous value as well as up to three quarterly lags of the proxy in a state-level version of equation (4).[23] As with the county-level data, Moran and Lagrange multiplier test statistics suggested that using an SEM model was the appropriate econometric model.

The results of using quarterly data for the period 1970 to 2005 for the nineteen coastal county states are given in column 1 of table 5. As with the county-level annual data, there is an immediate negative effect of a hurricane, where the estimated coefficient implies a 3.55 reduction in a state's growth rate. The coefficient on the $t-1$ lag value of

[22] I linearly interpolated the annual tract-level population figures to obtain quarterly values.

[23] Further lags proved insignificant in all state-level specifications.

HURR is, in contrast, positive and significant, suggesting that in the quarter immediately after the hurricane, there will be a net positive boost to a state's economy, likely due to disaster assistance, cleanup, and the production of replacement capital. The size of the coefficient suggests that such a recovery effect is about 7.25 percentage points of growth. A quarter later, at $t-2$, a negative effect again prevails, although at a smaller scale than the initial growth-reducing impact. By the third quarter, there are no longer any significant effects. While summing values of the coefficients across the three significant variables suggests a net positive effect of about 0.7 percentage points, a simple t-test of the hypothesis that the sum of the (significant) coefficients on the hurricane variables is equal to 0 cannot be rejected. Thus, at the state level, the impact of a hurricane is netted out within one year. These state-level results would also suggest that the annual county-level data may also mask any recovery effects of hurricanes that would be apparent in higher-frequency data.[24]

Another advantage of using state-level quarterly data is that they extend as far back as 1948 so that I can investigate whether my results are robust over the historical long term. One difficulty in this regard is, however, that tract-level population information is not available prior to 1970, so I cannot weight tract-level hurricane wind estimates by local population size. As shown earlier, using a simple average, unweighted, wind destruction within a county produces a larger negative effect. To see how using this alternative, but arguably inferior, measure might affect the estimated impact of hurricane strikes at the state level, I took county-level values, multiplied these by county-level shares of state-level population, and summed this product within states to obtain a state-level equivalent measure. Including this proxy in state-level regressions, as shown in column 2 of table 5, although qualitatively similar, confirms the quantitative discrepancy compared to a tract-level-based measure. Again, a simple t-test suggests that the net annual effect is 0.

I next calculated in column 3 the effect of hurricane strikes since 1948 with the quarterly state-level nonlocally weighted proxy. This qualitatively confirms the result for the period 1970 to 2005 where I found a large negative, followed by a large positive, and then a smaller negative effect. As with the shorter period, a t-test suggests that this overall annual net effect is not statistically significant.

The final task is to examine whether local natural disasters like hurricanes are economically important enough to make a significant net impact on the national economic growth path. Again the destruction proxy can easily be altered to arrive at a national measure by using shares of national-level population as weights. The results of using the locally unweighted measure of destruction for the shorter time period with quarterly data and standard OLS are shown in column 4 of table 5.[25] Accordingly, there is no evidence of any net impact of hurricanes on U.S. national growth rates. Extending the sample period back to 1948, depicted in column 5, confirms this lack of an impact. I also experimented with using the growth rate in national GDP as the dependent variable given that GDP will also capture the production value of other goods and services not reflected in personal income. However, as can be seen from the final two columns of table 5, similar to the personal income data, there is no effect of hurricane destruction on national growth rates.

V. Conclusion

I investigated whether hurricanes in the United States have had any impact on local economic growth rates and whether any effect in this regard was reflected at higher regional levels. To this end, I developed a measure of hurricane destruction based on a monetary loss equation, local wind speed estimates derived from a physical wind field model, and local exposure characteristics and employed this proxy within an economic growth framework on annual county-level panel data. The econometric results suggested that hurricanes have an arguably large—at least 0.45 percentage points—negative impact on coastal counties' annual growth rates. I also show that about 28% of the negative growth effects of a hurricane are due to relatively richer people moving away from affected counties in response to the hurricane. Results at the state level, where higher-frequency and long-term data were available, indicated an initial negative impact, a recovery effect in the subsequent quarter, followed again by a smaller negative effect. Overall, these translate into an overall net annual negligible impact of hurricanes in coastal states. For national-level economic growth rates, in contrast, there is no discernable effect even at a quarterly frequency.

These findings suggest overall that hurricanes may cause large economic growth losses and disruption to economic activity at the local level in any year. Moreover, the fact that hurricanes are generally spatially very limited means that in the long term, they have no net annual impact at the state level and do not show up in national growth volatility at all. As a final note of caution, these results should not be taken to suggest that at the state or national level, hurricanes are not bad for the economy. Naturally, resources used to replace destroyed capital cannot be used elsewhere, and hence growth, even at the level of the state, may be less in the much longer run than if the hurricane had not struck. Similarly, funds used to reimburse insurance claims and provide disaster relief assistance, while perhaps not coming

[24] Another possibility may be that the positive effect is due to noncoastal counties in a state not affected directly by the hurricane but that may experience an increase in output by providing resources for the relief and replacement activity in those affected. In this regard, I reran equation (4) for all noncoastal counties but found no significant effect of hurricanes.

[25] Using a tract-level weighted measure produced qualitatively similar results.

directly from the affected state, will have to come from somewhere, and thus sacrificed from other potentially more nationally growth-enhancing uses.

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